Asset Price Bubbles and Systemic Risk*

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December 31, 2017

Abstract

This paper documents that asset price bubbles go along with elevated systemic risk using data from 17 OECD countries over almost 30 years. This relationship can emerge already in the boom phase of the bubble and is strong for both stock market as well as real estate bubbles. Importantly, interaction terms with bank characteristics (loan growth, size, leverage, and maturity mismatch) show that this link is more pronounced for banks with higher loan growth and larger size. Moreover, larger bubbles are associated with higher systemic risk, while the findings with respect to the length of a bubble episode are mixed.

Keywords: Asset price bubbles, systemic risk, financial crises, credit booms, ΔCoVaR.

JEL-Classification: E32, G01, G12, G20, G32.

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*We thank our discussants Kerstin Bernoth, Kristina Bluwstein, Andrei Dubovik, Simon Gilchrist, Carolin Holzmann, Erik Lüders, Alberto Martin-Utrera, Deyan Radev, and Melanie Schienle, as well as Mark Carlson, Hans Degryse, Florian Heider, Vasso Ioannidou, Markus Pelger, Farzad Saidi, and Stefan Zeume, and conference participants of the Spring Meeting of Young Economists in Halle, the 6th Research Workshop in Financial Economics in Bonn, the FIRM Research Conference in Mainz, the annual meeting of the Verein für Socialpolitik in Wien, the 9th European Banking Center Network Conference in Lancaster, the Wharton Conference on Liquidity and Financial Fragility in Philadelphia, the CPB seminar in Den Haag, the Workshop on Bubbles in Macroeconomics in Barcelona, and the Conference "Women in Macroeconomics and Finance" in Cologne for valuable comments and suggestions. Financial support from the Frankfurt Institute for Risk Management and Regulation (FIRM) is gratefully acknowledged.

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1 Introduction

Financial crises are often accompanied by a boom and bust cycle in asset prices (Borio and Lowe, 2002; Kindleberger and Aliber, 2005). Bursting asset price bubbles can have detrimental effects on the financial system and give rise to systemic financial crises. Yet, not all bubbles are equally harmful. Some, like the one preceding the Great Financial Crisis, contribute to the collapse of the entire financial system, while others, like the dotcom bubble, cause high financial losses but do not have any wider macroeconomic consequences.

Historical evidence suggests that the severity of crises after the burst of a bubble depends on the involvement of the financial system. For example, bubbles accompanied by strong lending booms tend to be followed by more severe crises (Jordà, Schularick, and Taylor, 2015b; Brunnermeier and Schnabel, 2016). Moreover, disturbances in small market segments may be amplified through the financial sector. The US subprime mortgage market accounted for only 4 percent of the US mortgage market at the time of the burst of the bubble (Brunnermeier and Oehmke, 2013, p. 1223). Yet, the burst of the subprime housing bubble gave rise to one of the biggest financial crises in history because the initial shock was amplified by the materialization of imbalances that had built up in the financial sector. While the impact of asset price bubbles on macroeconomic variables has been well-documented (see, for example, Jordà, Schularick, and Taylor, 2013, 2015a,b), little is known about the role of individual financial institutions in the build-up of systemic risk in response to asset price bubbles. However, such knowledge is crucial if one wants to understand the channels through which asset price bubbles affect systemic risk and and if one wants to design appropriate policy responses.

We fill this gap in the literature by empirically analyzing the relationship between asset price bubbles and systemic risk at bank level. We analyze stock market and real estate bubbles in 17 countries over almost thirty years, focusing on the role of banks' size, loan growth, leverage, and maturity mismatch as contributing factors. Additionally, we study the role of bubble characteristics, namely their length and size. Together with differences in bank-level developments, these bubble characteristics provide an explanation for the large heterogeneity in the relationship between asset price bubbles and systemic risk across bubble episodes.

Our analysis is based on a broad, bank-level dataset spanning the time period from 1987 to 2015. The dataset contains monthly observations on 1,438 financial institutions. The empirical analysis aims to explain a bank's contribution to systemic risk as a function of the occurrence of financial bubbles as well as bank- and country-level characteristics. Our analysis distinguishes between the boom and bust phases of bubble episodes to be able to analyze both the build-up of financial imbalances as well as their bursting. We allow the effect of bubbles to depend on bank-level characteristics, namely bank size, loan growth, leverage, and maturity mismatch, as well as on bubble characteristics.

The key challenges for our analysis are twofold. First, bubble episodes need to be identified. Asset price bubbles that were followed by deeper turmoil when bursting have attracted most attention in the literature. Relying on such bubbles could lead us to overestimate the relationship between asset price bubbles and systemic risk. To prevent this sample selection bias, we instead estimate bubble episodes based on the Backward Sup Augmented Dickey-Fuller (BSADF) approach introduced by Phillips, Shi, and Yu (2015a,b). This approach identifies bubble episodes by systematically searching subsamples of price data for explosive episodes.

The second challenge lies in the quantification of systemic risk. We apply the ΔCoVaR (conditional value at risk) measure introduced by Adrian and Brunnermeier (2016). This measure estimates institution-specific contributions to systemic risk and allows us to conduct the analysis at the bank level. More precisely, it measures how much the risk of the whole financial system increases as the considered institution gets into financial distress. We calculate the ΔCoVaR for each of the 1,438 financial institutions in our sample using all available observations from 1987 to 2015. Unlike a financial crisis dummy, the continuous measure of systemic risk also accounts for periods of high risk in the financial sector that did not result in a crisis.

Our results are in line with the common conjecture that asset price bubbles pose a threat to financial stability. Specifically, our results show that the burst of an asset price bubble goes along with a 14 to 18 percent increase in systemic risk compared to its average level. This observation is not limited to the turmoil following the burst of a bubble, but it exists to some extent already during its emergence. Policies aimed at preventing financial turmoil resulting from an asset price bubble should thus not solely focus on the bust period of the bubble. Instead, the risks building up in the financial system should ideally be counteracted early on. While the strength of the relationship differs across asset classes, it is significant for both stock market and real estate bubbles.

Most importantly, the degree to which asset price bubbles are associated with increased systemic risk depends strongly on banks' balance sheet characteristics. In case of a large bank size, high loan growth, high leverage, and a large maturity mismatch, asset price bubbles go along with an up to 53 percent increase in systemic risk, which corresponds to an increase of the aggregate ΔCoVaR by more than two standard deviations. These results prove to be very robust. They are not specific to the way in which ΔCoVaR is estimated. Both small and large banks are affected, although to a different extent, and neither a certain country nor a specific time period drive the results. Consequently, strengthening the resilience of the financial system at the bank level can significantly decrease the system's vulnerability to asset price bubbles. Additionally, the relationship depends on the specific characteristics of bubble episodes. Longer and more sizeable bubbles tend to be more strongly related to systemic risk in a stock market boom (though not in a real estate boom), while a longer bust and a stronger previous deflation of the bubble in stocks and real estate goes along with lower systemic risk.

The paper proceeds as follows. We start with a brief discussion of the related literature in Section 2. Section 3 elaborates on the identification of bubble episodes, the estimation of ΔCoVaR, and the dataset used in the main analyses. The empirical model is presented in Section 4, followed by a discussion of results in Section 5 and of robustness checks in Section 6. We conclude with a brief discussion of policy implications in Section 7. The Appendix contains additional details on estimation procedures as well as further tables.

2 Related literature

Our paper contributes to the literature studying the connections between asset price bubbles, systemic risk, and financial crises. Asset price bubbles and financial crises related to the boom and bust of asset prices are recurrent features of financial systems in both developed and developing economies. Historical accounts of prominent financial bubbles have been given, among others, by

Shiller (2000), Garber (2000), Kindleberger and Aliber (2005), Allen and Gale (2007), Reinhart and Rogoff (2009), as well as Brunnermeier and Schnabel (2016).

The relationship between asset price bubbles and systemic risk has hardly been analyzed in a systematic way although the corresponding narrative has been known for a long time (cf. Minsky, 1982). A more precise notion of systemic risk as a concept for the stability of entire financial systems appeared only in the late 1990s and early 2000s, which has given rise to a large literature attempting to measure systemic risk, including Acharya, Engle, and Richardson (2012), Brownlees and Engle (2015), Adrian and Brunnermeier (2016), as well as Acharya, Pedersen, Philippon, and Richardson (2017). An early literature review on concepts of systemic risk is provided by de Bandt and Hartmann (2000). Bisias, Flood, Lo, and Valavanis (2012) provide a taxonomy and discussion of measurement approaches. Reviews that also consider the theoretical literature include Allen, Babus, and Carletti (2012) as well as Brunnermeier and Oehmke (2013). Gertler and Gilchrist (2017) describe how the recent theoretical and empirical literature can explain the developments during the Great Recession. They also provide an empirical analysis based on which they emphasize the importance of the disruption of financial intermediation relative to other contributing factors. Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013, 2015a,b) provide an econometric analysis of the impact of asset price bubbles on the likelihood and costliness of financial crises using long-run historical data. Another broad strand of the literature deals with the role of monetary policy for the development of asset price bubbles and financial stability (see, for example, Bordo and Jeanne, 2002; Galí, 2014; Galí and Gambetti, 2015; Brunnermeier and Schnabel, 2016).

Bursting asset price bubbles go along with declining asset prices that can set in motion loss and liquidity spirals in which distressed institutions are forced to sell assets, thereby further depressing prices and forcing further asset sales. Through such dynamics, systemic risk may spread well beyond the institutions affected by the initial shock. Brunnermeier (2009), Hellwig (2009) as well as Shleifer and Vishny (2011) argue that it is exactly such dynamics that allow risk to become systemic. Moreover, already Bernanke and Gertler (1989) as well as Bernanke, Gertler, and Gilchrist (1999) pointed out that consequences of losses in net worth are usually long-lasting. Loss and liquidity spirals are the subject of a large literature, including Shleifer and Vishny (1992, 1997, 2011), Allen and Gale (1994), Kiyotaki and Moore (1997, 2005), Xiong (2001), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Acharya, Gale, and Yorulmazer (2011), Acharya and Viswanathan (2011), Diamond and Rajan (2011), as well as Brunnermeier and Sannikov (2014). Empirical evidence on such spirals is provided, for example, by Schnabel and Shin (2004), Adrian and Shin (2010), and Gorton and Metrick (2012).

Moreover, asset price bubbles may not only trigger the materialization of financial imbalances. They can also cause the buildup of these imbalances. Rising prices increase the value of borrowers' collateral (Bernanke and Gertler, 1989) and the liquidity of assets (Kiyotaki and Moore, 2005), causing banks to increase lending and reduce precautionary liquidity holdings. If the increases in asset prices are due to a bubble, the increased lending might turn out to be excessive and liquidity provisions may prove insufficient. Shin (2008) provides a model considering demand-side and supply-side effects of asset prices on banks' balance sheets and the ensuing effects on individual institutions' risk in the financial sector.

Our paper contributes to this literature by analyzing whether the relationship between asset price bubbles and systemic risk depends on financial institutions. Hence, it takes the analysis of bubbles from the macroeconomic to the microeconomic level while maintaining a systemic perspective through the measurement of risk. Bubbles as well as systemic risk are measured on the basis of quantitative procedures (see Section 3) to avoid the selection bias inherent in historical accounts of bubbles and financial crises. Our paper considers both the emergence of systemic risk in the boom phase as well as the materialization of risk in the bust phase of the bubble. Finally, the paper focuses on a broad set of countries and a time period of almost thirty years, thereby going beyond the analysis of individual bubble episodes.

3 Data

Our analysis is based on a broad, bank-level dataset spanning the time period from 1987 to 2015. It hence includes not only the US subprime housing bubble which marks the beginning of the global financial crisis, but also many other bubble episodes, such as the dotcom stock market boom and bust at the end of the 1990s or the real estate boom and bust cycles around 1990 in many countries. The dataset contains monthly observations on 1,438 financial institutions located in 17 countries, yielding a total of 165,149 observations for our baseline regressions.[1] Table C.2 in the Appendix lists the number of observations per country. We see that the number of banks, and hence observations, differs widely across countries. Most importantly, the number of US banks is very large, which is driven by the large number of small publicly traded US banks. We analyze in robustness checks whether this affects our results.

In our main analyses, we explain banks' systemic risk contributions by the occurrence of bubbles in real estate or stock markets as well as by bank characteristics while controlling for macroeconomic variables. In the following subsections, we first explain the construction of the bubble indicators. Afterwards, we briefly describe the estimation of ΔCoVaR, our measure of banks' systemic risk contributions. Finally, we provide details on our bank-level data and the macroeconomic control variables.[2]

3.1 Bubble indicators

We identify bubble episodes by applying the Backward Sup Augmented Dickey-Fuller (BSADF) approach introduced by Phillips, Shi, and Yu (2015a,b) and recently developed further by Phillips and Shi (forthcoming). It is well established in the literature.[3] Like many other bubble identification approaches, the BSADF approach is built around tests for explosive behavior in price data. Repeated episodes of such explosive behavior are generally difficult to distinguish from a stationary time series. For this reason, the BSADF approach applies sequences of Augmented Dickey-Fuller (ADF) tests to systematically changing fractions of a sample of price data, which allows to detect asset price bubbles even when emerging in rapid succession. This property is valuable for our study as the analyzed sample typically covers more than one bubble episode per price series. The simulations in Breitung and Homm (2012) and Phillips, Shi, and Yu (2015a) confirm that the BSADF approach outperforms comparable methods in terms of size and power when multiple bubble episodes occur within a dataset.[4] Appendix A provides a detailed description of the estimation procedure.

[1] The included countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[2] Variable definitions and data sources are provided in Table C.1 in the Appendix.

[3] See, e. g. Gutierrez (2013); Bohl, Kaufmann, and Stephan (2013); Etienne, Irwin, and Garcia (2014); Jiang, Phillips, and Yu (2015).

[4] Similar approaches are proposed by Kim (2000), Kim and Amador (2002), Busetti and Taylor (2004), Phillips, Shi, and Yu (2011) and Breitung and Homm (2012). Early contributions were the approaches in Shiller (1981),

We identify real estate bubbles using quarterly real house prices provided by the OECD for the period 1976 to 2016. Stock market bubbles are estimated based on monthly observations of country-specific MSCI indices over the period 1973 to 2016 obtained from Thomson Reuters Datastream.[5] Each MSCI index covers 85 percent of a country's total market capitalization. The MSCI indices are computed based on a single methodological framework, which makes them comparable across countries. We include all countries for which data on both real estate and stock markets are available, which leaves us with a total of 17 OECD countries.

The BSADF approach identifies the beginning of a bubble episode as the point in time at which the sequence of BSADF test statistics first exceeds its critical value (cf. the blue and red dotted lines in Figure 1) and thus signals the price data (cf. the black line in Figure 1) being on an explosive trajectory. The end of a bubble episode is reached once the test statistics fall back below their critical values. Additionally, we distinguish between the boom and the bust phase of a bubble (cf. the blue and grey shaded areas in Figure 1) based on the peak of the price series during each bubble episode. Using this approach, we construct four binary variables for each country, indicating episodes in which a real estate or stock market bubble emerges or collapses. We make these distinctions as the relationship between asset price bubbles and systemic risk is likely to differ across asset classes as well as phases of the asset price cycle. Since the real estate data are available only at quarterly frequency, while our main analyses rely on a monthly frequency, the real estate bubble indicators take on the value of the corresponding quarter for each month of the quarter.

[Figure 1 about here]

Table 1 gives an overview of the estimated bubble episodes. We see that stock market bubbles occur more frequently but are much shorter than real estate bubbles. Overall, our sample comprises

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LeRoy and Porter (1981), West's (1987) two-step tests, integration and co-integration based tests as proposed by Diba and Grossman (1988), and tests for intrinsic bubbles as in Froot and Obstfeld (1991). See Gürkaynak (2008) for a discussion of these approaches.

[5]The data used to estimate the bubble episodes go back further than the data used in the main analysis. The larger historical coverage improves the properties of the BSADF test. Its size distortions vary between 1 and 2.2 percentage points for sample lengths between 100 and 1,600 observations. The evolution of the size distortions over increasing sample lengths is U-shaped. The power of the test is reported with 0.7 for T=100, 0.9 for T=200 and approaching 1 for T=1600 (Phillips, Shi, and Yu, 2015b).

35 real estate booms and 28 busts, while it contains 50 stock market booms and 49 busts. The number of booms and busts may differ for a country if a bubble is already in the bust phase in the beginning of our sample period or if a bubble is still in the boom phase at the end of our sample. On average, countries experienced around two real estate and three stock market bubbles. Real estate booms last on average for five years, while the bust lasts for only one year. Stock market booms last on average less than two years and the busts last only half a year. The shorter lifespan of stock market bubbles is consistent with stock prices moving more quickly than real estate prices.

[Table 1 about here]

Figure 2 displays the occurrence of booms and busts per country. We see that stock market bubble episodes are clustered around but not limited to the run-up to the global financial crisis, the dotcom bubble as well as the mid-1980s. Real estate bubbles are much more persistent, especially since the 2000s when most countries experienced a real estate bubble.

[Figure 2 about here]

We cross-check our estimation results by comparing the estimated bubble episodes with those identified in the literature. All episodes discussed in the literature are also identified by our estimations. It is still conceivable that we identify too many bubble episodes. However, the prevalent bubble episodes in the literature are mostly those which were followed by financial sector turmoil after their burst. Since we find a positive relationship between asset price bubbles and systemic risk, falsely labeling episodes free of such repercussions as bubbles would bias our results towards not finding a relationship between bubbles and systemic risk, i. e., to an underestimation of the true effect.

3.2 Systemic risk contributions

Our goal is to analyze the link between the occurrence of asset price bubbles and systemic risk contributions of individual financial institutions. One prominent measure of systemic risk contributions is ΔCoVaR introduced by Adrian and Brunnermeier (2016).[6] It quantifies the contribution of a financial institution to the overall level of systemic risk by estimating the additional value at risk (VaR) of the entire financial system associated with this institution experiencing distress.

The VaR is the maximum return loss x_i of institution i that will not be exceeded with probability q within a certain time:

$$Pr(X^i \leq VaR_q^i) = q\% \ . \tag{1}$$

CoVaR is defined as the VaR of the system conditional on event $C(X^i)$ of institution i:

$$Pr(X^{system}|C(X^i) \leq CoVaR_q^{system|C(X^i)}) = q\% \ . \tag{2}$$

$\Delta CoVaR_q^{system|i}$ captures the difference between the financial system's value at risk conditional on institution i realizing return losses at the q^{th} percentile of its return loss distribution and the system's value at risk conditional on institution i realizing return losses at the 50^{th} percentile:

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i = VaR_q^i} - CoVaR_q^{system|X^i = VaR_{50}^i} \ . \tag{3}$$

A larger value of ΔCoVaR thus corresponds to a higher systemic risk contribution of institution i.

The measure is based on tail dependencies of equity returns, which are estimated in three steps using quantile regressions.[7] First, we estimate the VaR of institution i as

$$\widehat{VaR}_{q,t}^i = \hat{X}_t^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \ . \tag{4}$$

[6] Alternative measures of systemic risk include the Option-iPoD (Capuano, 2008), the DIP (Huang, Zhou, and Zhu, 2009), the measures introduced in Segoviano and Goodhart (2009) as well as in Gray and Jobst (2010), SES (Acharya, Engle, and Richardson, 2012; Acharya, Pedersen, Philippon, and Richardson, 2017), ΔCoJPoD (Radev, 2013, 2014), realized systemic risk beta (Hautsch, Schaumburg, and Schienle, 2015), and SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2015).

[7] Quantile regressions allow the estimated coefficient to depend on a quantile of the distribution of the dependent variable. This is achieved by minimizing the weighted absolute difference between some quantile q of the dependent variable and its fit. Unlike OLS, this least absolute deviation (LAD) estimator does thus not assign equal weight to all observations. For a detailed exposition of quantile regressions, see Koenker (2005). The literature suggests a number of alternative estimation techniques: MGARCH (Girardi and Tolga Ergün, 2013), copulas (Mainik and Schaanning, 2012; Oh and Patton, 2015), maximum likelihood (Cao, 2013), and Bayesian inference (Bernardi, Gayraud, and Petrella, 2013). All of these alternative approaches are less frequently applied than the quantile regression approach.

M_{t-1} is a vector of control variables consisting of general risk factors listed in Appendix B, and X_t^i denotes return losses on equity of institution i. We apply a stress level of $q = 98\%$ in all regressions. Next, the relationship between institution-specific losses and system losses is estimated as

$$\hat{X}_{q,t}^{system|i} = \hat{\alpha}_q^{system|i} + \hat{\gamma}_q^{system|i} M_{t-1} + \hat{\beta}_q^{system|i} X_t^i \ . \tag{5}$$

The conditional value at risk is calculated by combining estimates from the two previous regressions:

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{system|i} + \hat{\gamma}_q^{system|i} M_{t-1} + \hat{\beta}_q^{system|i} \widehat{VaR}_{q,t}^i \ . \tag{6}$$

Following the definition provided in Equation (3), the time series of ΔCoVaR are calculated as

$$\Delta CoVaR_{q,t}^i = \hat{\beta}_q^{system|i} (\widehat{VaR}_{q,t}^i - \widehat{VaR}_{50,t}^i) \ . \tag{7}$$

Appendix B elaborates on the data, its sources and further details of the estimation strategy.

This approach leaves us with monthly estimates of ΔCoVaR for 1,438 financial institutions. Table 2 provides summary statistics for ΔCoVaR and the further covariates described subsequently. The mean of ΔCoVaR equals 1.96 such that distress at one institution is associated with an average increase in the financial system's conditional value at risk by 1.96 percentage points. Figure 3 displays the evolution of the average ΔCoVaR in the four considered financial systems over time. All four financial systems show a marked peak in ΔCoVaR at the time of the global financial crisis. However, this crisis does not drive our results (cf. Section 6.3). The peak is more pronounced in Europe compared to the US, potentially due to the larger number of small financial institutions in the US. To account for such differences in the composition of financial systems, we make use of sample splits and regressions with observations weighted by bank size (cf. Section 6.2); the results are robust. Other times of financial system distress, such as the euro area crisis or the Japanese banking crisis at the beginning of the 1990s, are visible as well. In contrast, the dotcom crisis is hardly reflected in the ΔCoVaR series.

[Table 2 about here]

[Figure 3 about here]

3.3 Bank-level variables and macroeconomic controls

Systemic risk at the individual level is partly driven by bank characteristics. Therefore, we control for important balance sheet characteristics, namely bank size, loan growth, leverage, and maturity mismatch. In addition, the relationship between asset price bubbles and systemic risk may also depend on bank characteristics. For instance, if banks individually are in bad shape, the financial system is likely to be more vulnerable to asset price bubbles. Hence, we interact the bank characteristics with the bubble indicators in order to capture the varying susceptibility of banks to systemic effects from asset price bubbles.

Bank balance sheet data are obtained from Bankscope. It has been shown in earlier research that size (measured as the logarithm of total assets), leverage (defined as total assets divided by equity), and maturity mismatch (i. e., short-term liabilities minus short-term assets, divided by total assets) drive an institution's systemic risk contribution (Adrian and Brunnermeier, 2016). We additionally shed light on the role of loan growth (Δlog(loans)), as credit-fueled bubbles are perceived to be particularly harmful (Jordà, Schularick, and Taylor, 2015b; Brunnermeier and Schnabel, 2016). We apply cubic spline interpolations to obtain monthly observations. Moreover, we winsorize the bank-level variables at the 1-percent and 99-percent level to deal, for example, with extreme values of leverage of institutions on the brink of default and extraordinary high loan growth of institutions starting from a very low level of loans.

Table 2 shows that the median bank is very small with total assets of around 2 billion US dollars and that size varies greatly. In our analyses, we also address whether the link between small and large banks' systemic risk contributions and asset price bubbles differs beyond what is captured by controlling for total assets (cf. Section 6.2). Average loan growth is close to zero but our sample contains many observations with high positive and high negative growth rates. The median bank has a leverage of 11.7 and a median maturity mismatch of 0.75, again with a wide variation.

In addition to bank-level variables, we control for a number of macroeconomic variables. To this end, we obtain data on credit to the private non-financial sector from the BIS. Data on investment, 10-year government bond rates, the CPI and GDP are from the OECD. Data on policy rates are taken from the OECD, Thomson Reuters Datastream and national central banks. Variables at quarterly frequency are adjusted to monthly frequency using cubic spline interpolations.

As seen in Table 2, average real GDP growth is 2.1 percent in our sample period. 10-year government bond rates are on average 4.2 percent and inflation rates 2.2 percent. Investment-to-GDP growth is slightly negative on average, and credit-to-GDP growth is equal to 1 percent. Looking at the maxima and minima, we can see that the sample includes severe recessions as well as strong booms, hence it mirrors the diverse macroeconomic developments of our 17 sample countries over the sample period of almost thirty years.

4 Empirical model

To analyze the relationship between asset price bubbles and systemic risk, we regress the systemic risk contributions ($\Delta CoVaR_{i,t}$) of institution i at time t on bank fixed effects (α_i), the four bubble indicators for the episodes of booms and busts of stock market and real estate bubbles ($Bubble_{c,t}$) in country c at time t, the lagged bank-level variables size, loan growth, leverage, and maturity mismatch ($B_{i,t-1}$), the respective interaction terms with the bubble indicators, and the lagged country-specific macroeconomic control variables ($C_{c,t-1}$):

$$\Delta CoVaR_{i,t} = \alpha_i + \beta \cdot Bubble_{c,t} + \gamma \cdot B_{i,t-1} + \delta \cdot Bubble_{c,t} \cdot B_{i,t-1} + \lambda \cdot C_{c,t-1} + u_{i,t} \ . \tag{8}$$

A larger value of ΔCoVaR corresponds to a higher systemic risk contribution. Consequently, we expect a positive sign for all coefficients included in β as this would represent a positive relationship between asset price bubbles and systemic risk. The bank-level variables allow us to control for the most important bank-specific risk factors that are known to drive the systemic risk contributions measured by ΔCoVaR (Adrian and Brunnermeier, 2016). The interaction terms with the bubble indicators are included as we expect the bank characteristics to play a different role during bubble episodes compared to normal times. For instance, loan growth at the bank level might be beneficial for financial stability in normal times. However, in the presence of a bubble and to the extent that the loans finance the bubble, loan growth increases a bank's exposure to the bubble itself and should thus increase its systemic risk contribution. Put differently, the relationship between a bubble and institution-specific systemic risk is likely to depend on this institution's balance sheet characteristics. Unless otherwise stated, the bank-level variables enter our regressions in a demeaned fashion such that the coefficients on the bubble indicators can be interpreted as a bubble's link with the systemic risk contribution of a bank of *average* size, loan growth, leverage, and maturity mismatch.

On country level, we control for real GDP growth (Δlog(real GDP)) to capture national business cycles. The 10-year government bond rates (in logs) account for the potential nexus between sovereigns and banks. In a robustness check (not reported), we used monetary policy rates instead, as extended periods of low rates can cause the build-up of risks in the financial sector by driving banks into overly risky investments and inadequate risk buffers (Diamond and Rajan, 2012).[8] Our results are robust towards the choice of the interest rate. The inflation rate (Δlog(CPI)) has been identified as a factor contributing to the occurrence of financial crises (Demirgüç-Kunt and Detragiache, 1998). Growth of investment to GDP (Δlog(investment/GDP)) is included to control for the use of credit (investment versus consumption, see Schularick and Taylor, 2012). Finally, credit-to-GDP growth (Δlog(credit/GDP)) is used to control for potentially harmful credit booms on an aggregate level, where we use credit to the private non-financial sector as it is more likely to fuel a bubble.

Standard errors are clustered at the bank and country-time level. The latter corresponds to the level at which the main explanatory variables, the bubble indicators, display variation. The clustering at the bank level accounts for autocorrelation, including the one introduced by interpolation of the data (see Section 3). Clustering at the bank and country level (as opposed to the bank and country-time level) does not alter the estimated significance levels qualitatively.

We do not include time fixed effects as they would capture global factors and thereby alter the interpretation of the estimated coefficients in an undesirable way. To clarify the argument, suppose we had only two countries in the sample and both countries would exhibit a bubble at the same time. In specifications with global time fixed effects, the coefficients on the bubble indicators would

[8] Also see the discussion in the context of the recent financial crisis in Deutsche Bundesbank (2014).

capture a relationship relative to the global average. That is, in the country with a weaker relation between the bubble and systemic risk, the coefficients would signal a negative link (relative to the global average). However, we do not want to estimate such relative relations, but the absolute relationship with systemic risk. Including country-time fixed effects improves identification, but absorbs a lot of the variation we are interested in. Nevertheless, the results are qualitatively robust to this alternative specification (cf. Section 6.1).

5 Results

The subsequent exposition of results starts with the exploration of the relationship between bubble episodes and systemic risk in Section 5.1. In Section 5.2, we analyze the relevance of bank-level developments during bubble episodes. We then focus on the role of bubble characteristics in Section 5.3.

5.1 Asset price bubbles and systemic risk in booms and busts

We start this subsection by illustrating the underlying correlations without allowing for heterogeneous effects across banks, by regressing ΔCoVaR on the bubble indicators and bank fixed effects only. The coefficients of three out of the four bubble indicators are positive and significant (Table 3, column 1). Overall, asset price bubbles are associated with a significant increase in systemic risk, which is in line with our expectations. The strongest relationship is found for real estate busts. Only real estate booms are not significantly related to systemic risk in this regression.

When looking at individual countries (results not reported), we find a significant positive association between asset price bubbles and systemic risk for twelve out of 17 countries in our sample. The relationship is insignificant in four countries and significantly negative only in a single country and only in the boom period.[9] Hence, the underlying correlation is pervasive in our sample and is not driven by individual countries.

[Table 3 about here]

[9] The negative correlation is found for the asset price bubbles in Denmark. Insignificant correlations are estimated for Switzerland, Germany, Portugal and Sweden. These results are obtained without distinguishing between asset classes due to the low number of bubble episodes per country per asset class.

When including the macroeconomic control variables, the size of the coefficients of the bubble indicators change but the sign of the estimated relationships and their significance prevail (Table 3, column 2). The coefficient of real estate busts decreases, while that on stock market booms increases. This is driven by the fact that part of the variation of bubble indicators is now captured by the macroeconomic control variables. When adding the bank-level variables, the estimated coefficients again change only quantitatively (Table 3, column 3). Specifically, the estimated coefficient in the bust phase of real estate bubbles becomes smaller while remaining significant. The estimated coefficients of stock market bubbles increase slightly.

To assess the economic significance of the results, consider a stock market boom or bust. Such episodes ceteris paribus go along with an increase in the financial system's conditional VaR by 0.36 percentage points. Intuitively, this coefficient reflects how much more a single institution's distress endangers the functioning of the financial system during a stock market boom or bust. Since this occurs for all institutions within a country at the same time, it translates into an increase in systemic risk at the country level. Hence, the increase in systemic risk associated with a stock market boom or bust corresponds to 18 percent (=0.36/1.96) relative to the mean level of ΔCoVaR (or 21 percent relative to the median of 1.68).

The corresponding increase associated with the burst of real estate bubbles amounts to 14 percent (or 17 percent relative to the median). Asset price bubbles are thus associated with a significant increase in systemic risk and could hence threaten to impair the functioning of the financial system. While the relationship is stronger during real estate busts than during corresponding booms, it is equally pronounced during both phases of stock market bubbles.

The coefficients of bank-level controls are in line with the previous literature. As in Adrian and Brunnermeier (2016), the systemic risk contributions increase in the size of an institution as well as in leverage, but decrease in an institution's maturity mismatch.[10] Moreover, higher bank lending appears to be conducive to lower systemic risk. Note, however, that we are already controlling for aggregate lending growth.

[10] Adrian and Brunnermeier (2016) define the maturity mismatch inversely to our definition such that the different sign of the corresponding coefficient in our paper is in line with the respective finding in Adrian and Brunnermeier (2016).

The coefficients of the macroeconomic control variables are largely in line with expectations. High GDP growth goes along with lower systemic risk, higher inflation with higher systemic risk. A credit boom on the aggregate level is associated with higher systemic risk (though not significantly). High investment-to-GDP growth is negatively related to systemic risk. Somewhat surprisingly, the coefficient of the 10-year government bond rate is negative and significant. Hence, there is no evidence of a sovereign-bank nexus over this broad sample period.

5.2 The role of bank characteristics

The results presented in the previous subsection point towards a harmful effect of asset price bubbles on financial stability. Additionally, they underline the importance of bank-level characteristics for banks' systemic risk contributions. We now turn to the core of our analysis, which is the role of bank characteristics for the relationship between asset price bubbles and systemic risk. While the burst of an asset price bubble is a shock that itself threatens financial stability, a bank's susceptibility to asset price bubbles is likely to depend on its balance sheet characteristics. Moreover, the emergence of asset price bubbles can lure banks into behavior such as over-lending and inadequate liquidity management, which threatens the stability of the financial system, thereby increasing the financial system's vulnerability to the subsequent shock of the burst. Therefore, we now additionally interact the four bubble indicators with the bank characteristics.

Columns 1 to 4 of Table 4 report regressions including only one bank-level variable at a time and its interactions with the bubble indicators in addition to these bubble indicators themselves, the macroeconomic control variables, and the bank fixed effects. Column 5 of Table 4 displays our baseline regression which includes *all four* bank-level variables and their interactions with the bubble indicators together with these bubble indicators and all the control variables. In Column 6, the same regression is displayed using quarterly data as a robustness check.

[Table 4 about here]

The inclusion of interaction terms leaves the coefficients of the bubble indicators largely unchanged. However, it changes their interpretation. They now quantify the relationship between asset price bubbles and systemic risk in case of bank characteristics corresponding to their average levels in our sample. Moreover, the inclusion of the interaction terms changes the interpretation of the coefficients of the bank characteristics. They now refer to the relationship in normal times, i. e., outside of bubble episodes. The estimated coefficients of bank characteristics during non-bubble times are very similar to the average effects before. While size and leverage go along with higher systemic risk, individual loan growth and maturity mismatch are associated with lower systemic risk, regardless of whether we include only one of the variables and its interactions with the bubble indicators (columns 1 to 4) or all four at the same time (column 5).

More importantly, the coefficients change markedly during bubble episodes. For example, the coefficient of size rises sharply during real estate busts, stock market busts, and to a lesser extent also during stock market booms. Loan growth has a significantly more positive coefficient during all types of bubble episodes. We thus find no evidence of a beneficial effect of loan growth once a bubble is underway. For real estate busts, the results suggest that systemic risk contributions even increase in lending growth, as the sum of the coefficients of loan growth and of its interaction with real estate busts is positive and statistically significant (test not reported). Similarly, our baseline regression shows significantly more positive coefficients of maturity mismatch during all types of bubble episodes. The results on leverage are more mixed as its coefficient is higher only during real estate booms, while it is not significantly different during real estate busts and lower during stock market bubbles. Overall, these regressions strongly support the relevance of banks' balance sheet characteristics for the relationship between asset price bubbles and systemic risk.

Column 6 of Table 4 contains a robustness check, in which we rerun our baseline regression using quarterly data to exclude any results being driven by the interpolation of the real estate bubble indicator. While standard errors increase due to the much smaller number of observations, the overall results are unchanged.

In order to illustrate the economic significance of bank characteristics, we condition the bubble indicators on different percentiles of the bank-level variables. While the coefficients of the bubble indicators in Table 4 quantify the link between asset price bubbles and systemic risk at the mean of all bank-level variables, Table 5 displays this relation at different percentiles of the bank-level variables, starting from the median and going up to the 95^{th} percentile of size, loan growth, leverage, and maturity mismatch *simultaneously.* Since all other coefficients in the regression are unaffected by the alternative conditioning compared to column 5 of Table 4, we do not display them again in Table 5.

[Table 5 about here]

Moving from the left to the right, Table 5 shows that the relationship between asset price bubbles and systemic risk strengthens with the percentiles on which we condition. All coefficients increase sharply when moving to higher percentiles of bank characteristics. Hence, these results suggest that the financial system is more vulnerable to asset price bubbles the higher the bank-specific risk factors are.

Interestingly, we now find a positive link between real estate bubbles and systemic risk already during their emergence if accompanied by sufficiently unfavorable developments at bank level (Table 5, columns 3 and 4). Like in the case of stock market bubbles, the increased systemic risk during real estate bubbles is thus not limited to the turmoil induced by the burst of the bubble. Generally, the rise in systemic risk is more pronounced during the bust period compared to the boom. During the burst of an asset price bubble, systemic risk increases by up to 53% (=1.04/1.96) compared to average levels of ΔCoVaR. This is equivalent to an increase of more than two standard deviations of ΔCoVaR aggregated at the financial system level. The risks connected to the emergence of an asset price bubble cannot be neglected either. During the boom phase of a bubble, systemic risk rises by up to 27% (=0.52/1.96) or more than one standard deviation of the aggregate ΔCoVaR.

Turning to the economic significance of *individual* bank characteristics (regressions not reported), large size and high loan growth strengthen the relationship between asset price bubbles and systemic risk contributions substantially. Comparing a median bank and a bank of a size equal to the 85^{th} percentile of the size distribution, real estate booms, stock market booms, and stock market busts are associated with increased systemic risk contributions of the larger bank by 37 to 314 percent more compared to its median counterpart. The corresponding comparison of a median bank and a bank with loan growth at the 85^{th} percentile of this distribution results in an 11 to 48 percent larger link of those bubble phases for the bank with the elevated risk characteristic. Leverage and maturity mismatch do not significantly increase the relationship between asset price bubbles and systemic risk contributions.

Parts of the literature (e. g., Jordà, Schularick, and Taylor, 2015b) conclude that real estate bubbles are more harmful than their stock market counterparts. Our results do not support this general ordering. Instead, we find the bust phase of real estate bubble episodes to be more harmful only if accompanied by a very large size of banks, high loan growth, high maturity mismatch and high leverage, i. e., if bank-specific risk factors are beyond the 75^{th} percentile of their distribution. If banks display more favorable risk characteristics during bubble episodes, stock market bubbles appear to be more harmful than real estate bubbles (see Table 5), and the size of the relationship changes more strongly with banks' characteristics than across bubble types. This supports the view that developments within the financial sector are more relevant than a bubble's asset class, as has already been advocated by Brunnermeier and Schnabel (2016) with respect to loan growth.

While we emphasize the importance of bank characteristics, we interpret our results on specific variables with caution. Our dependent variable is an estimate of systemic risk. While the measure we rely on is widely used, other measures, such as SRISK (Brownlees and Engle, 2015; Acharya, Pedersen, Philippon, and Richardson, 2017), offer a reasonable alternative for the estimation of systemic risk contributions. In the aggregate, this measure shows a similar evolution over time as ΔCoVaR. However, ΔCoVaR, e. g., reacts more to the size of banks, while SRISK is driven more by leverage (cf. e. g., Benoit, Colletaz, Hurlin, and Pérignon, 2013). The size of the importance of specific bank-level variables for the relation between asset price bubbles and systemic risk should thus not be over-interpreted.

5.3 The role of bubble characteristics

The observed heterogeneity across the relationship of different bubble episodes with systemic risk is likely to be driven not only by differences in bank characteristics but also by differences in bubble characteristics. One important characteristic is the duration of a bubble episode (*length*). Emerging asset price bubbles might be more harmful the longer they have lasted already as they may feed back into banks' risk-taking and thereby become self-reinforcing. In contrast, after a longer bust phase, the bubble may be less harmful because the shock of its burst fades out. A second characteristic is the size of a bubble (*size*). The larger the emerging bubble, the higher is the potential for a pronounced bust. Hence, larger bubbles would be expected to increase systemic risk more. During the bust, the remaining risk should be smaller the more the bubble has deflated already.

As before, we distinguish between the booms and busts of real estate and stock market bubbles, respectively. Consequently, we construct four new variables for each bubble characteristic, resulting in a total of eight new variables. *Length* counts the number of months that a bubble has been building up since its inception or that it has been collapsing since its peak. During the boom phase, *size* is the underlying asset's price relative to its pre-bubble level. During the bust, *size* measures the size of the bust (as opposed to the size of the bubble) as the negative of the asset's price series relative to the current bubble episode's peak level. Outside of the respective bubble phases, all *length* and *size* variables are set to zero.

Table 6 displays the summary statistics of the bubble characteristics *during* bubble episodes, i. e., when *length* and *size* are not set to zero. In contrast to Table 1, where we report summary statistics on the length of bubble episodes, the variable *length* counts the months that have passed since the inception or peak of the bubbles so that the numbers differ. In a stock market boom, prices are on average 78% above the initial value. In a real estate boom, the corresponding number is only 38%. The maximum size of stock market booms is 842% above the initial value. For real estate booms, the maximum is only 171%. In a stock market bust, prices are on average 12% below the peak price, while in a real estate bust, prices are only 6% below the peak. The maximum drop in a stock market bust amounts to 35% below its peak, whereas this number is 43% for real estate busts.

[Table 6 about here]

Adding these variables to our baseline model (see Equation (8)), we estimate regressions of the following form:

$$\begin{aligned}\Delta CoVaR_{i,t} = \alpha_i + \beta_1 \cdot Bubble_{c,t} + \beta_2 \cdot Bubble\_characteristics_{c,t} \\ + \gamma \cdot B_{i,t-1} + \delta \cdot Bubble_{c,t} * \cdot B_{i,t-1} + \lambda \cdot C_{c,t-1} + u_{i,t}\ .\end{aligned} \tag{9}$$

The variables capturing bubble characteristics enter the regressions demeaned such that the coefficients on the bubble indicators quantify the relationship between bubbles with average bubble characteristics and systemic risk.

As expected, we find stock market bubbles to be associated with more increased systemic risk the longer they have lasted and the larger their size is during the emergence (Table 7, columns 2 and 3). Since *length* and *size* are highly correlated during the emergence of stock market bubbles (0.97), it is difficult to distinguish their effects empirically. The economic significance is large for both characteristics. For example, an emerging stock market bubble of a size at the 75^{th} percentile of the size distribution (1.32) goes along with an increase in ΔCoVaR by 0.45 percentage points more than a bubble of a size at the 25^{th} percentile (0.26), which is large compared to the sample average of ΔCoVaR (1.96). The equivalent comparison for *length* reveals a similarly large difference of 0.47 percentage points. During stock market busts, the increase in systemic risk becomes smaller the more time has passed since the burst of the bubble, which is in line with our expectations. The economic significance of *length* is smaller during the bust than during the boom. The change from the 25^{th} (14) to the 75^{th} percentile (45) of the distribution of length results in a 0.18 percentage points less increased ΔCoVaR. This is in line with an initial shock of the bursting bubble that fades out. Additionally, policy interventions might alleviate the consequences of the burst at later stages of the bust. The size of the bust is negatively related to systemic risk but the coefficient is insignificant.

[Table 7 about here]

Regarding real estate booms, bubbles that have built up over a long time unexpectedly are less associated with increased systemic risk than those that emerged only recently. Hence, the reinforcing mechanisms described above appear to be less prevalent in real estate markets. The coefficient of the size of the bubble is negative but insignificant. During the bust phase of real estate bubbles and in line with our results on stock market busts, the coefficients of *length* and *size* are negative and significant. The relationship between a bubble and systemic risk is weaker the more time has passed since the burst and the more a bubble has deflated already. A real estate bust at the 75^{th} percentile of the corresponding size distribution (0.09) is associated with ΔCoVaR increased by 0.13 percentage points less than such a bust at the 25^{th} percentile (0.01). The equivalent comparison for the length of the bust (16 vs. 5) reveals a 0.10 percentage point difference. This again points towards a fading effect of the burst and policy interventions alleviating financial sector turmoil.

The results show that bubble characteristics such as length and size influence the relationship between asset price bubbles and systemic risk in addition to bank characteristics. Consequently, differences in the developments of bubbles themselves provide an explanation for the heterogeneity of the link between asset price bubbles and financial stability across bubble episodes.

6 Robustness

In this section, we assess the robustness of our baseline results in several directions. First, we account for ΔCoVaR's variation coming from developments on a macro level by considering additional control variables and an alternative estimation strategy for ΔCoVaR. Second, we analyze the sensitivity of results with respect to banks' size by considering sample splits and, alternatively, by weighting observations by bank size. At the same time, we exclude that the large number of small US banks in our sample drives the results. Third, we evaluate whether the results are driven by the global financial crisis, which stands out due to its spike in systemic risk.

6.1 Controlling for additional variation at the macro level

The motivation for the robustness tests in this subsection becomes apparent when rewriting Equation (7) with the help of Equation (4):

$$\begin{aligned}\Delta CoVaR^i_{q,t} &= \hat{\beta}^{system|i}_q(\widehat{VaR}^i_{q,t} - \widehat{VaR}^i_{50,t}) \\ &= \hat{\beta}^{system|i}_q(\hat{\alpha}^i_q + \hat{\gamma}^i_q M_{t-1} - (\hat{\alpha}^i_{50} + \hat{\gamma}^i_{50} M_{t-1})) \\ &= \sigma^i_q + \omega^i_q M_{t-1}\ , \end{aligned} \tag{10}$$

where $\sigma^i_q = \hat{\beta}^{system|i}_q(\hat{\alpha}^i_q - \hat{\alpha}^i_{50})$ and $\omega^i_q = \hat{\beta}^{system|i}_q(\hat{\gamma}^i_q - \hat{\gamma}^i_{50})$. While the cross-sectional variation in ΔCoVaR is driven by bank-specific factors, its time-series variation is driven by the system variables M_{t-1} (see Equation (10)). These variables vary over time and at the financial-system level (cf. Appendix B). Since we aim to analyze the relationship between asset price bubbles and systemic risk at the bank level, we subsequently assess to what degree our results are driven by M_{t-1}.

Column 1 of Table 8 is identical to our baseline regression. In column 2 of this table, we add the financial system variables M_{t-1} as additional controls to absorb the corresponding variation. Interestingly, we now see a positive and significant coefficient of real estate booms. The coefficients of the other three bubble phases shrink but remain significant and positive with the exception of real estate busts. The signs of the coefficients of all bank characteristics and their interactions with the bubble indicators are unchanged. While some significance levels change slightly, only the interactions between maturity mismatch and the stock market bubble indicators turn insignificant.

Next, we add country-time fixed effects to our baseline regression instead of the financial system variables. In this specification (column 3 of Table 8), the bubble indicators and macroeconomic control variables drop out as they vary only at the country-time level. However, we can assess the robustness of our results regarding the bank-level variables as well as their interactions with the bubble indicators. The statistical significance of the estimated coefficients is reduced due to the reduction in the degrees of freedom. At the same time, the basic results are again maintained remarkably well, which provides strong support for our previous results.

[Table 8 about here]

We perform an additional robustness check to address ΔCoVaR's dependence on the financial system variables M_{t-1} by modifying ΔCoVaR's estimation procedure. So far, ΔCoVaR relied on estimates of financial institutions' VaR (cf. Equation (4)). This estimated VaR introduces ΔCoVaR's dependence on financial system variables (cf. Equation (10)). As an alternative, we now calculate financial institutions' VaR directly from their past equity returns using one-year rolling windows. The windows are overlapping, as they move forward on a monthly basis. All other estimation details remain unchanged. The rolling ΔCoVaR can be expressed as

$$\Delta CoVaR^i_{q,t} = \hat{\beta}_q^{system|i}(VaR^i_{q,t} - VaR^i_{50,t}) \ , \tag{11}$$

where we drop the hats of the VaR as it is now calculated as opposed to estimated. The time variation in both the calculated VaR and the rolling ΔCoVaR is independent of the financial system variables M_{t-1}. These variables are now exclusively used to control for general risk factors when estimating the dependence between bank returns and financial system returns (cf. Equation (5)).

While the mean and the median of this rolling version of ΔCoVaR are slightly lower (1.59 and 1.23 vs. 1.96 and 1.68), the standard deviation is slightly higher (1.77 vs. 1.65). The evolution of the average rolling ΔCoVaR in all four financial systems is similar to its original counterpart. As displayed in Figure 4, there is a pronounced peak at the time of the global financial crisis. Again, the euro area crisis and the Japanese banking crisis at the beginning of the 1990s are visible, while the dotcom bubble is hardly reflected in the US series.

[Figure 4 about here]

We re-estimate our baseline regression with the rolling ΔCoVaR as dependent variable. As shown in column 4 of Table 8, the coefficients of both real estate booms and busts are positive but insignificant. The coefficients of stock market bubbles remain positive and significant. The coefficients of size, leverage, and maturity mismatch during non-bubble times are well in line with our previous estimates. The coefficient of loan growth remains negative and highly significant but becomes more than twice as large. The coefficients of both the interaction of bank size with stock market booms and the interaction of bank size with real estate busts become insignificant. During real estate booms, the coefficient of bank size becomes less pronounced. The estimated coefficients of all other interaction terms are highly robust towards the alternative definition of ΔCoVaR such that we overall find strong additional support for our previous results.

Finally, we repeat the exercise of conditioning the bubble indicators on different percentiles of the bank-level variables, starting from the median and moving up to the 95^{th} percentile of size, loan growth, leverage, and maturity mismatch simultaneously. The results are reported in Table 9. While real estate booms have no significant effect at elevated levels of these bank risk factors, the effects of all other bubble phases again increase significantly. This provides additional support for a strong dependence of the degree to which asset price bubbles threaten financial stability on bank-level characteristics. When looking at the contributions of individual bank characteristics to this overall relationship (results not displayed), leverage is more and bank size less important according to the rolling ΔCoVaR results compared to the original ΔCoVaR. The contribution of loan growth is again large and the maturity mismatch remains less relevant in economic terms.

[Table 9 about here]

6.2 Large and small banks

Next we check whether the results are driven by banks of a specific size. This distinction serves three purposes. First, as mentioned in Section 3, the dataset is dominated by relatively small banks, which are mostly located in the US (see Table C.2). Small US banks are much more frequently listed than, e. g., small European banks. Therefore, we assess the importance of US observations for our results. Second, in the baseline regressions, we assume that a bank is affected only by a bubble in its home country. For large and internationally active banks, this assumption is rather strong. A focus on small, locally active banks allows us to address this potential concern. Third, small and large banks display different business models and dynamics, which might not be fully captured by bank fixed effects and the size variable.

In order to check whether the results differ across banks of different size, we first split the sample into large and small banks. In order to avoid banks switching groups over time, the split is based on a bank's mean size over the sample period. Banks with a mean size below (above) 30 billion USD are considered as small (large). The results are robust towards the choice of the cut-off value. While the dominance of US banks is mitigated substantially in the sample of large banks, the same is not true for the sample of small banks. Therefore, we drop the smallest US banks (again based on mean bank size) such that the number of observations from the US is no larger than that of the country with the second largest number of observations on small banks (France).

Columns 2 and 3 in Table 10 show the results for large and small banks. The results for both bank groups are qualitatively very similar to our baseline results (column 1). As before, real estate busts as well as stock market booms and busts go along with significantly increased systemic risk contributions. We also find support for the previous finding that the emergence of real estate bubbles is associated with increased systemic risk when individual bank risk factors are at elevated levels (results not displayed).

Moreover, many of the interaction terms remain significant, pointing towards a more pronounced link in case of riskier banks. Only the coefficients on the size interactions are somewhat different from previous results, at least for large banks. In general, the coefficients for large banks are substantially larger than for small banks. However, this result disappears when the left-hand-side variable is transformed into logs (see columns 4 and 5). Hence, in proportional terms, the size of the coefficients is comparable. Given the similarity of results across bank groups, we can exclude that the baseline results are driven by small banks. Moreover, our previous results do not appear to be driven by asset price bubbles emerging outside of their home country.

As a further robustness check, we rerun our baseline regression including the full sample of banks, but weight each bank's observations by their mean bank size relative to the size of their financial system. We thereby limit the relevance of observations of small banks and eliminate the US bias in our sample. The results are reported in column 6 of Table 10. Once more, they are well in line with our previous findings.

[Table 10 about here]

6.3 Choice of sample period

As a further robustness check, we analyze the sensitivity of our results to the choice of the sample period. As Figure 3 shows, ΔCoVaR spikes especially during the global financial crisis. To exclude that the results are driven by either particular bubble episodes, we re-estimate our baseline regressions for different sample periods. First, we leave out the year 2008, in which ΔCoVaR spikes, to avoid that these extreme observations drive our results. Second, we exclude the entire financial crisis and consider only the period up to 2006. Moreover, in the beginning of our sample, the number of included banks is relatively small and the sample of included banks may not be representative for this time period. Therefore, we run a regression excluding observations before 1995.

As shown in Table 11, the results are very consistent across different sample periods. The signs and significance of coefficients are almost always identical to the baseline regression shown in column 1. The results are highly robust to the exclusion of the initial period of our sample (see Table 11, column 2). Excluding the global financial crisis yields an even stronger relationship between asset price bubbles and systemic risk, especially for real estate booms (Table 11, columns 3 and 4). Most importantly, the coefficient of the real estate booms now becomes highly significant.

[Table 11 about here]

Consequently, none of our results is driven by banks of a particular size or by particular bubble episodes.

7 Conclusion

Analyzing a broad sample of banks in 17 OECD countries over the period 1987 to 2015, this paper has empirically assessed the relationship between asset price bubbles and systemic risk. While most of the previous empirical literature has approached this question at a macroeconomic level, we provide evidence on the relationship between asset price bubbles and systemic risk at the level of individual financial institutions.

Our results show that asset price bubbles are indeed associated with increased systemic risk at bank level. This relationship is not limited to the turmoil following the burst of a bubble, but it partly exists already during its emergence. Most importantly, we show that the relationship between bubbles and systemic risk depends strongly on bank characteristics. A large bank size, higher loan growth, higher leverage, and a stronger maturity mismatch tend to make financial institutions, and hence the financial system, vulnerable to asset price bubbles. If accompanied by sufficiently elevated levels of these bank-specific risk factors, systemic risk during times of asset price bubbles can be increased by up to 53 percent. Moreover, our results do not support the common conjecture that real estate bubbles are generally more harmful than stock market bubbles. In fact, our findings suggest that the ordering may even be reversed for certain levels of bank characteristics. The results are neither driven by banks of a particular size nor by specific sample periods. Finally, the analysis of bubble characteristics reveals the importance of the length and the size of the bubble for their relationship with systemic risk.

Based on our results, one can draw a number of important policy implications. First, stock market bubbles cannot be dismissed as a source of financial instability but have to be watched just as closely as real estate bubbles. Second, policies focusing on managing the turmoil after the burst of a bubble are insufficient. Systemic risk rises already in the boom phase and it is well-advisable to counteract such a build-up of systemic risk early on to avoid a harmful collapse later on. Finally, and most importantly, our results suggest that the adverse effects of bubbles may be mitigated substantially by strengthening the resilience of financial institutions. Especially bank size and loan growth contribute to the build-up of financial instability through asset price bubbles and hence increase the system's vulnerability. With strong and resilient financial institutions, the fallout from bursting bubbles is likely to be much smaller.

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Figures and tables

Figure 1: Construction of the bubble indicators

The BSADF approach identifies the beginning of a bubble episode as the point in time at which the sequence of BSADF test statistics (blue dotted line) first exceeds its critical value (red dotted line) and thus signals the price data (black line) being on an explosive trajectory. The end of a bubble episode is reached once the test statistics fall back below their critical values. Additionally, we distinguish between the boom and the bust phase of a bubble (the blue and grey shaded areas) based on the peak of the price series during each bubble episode. Using this approach, we construct four binary variables for each country, indicating episodes in which a real estate or stock market bubble emerges or collapses. The figure illustrates the construction of these indicators based on the recent Spanish housing bubble. Details on the BSADF approach are provided in Section 3.1 and Appendix A.

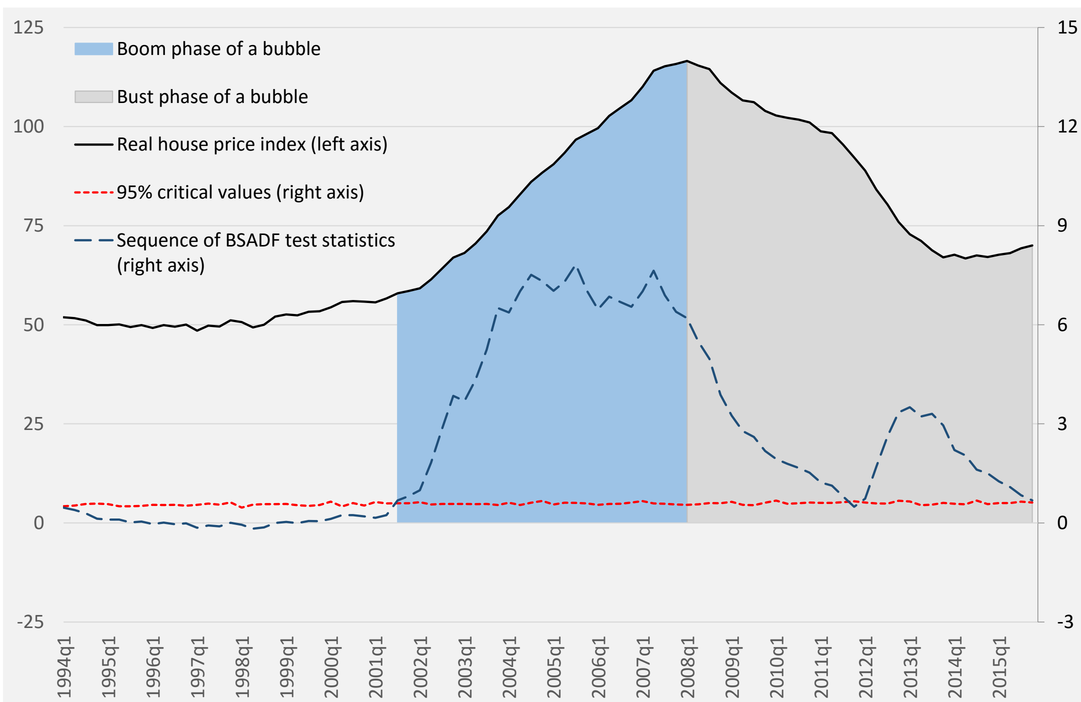
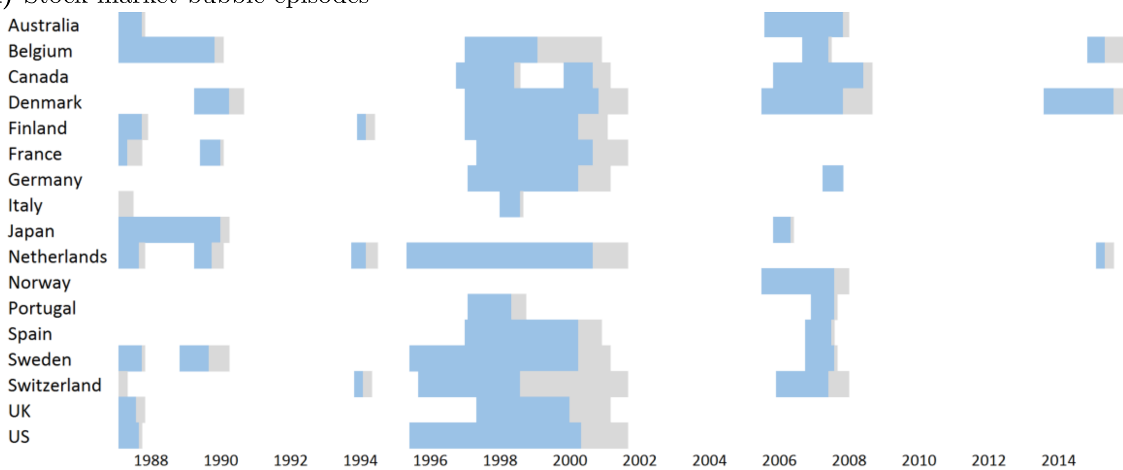


Figure 2: Bubble episodes by country and asset class

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. For details on the estimation procedure see Section 3.1 and Appendix A.

(a) Stock market bubble episodes



(b) Real estate bubble episodes

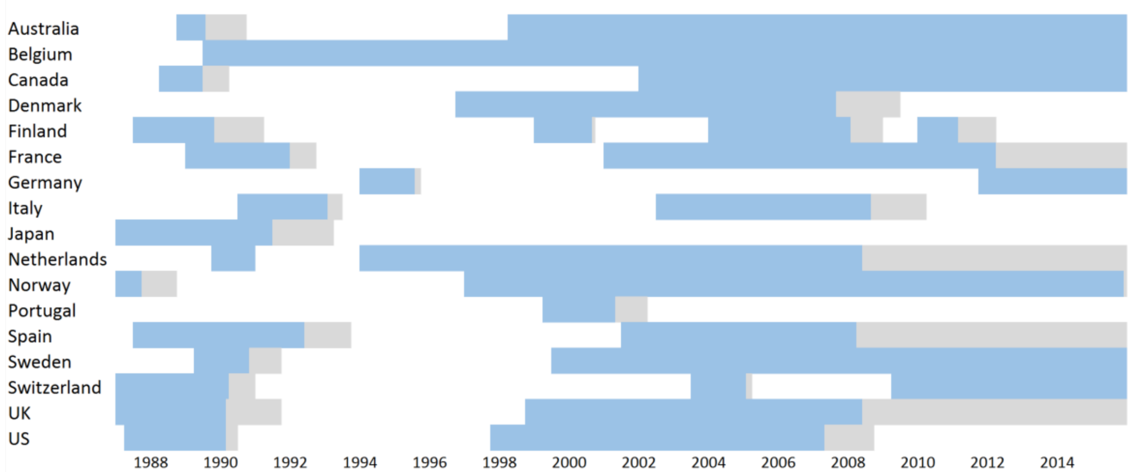


Figure 3: Evolution of ΔCoVaR over time

The figure displays the unweighted mean of ΔCoVaR in weekly percentage points for the four financial systems in our sample: North America, Europe, Japan, and Australia. Details on the estimation procedure are provided in Section 3.2 and Appendix B.

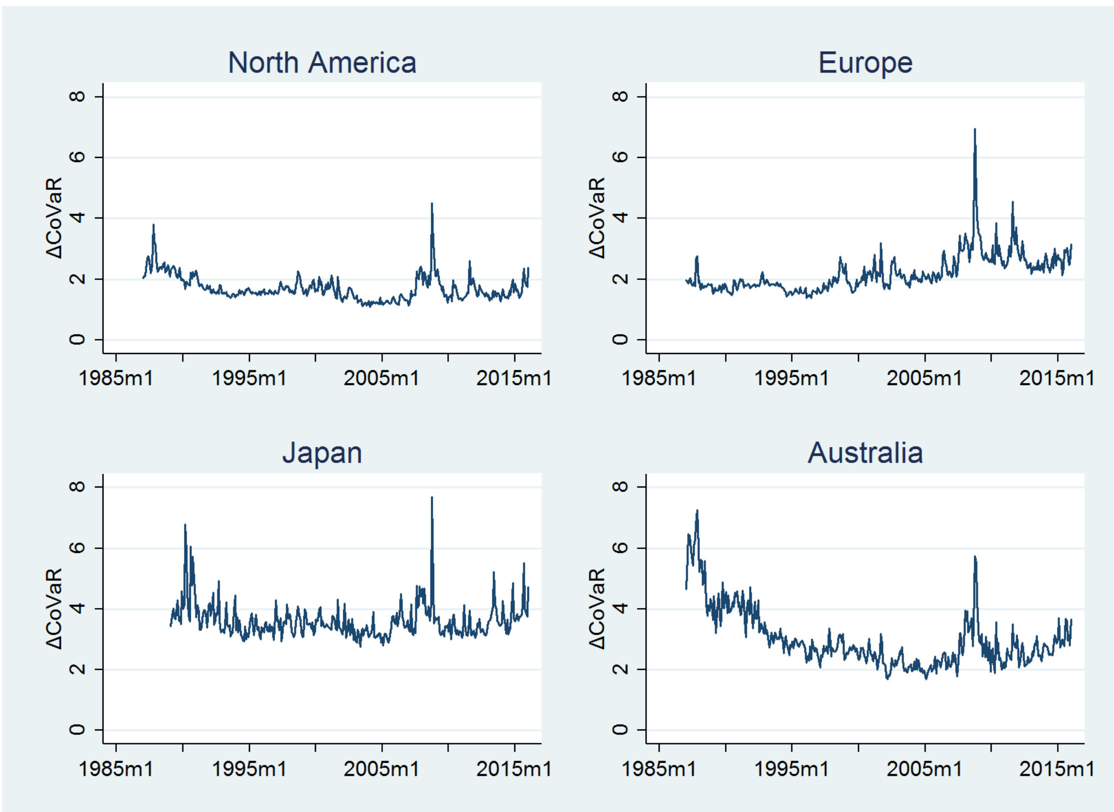


Figure 4: Evolution of the rolling ΔCoVaR over time

The figure displays the unweighted mean of the rolling ΔCoVaR in weekly percentage points for the four financial systems in our sample: North America, Europe, Japan, and Australia. The estimation procedure is described in Section 6.1.

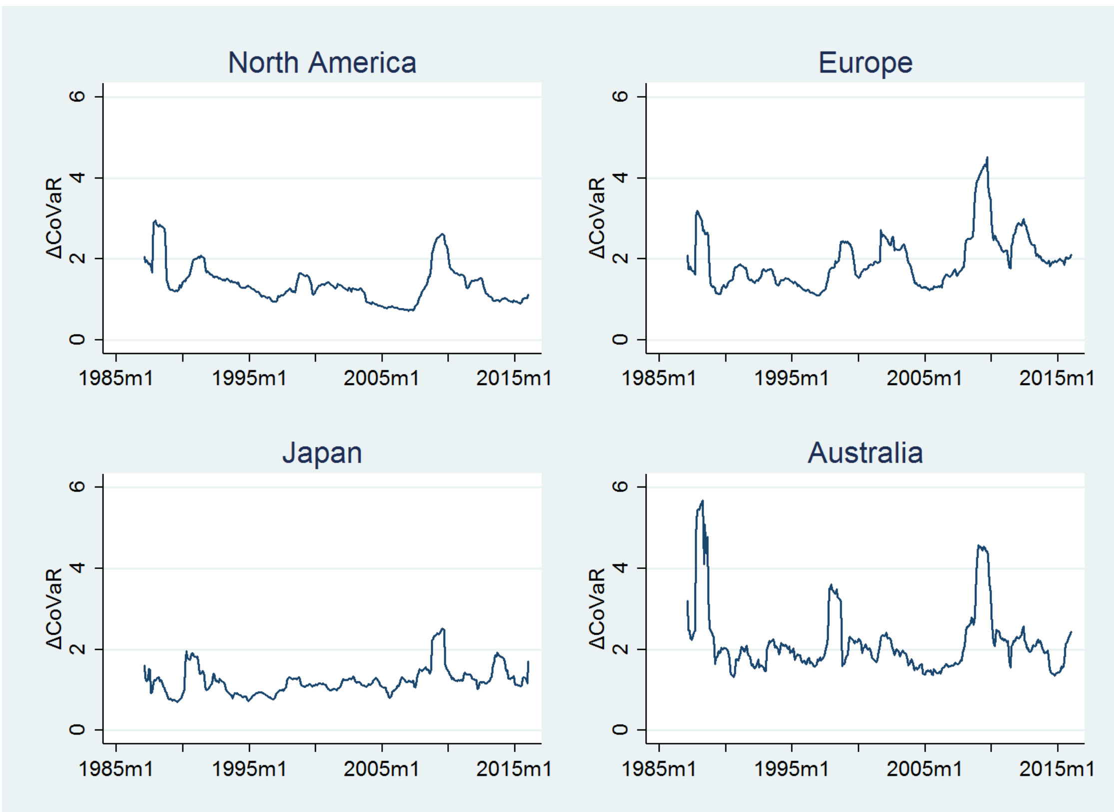


Table 1: Descriptive statistics on bubble episodes

The statistics are computed for the dataset used in the main analyses. Figure 2 provides an overview of bubble episodes estimated per country. Differences in the number of booms and busts of bubble episodes are due to bubbles that take place only partly during the sample period.

	Real estate		**Stock market**	
	Boom	**Bust**	**Boom**	**Bust**
Number of episodes				
Average per country	1.9	1.6	2.8	2.7
Min per country	1	0	1	1
Max per country	4	5	5	5
Total	35	28	50	49
Length of episodes				
Average	60	13	21	6
Min	10	1	3	1
Max	318	93	64	37

Table 2: Descriptive statistics

The statistics are computed for the dataset used in the main analyses. "Size" and "Interest rate" enter the regressions in logs. "Interest rate" refers to 10-year government bond rates. For descriptive statistics on the bubble episodes, see Table 1. Variable definitions are provided in Table C.1.

Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Dependent variable					
ΔCoVaR	1.96	1.68	1.65	-9.33	26.12
Bank characteristics					
Bank size [billion USD]	64.58	1.88	260.79	0.02	3,972.50
log(bank size)	1.22	0.63	2.19	-2.39	7.20
Loan growth	0.007	0.006	0.015	-0.046	0.074
Leverage	13.43	11.70	7.15	1.04	52.51
Maturity mismatch	0.69	0.75	0.19	-0.10	0.89
Macroeconomic variables					
Real GDP growth	0.021	0.023	0.020	-0.102	0.076
Interest rate	4.23	4.20	1.81	0.01	15.14
log(interest rate)	1.33	1.44	0.51	-4.61	2.72
Inflation	0.022	0.021	0.013	-0.025	0.123
Investment-to-GDP growth	-0.004	0.010	0.061	-0.501	0.274
Credit-to-GDP growth	0.010	0.014	0.035	-0.129	0.207

Table 3: Asset price bubbles and systemic risk in booms and busts

Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated by the BSADF approach. "Interest rate" refers to 10-year government bond rates. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)
Real estate boom	0.02	0.07	0.04
	(0.604)	(0.251)	(0.573)
Real estate bust	0.50***	0.38***	0.28**
	(0.000)	(0.003)	(0.032)
Stock market boom	0.11**	0.29***	0.36***
	(0.027)	(0.000)	(0.000)
Stock market bust	0.27***	0.33***	0.36***
	(0.000)	(0.000)	(0.000)
log(Bank size)			0.28***
			(0.000)
Loan growth			-0.84**
			(0.047)
Leverage			0.01***
			(0.001)
Maturity mismatch			-0.45***
			(0.000)
GDP growth		-5.90***	-4.32***
		(0.000)	(0.001)
log(Interest rate)		-0.28***	-0.06*
		(0.000)	(0.076)
Inflation		6.25*	6.80**
		(0.064)	(0.041)
Investment-to-GDP growth		-0.50	-0.72**
		(0.123)	(0.031)
Credit-to-GDP growth		1.15	1.18
		(0.117)	(0.100)
Bank FE	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,149
Adj. R^2	0.810	0.817	0.823
Adj. R^2 within	0.037	0.073	0.100

Table 4: The role of bank characteristics during bubble episodes

Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated by the BSADF approach. "Interest rate" refers to 10-year government bond rates. Variable definitions are provided in Table C.1. The results in column 6 are obtained from regressions based on quarterly frequency as a robustness check regarding our use of interpolated data. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Real estate boom	0.02	0.07	0.08	0.05	0.00	0.06
	(0.716)	(0.269)	(0.215)	(0.455)	(0.935)	(0.288)
Real estate bust	0.26**	0.38***	0.39***	0.36***	0.24*	0.37***
	(0.043)	(0.003)	(0.003)	(0.005)	(0.055)	(0.002)
Stock market boom	0.36***	0.28***	0.29***	0.28***	0.33***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock market bust	0.38***	0.32***	0.33***	0.33***	0.36***	0.49***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.27***				0.27***	0.22***
	(0.000)				(0.000)	(0.000)
log(Bank size) · Real estate boom	0.01				0.00	0.01
	(0.342)				(0.895)	(0.500)
log(Bank size) · Real estate bust	0.13***				0.15***	0.15***
	(0.000)				(0.000)	(0.001)
log(Bank size) · Stock market boom	0.00				0.05***	0.03
	(0.949)				(0.007)	(0.122)
log(Bank size) · Stock market bust	0.07***				0.11***	0.14***
	(0.000)				(0.000)	(0.000)
Loan growth		-4.95***			-4.38***	-4.33***
		(0.000)			(0.000)	(0.000)
Loan growth · Real estate boom		4.69***			4.38***	4.21***
		(0.000)			(0.000)	(0.000)
Loan growth · Real estate bust		7.13***			7.95***	7.86***
		(0.000)			(0.000)	(0.000)
Loan growth · Stock market boom		3.41***			3.26***	3.36***
		(0.000)			(0.000)	(0.001)
Loan growth · Stock market bust		2.83***			3.92***	4.28***
		(0.002)			(0.000)	(0.000)
Leverage			0.01***		0.01***	0.01***
			(0.003)		(0.005)	(0.004)
Leverage · Real estate boom			0.01*		0.01**	0.01
			(0.088)		(0.030)	(0.153)
Leverage · Real estate bust			0.01		-0.01	-0.01
			(0.163)		(0.196)	(0.180)
Leverage · Stock market boom			-0.01***		-0.01***	-0.01**
			(0.002)		(0.001)	(0.013)
Leverage · Stock market bust			-0.00		-0.02***	-0.02***
			(0.868)		(0.000)	(0.004)

(*table continued on next page*)

Table 4 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity mismatch				-0.61***	-0.68***	-0.64***
				(0.000)	(0.000)	(0.000)
Maturity mismatch · Real estate boom				0.19*	0.27***	0.30***
				(0.051)	(0.006)	(0.010)
Maturity mismatch · Real estate bust				-0.39	0.45**	0.56**
				(0.112)	(0.034)	(0.042)
Maturity mismatch · Stock market boom				0.50***	0.67***	0.59***
				(0.000)	(0.000)	(0.000)
Maturity mismatch · Stock market bust				-0.02	0.38***	0.54***
				(0.843)	(0.007)	(0.009)
GDP growth	-4.15***	-5.64***	-5.64***	-5.64***	-3.78***	-3.64
	(0.002)	(0.000)	(0.000)	(0.000)	(0.004)	(0.130)
log(Interest rate)	-0.05	-0.27***	-0.28***	-0.28***	-0.05	-0.02
	(0.237)	(0.000)	(0.000)	(0.000)	(0.173)	(0.676)
Inflation	7.51**	6.20*	6.05*	6.28*	7.19**	1.94
	(0.023)	(0.067)	(0.074)	(0.064)	(0.031)	(0.366)
Investment-to-GDP growth	-0.87**	-0.51	-0.52	-0.56*	-0.85**	-0.51
	(0.010)	(0.118)	(0.111)	(0.092)	(0.012)	(0.201)
Credit-to-GDP growth	1.45**	1.36*	1.27*	1.31*	1.76**	1.79*
	(0.045)	(0.068)	(0.084)	(0.077)	(0.017)	(0.056)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264	1,264	1,264	1,262
No. of obs.	165,149	165,149	165,149	165,149	165,149	55,128
Adj. R^2	0.824	0.818	0.818	0.818	0.827	0.849
Adj. R^2 within	0.109	0.077	0.077	0.078	0.120	0.137

Table 5: The importance of bank-level developments

Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. The coefficients report the effect of the bubble phases conditional on all bank-level variables being at the indicated percentile of their distributions. The coefficients on bank characteristics, the interactions between bank characteristics and bubble indicators, and the coefficients on macroeconomic control variables are identical to the ones reported in Table 4, column 5. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

Percentile of bank characteristics:	(1) 50^{th}	(2) 75^{th}	(3) 85^{th}	(4) 95^{th}
Real estate boom	0.00	0.09	0.15*	0.30***
	(0.977)	(0.285)	(0.100)	(0.006)
Real estate bust	0.21	0.55***	0.72***	1.04***
	(0.106)	(0.001)	(0.000)	(0.000)
Stock market boom	0.38***	0.48***	0.50***	0.52***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock market bust	0.37***	0.56***	0.62***	0.70***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes
Bank characteristics · Bubble indicators	Yes	Yes	Yes	Yes
Macroeconomic control variables	Yes	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,149	165,149
Adj. R^2	0.827	0.827	0.827	0.827
Adj. R^2 within	0.120	0.120	0.120	0.120

Table 6: Descriptive statistics on bubble characteristics during bubble episodes

The statistics are calculated conditional on the corresponding bubble indicator being equal to one. For example, within stock market boom periods, a stock market boom has on average been present for 29 months and features a 78% price increase relative to the pre-bubble level. For variable definitions, see Section 5.3 and Table C.1.

Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Length					
Stock market boom	29	28	17.8	1	64
Stock market bust	8	8	5.5	1	37
Real estate boom	69	68	40.1	1	318
Real estate bust	15	10	16.8	1	93
Size					
Stock market boom	0.78	0.72	0.54	0.00	8.42
Stock market bust	0.12	0.13	0.08	0.00	0.35
Real estate boom	0.38	0.33	0.29	0.00	1.71
Real estate bust	0.06	0.05	0.07	0.00	0.43

Table 7: The role of bubble characteristics

Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. "Length" and "size" capture bubble characteristics. Estimation results for bank characteristics (bank size, loan growth, leverage, and maturity mismatch), interactions between bank characteristics and bubble indicators, and macroeconomic control variables (GDP growth, interest rate, inflation, investment-to-GDP growth, and credit-to-GDP growth) are reported in Table C.3. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)
Stock market boom	0.335***	0.313***	0.340***
	(0.000)	(0.000)	(0.000)
Length (Stock market boom)		0.015***	
		(0.000)	
Size (Stock market boom)			0.423***
			(0.000)
Stock market bust	0.364***	0.337***	0.360***
	(0.000)	(0.000)	(0.000)
Length (Stock market bust)		-0.022***	
		(0.005)	
Size (Stock market bust)			-1.077
			(0.152)
Real estate boom	0.005	-0.067	-0.046
	(0.935)	(0.331)	(0.497)
Length (Real estate boom)		-0.002**	
		(0.023)	
Size (Real estate boom)			-0.123
			(0.259)
Real estate bust	0.244*	0.155	0.178
	(0.055)	(0.253)	(0.198)
Length (Real estate bust)		-0.009***	
		(0.008)	
Size (Real estate bust)			-1.679**
			(0.032)
Bank FE	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,149
Adj. R^2	0.827	0.831	0.829
Adj. R^2 within	0.120	0.142	0.134

Table 8: Controlling for additional variation at the macro level

"... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. The additional macroeconomic variables in column 2 are identical to those used during the estimation of ΔCoVaR (cf. Appendix B). The estimation strategy of the rolling ΔCoVaR is described in Section 6.1. "Interest rate" refers to 10-year government bond rates. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:		ΔCoVaR		Rolling ΔCoVaR
Specification:	Baseline	ΔCoVaR Controls	Country-time FE	Baseline
Real estate boom	0.00	0.06***		0.07
	(0.935)	(0.002)		(0.120)
Real estate bust	0.24*	-0.02		0.10
	(0.055)	(0.711)		(0.207)
Stock market boom	0.33***	0.07***		0.22***
	(0.000)	(0.006)		(0.000)
Stock market bust	0.36***	0.08***		0.46***
	(0.000)	(0.006)		(0.000)
log(Bank size)	0.27***	0.08***	0.01	0.20***
	(0.000)	(0.001)	(0.818)	(0.000)
log(Bank size) · Real estate boom	0.00	-0.02	-0.04*	-0.13***
	(0.895)	(0.289)	(0.093)	(0.000)
log(Bank size) · Real estate bust	0.15***	0.16***	0.20***	-0.03
	(0.000)	(0.000)	(0.000)	(0.336)
log(Bank size) · Stock market boom	0.05***	0.07***	0.07***	-0.02
	(0.007)	(0.000)	(0.001)	(0.525)
log(Bank size) · Stock market bust	0.11***	0.13***	0.14***	0.13***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-4.38***	-2.99***	-2.01***	-10.23***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth · Real estate boom	4.38***	2.86***	2.22***	6.09***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth · Real estate bust	7.95***	5.97***	3.17**	6.61*
	(0.000)	(0.000)	(0.015)	(0.084)
Loan growth · Stock market boom	3.26***	1.31**	0.69	5.93***
	(0.000)	(0.031)	(0.194)	(0.000)
Loan growth · Stock market bust	3.92***	2.13***	1.14*	5.39**
	(0.000)	(0.003)	(0.082)	(0.043)
Leverage	0.01***	0.00**	0.00**	0.01***
	(0.005)	(0.013)	(0.040)	(0.002)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01**
	(0.030)	(0.010)	(0.000)	(0.015)
Leverage · Real estate bust	-0.01	-0.01**	-0.01***	0.03*
	(0.196)	(0.041)	(0.004)	(0.056)
Leverage · Stock market boom	-0.01***	-0.01***	-0.01***	0.00
	(0.001)	(0.002)	(0.002)	(0.674)
Leverage · Stock market bust	-0.02***	-0.02***	-0.02***	-0.03***
	(0.000)	(0.000)	(0.000)	(0.000)

(*table continued on next page*)

Table 8 - *continued*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔCoVaR		Rolling ΔCoVaR
Specification:	Baseline	CoVaR Controls	Country-time FE	Baseline
Maturity mismatch	-0.68***	-0.48***	-0.32***	-0.87***
	(0.000)	(0.000)	(0.006)	(0.000)
Maturity mismatch · Real estate boom	0.27***	0.28***	0.18**	0.32*
	(0.006)	(0.000)	(0.033)	(0.067)
Maturity mismatch · Real estate bust	0.45**	0.36**	-0.13	0.76***
	(0.034)	(0.041)	(0.436)	(0.010)
Maturity mismatch · Stock market boom	0.67***	0.04	0.03	0.32*
	(0.000)	(0.639)	(0.743)	(0.080)
Maturity mismatch · Stock market bust	0.38***	0.04	-0.02	0.36*
	(0.007)	(0.649)	(0.787)	(0.080)
GDP growth	-3.78***	0.71		-16.81***
	(0.004)	(0.243)		(0.000)
log(Interest rate)	-0.05	-0.03		-0.02
	(0.173)	(0.180)		(0.726)
Inflation	7.19**	-0.93		-3.39**
	(0.031)	(0.288)		(0.032)
Investment-to-GDP growth	-0.85**	-0.45***		-0.36
	(0.012)	(0.002)		(0.290)
Credit-to-GDP growth	1.76**	0.59*		-1.94***
	(0.017)	(0.066)		(0.000)
Equity market returns		-0.00		
		(0.284)		
Equity market volatiliy		0.02***		
		(0.000)		
Change in the 3M yield		-0.17		
		(0.452)		
Change in the slope of the yield curve		-0.36**		
		(0.041)		
TED spread		0.51***		
		(0.000)		
Credit spread		0.06		
		(0.656)		
Bank FE	Yes	Yes	Yes	Yes
Country-time FE	No	No	Yes	No
No. of banks	1,264	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,192	165,149
Adj. R^2	0.827	0.874	0.891	0.667
Adj. R^2 within	0.120	0.361	0.044	0.139

Table 9: The importance of bank-level developments revisited

Dependent variable: systemic risk estimated by the rolling ΔCoVaR (cf. Section 6.1). "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. The coefficients report the effect of the bubble phases conditional on all bank-level variables being at the indicated percentile of their distributions. The coefficients on bank characteristics, the interactions between bank characteristics and bubble indicators, and the coefficients on macroeconomic control variables are identical to the ones reported in Table 8, column 4. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Percentile of bank characteristics:	50^{th}	75^{th}	85^{th}	95^{th}
Real estate boom	0.11**	-0.01	-0.08	-0.12
	(0.021)	(0.919)	(0.359)	(0.333)
Real estate bust	0.09	0.23*	0.33**	0.65**
	(0.227)	(0.058)	(0.050)	(0.032)
Stock market boom	0.23***	0.28***	0.30***	0.39***
	(0.000)	(0.000)	(0.001)	(0.006)
Stock market bust	0.47***	0.64***	0.74***	0.81***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	Yes	Yes	Yes	Yes
Bank characteristics	Yes	Yes	Yes	Yes
Bank characteristics · Bubble indicators	Yes	Yes	Yes	Yes
Macroeconomic control variables	Yes	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,149	165,149
Adj. R^2	0.667	0.667	0.667	0.667
Adj. R^2 within	0.139	0.139	0.139	0.139

Table 10: Large and small banks

Columns 2 to 5 provide estimates of the baseline regression (Equation (8)) for small and large banks separately. To eliminate the US bias in our sample of small banks, we exclude the smallest US banks such that the number of US observations falls below the number of observations coming from the country contributing the second largest share of observations on small banks (France). See Table C.2 for an overview of the number of banks and observations per country. Column 6 provides estimates of a regression with each bank's observations weighted by their mean bank size relative to the size of their financial system, where the financial system is North America, Europe, Japan, or Australia. "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. "MM" refers to maturity mismatch. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Baseline	large banks	small banks	large banks	small banks	weighted by size
Dependent variable:		ΔCoVaR		log(ΔCoVaR)		ΔCoVaR
	(1)	(2)	(3)	(4)	(5)	(6)
Real estate boom	0.00	-0.05	0.03	0.01	0.02	-0.10
	(0.935)	(0.594)	(0.435)	(0.657)	(0.392)	(0.379)
Real estate bust	0.24*	0.49***	0.18***	0.13***	0.10***	0.45**
	(0.055)	(0.006)	(0.004)	(0.000)	(0.000)	(0.017)
Stock market boom	0.33***	0.43***	0.13***	0.12***	0.05**	0.27**
	(0.000)	(0.000)	(0.005)	(0.000)	(0.012)	(0.031)
Stock market bust	0.36***	0.67***	0.27***	0.19***	0.14***	0.58***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.27***	0.58***	0.29***	0.14***	0.12***	0.47***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	0.00	-0.10**	-0.01	-0.03***	-0.00	-0.06
	(0.895)	(0.017)	(0.615)	(0.006)	(0.838)	(0.175)
log(Bank size) · Real estate bust	0.15***	0.14*	0.08	0.00	-0.01	0.30***
	(0.000)	(0.063)	(0.103)	(0.832)	(0.515)	(0.001)
log(Bank size) · Stock market boom	0.05***	0.04	0.08***	0.01	0.07***	0.09
	(0.007)	(0.478)	(0.006)	(0.564)	(0.000)	(0.125)
log(Bank size) · Stock market bust	0.11***	0.13***	0.10***	0.02***	0.01	0.15***
	(0.000)	(0.000)	(0.001)	(0.005)	(0.426)	(0.000)
Loan growth	-4.38***	-7.62***	-1.59*	-2.19***	-0.79**	-7.05***
	(0.000)	(0.000)	(0.053)	(0.000)	(0.020)	(0.006)
Loan growth · Real estate boom	4.38***	4.06**	1.06	1.17**	0.97**	6.66**
	(0.000)	(0.038)	(0.210)	(0.016)	(0.025)	(0.013)
Loan growth · Real estate bust	7.95***	17.63***	4.46*	4.18***	1.85**	13.33***
	(0.000)	(0.000)	(0.068)	(0.000)	(0.022)	(0.002)
Loan growth · Stock market boom	3.26***	5.87**	-0.39	1.59***	0.44	2.57
	(0.000)	(0.010)	(0.721)	(0.003)	(0.443)	(0.371)
Loan growth · Stock market bust	3.92***	7.57***	0.02	1.71**	0.59	4.34
	(0.000)	(0.005)	(0.990)	(0.011)	(0.407)	(0.120)

(*table continued on next page*)

Table 10 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Baseline	large banks	small banks	large banks	small banks	weighted by size
Dependent variable:		ΔCoVaR		log(ΔCoVaR)		ΔCoVaR
Leverage	0.01***	0.02**	0.00	0.00*	0.00	0.03***
	(0.005)	(0.029)	(0.389)	(0.054)	(0.522)	(0.009)
Leverage · Real estate boom	0.01**	0.01	-0.01	0.00	-0.00	0.03**
	(0.030)	(0.178)	(0.232)	(0.218)	(0.221)	(0.020)
Leverage · Real estate bust	-0.01	-0.03*	0.01	-0.01*	0.01*	-0.01
	(0.196)	(0.085)	(0.121)	(0.066)	(0.063)	(0.685)
Leverage · Stock market boom	-0.01***	-0.02***	-0.01*	-0.00***	-0.00*	-0.02*
	(0.001)	(0.006)	(0.067)	(0.010)	(0.085)	(0.054)
Leverage · Stock market bust	-0.02***	-0.03***	-0.01**	-0.01***	0.00	-0.03***
	(0.000)	(0.000)	(0.022)	(0.000)	(0.907)	(0.001)
Maturity mismatch	-0.68***	-0.92**	-0.42**	-0.18*	-0.23***	-1.52***
	(0.000)	(0.023)	(0.023)	(0.070)	(0.004)	(0.001)
MM · Real estate boom	0.27***	0.44	0.37***	0.11	0.17***	0.97*
	(0.006)	(0.128)	(0.008)	(0.148)	(0.007)	(0.052)
MM · Real estate bust	0.45**	0.60	0.14	0.13	0.20**	1.41**
	(0.034)	(0.361)	(0.501)	(0.330)	(0.046)	(0.044)
MM · Stock market boom	0.67***	0.74**	0.24	0.18*	-0.09	0.52
	(0.000)	(0.036)	(0.155)	(0.075)	(0.293)	(0.348)
MM · Stock market bust	0.38***	0.71**	-0.05	0.15**	-0.00	0.60
	(0.007)	(0.017)	(0.761)	(0.042)	(0.982)	(0.190)
GDP growth	-3.78***	-1.02	-1.87***	-0.15	-0.97***	-0.01
	(0.004)	(0.497)	(0.005)	(0.643)	(0.000)	(0.995)
log(Interest rate)	-0.05	-0.07	0.03	-0.04**	-0.01	0.03
	(0.173)	(0.339)	(0.342)	(0.021)	(0.266)	(0.763)
Inflation	7.19**	12.74***	7.04***	2.22***	2.23***	8.00**
	(0.031)	(0.001)	(0.000)	(0.001)	(0.000)	(0.028)
Investment-to-GDP growth	-0.85**	-1.62***	-0.14	-0.38***	-0.11*	-1.08**
	(0.012)	(0.002)	(0.389)	(0.000)	(0.075)	(0.034)
Credit-to-GDP growth	1.76**	2.57***	0.97**	0.50***	0.48***	3.38***
	(0.017)	(0.004)	(0.028)	(0.007)	(0.008)	(0.002)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of banks	1,264	203	256	201	246	1,264
No. of obs.	165,149	30,639	31,053	30,543	30,155	165,149
Adj. R^2	0.827	0.592	0.821	0.786	0.915	0.623
Adj. R^2 within	0.120	0.173	0.109	0.209	0.161	0.182

Table 11: Choice of sample period

The first column shows our baseline regression formulated in Equation (8) and already reported in Table 4, column 5. Columns 2 to 4 restrict the sample period as indicated. Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1) full sample	(2) t>1995m1	(3) without 2008	(4) t<2007m12
Real estate boom	0.00	-0.01	0.12***	0.25***
	(0.935)	(0.900)	(0.000)	(0.000)
Real estate bust	0.24*	0.24*	0.41***	0.72***
	(0.055)	(0.069)	(0.000)	(0.000)
Stock market boom	0.33***	0.31***	0.32***	0.30***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock market bust	0.36***	0.34***	0.44***	0.42***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.27***	0.24***	0.18***	0.04
	(0.000)	(0.000)	(0.000)	(0.259)
log(Bank size) · Real estate boom	0.00	-0.01	0.01	0.07***
	(0.895)	(0.632)	(0.270)	(0.000)
log(Bank size) · Real estate bust	0.15***	0.15***	0.12***	0.27***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock market boom	0.05***	0.04*	0.06***	0.10***
	(0.007)	(0.057)	(0.000)	(0.000)
log(Bank size) · Stock market bust	0.11***	0.11***	0.12***	0.15***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-4.38***	-4.21***	-3.35***	-2.60***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth · Real estate boom	4.38***	4.46***	2.79***	1.98***
	(0.000)	(0.000)	(0.000)	(0.005)
Loan growth · Real estate bust	7.95***	8.56***	7.63***	3.12*
	(0.000)	(0.000)	(0.000)	(0.093)
Loan growth · Stock market boom	3.26***	3.22***	2.77***	1.95***
	(0.000)	(0.000)	(0.000)	(0.005)
Loan growth · Stock market bust	3.92***	3.84***	3.77***	2.41***
	(0.000)	(0.000)	(0.000)	(0.004)
Leverage	0.01***	0.01**	0.00***	0.02***
	(0.005)	(0.012)	(0.003)	(0.000)
Leverage · Real estate boom	0.01**	0.01***	0.01*	-0.01***
	(0.030)	(0.007)	(0.091)	(0.007)
Leverage · Real estate bust	-0.01	-0.00	-0.01	-0.05***
	(0.196)	(0.587)	(0.186)	(0.000)
Leverage · Stock market boom	-0.01***	-0.01***	-0.01***	-0.02***
	(0.001)	(0.003)	(0.001)	(0.000)
Leverage · Stock market bust	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)

(*table continued on next page*)

Table 11 - *continued*

	(1) full sample	(2) t>1995m1	(3) without 2008	(4) t<2007m12
Maturity mismatch	-0.68***	-0.61***	-0.59***	-0.59***
	(0.000)	(0.000)	(0.000)	(0.001)
Maturity mismatch · Real estate boom	0.27***	0.20**	0.30***	0.55***
	(0.006)	(0.042)	(0.001)	(0.000)
Maturity mismatch · Real estate bust	0.45**	0.41*	0.61***	0.84***
	(0.034)	(0.065)	(0.008)	(0.000)
Maturity mismatch · Stock market boom	0.67***	0.66***	0.60***	0.55***
	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch · Stock market bust	0.38***	0.38***	0.40***	0.32***
	(0.007)	(0.006)	(0.001)	(0.006)
GDP growth	-3.78***	-4.44***	-0.94	4.59***
	(0.004)	(0.002)	(0.315)	(0.000)
log(Interest rate)	-0.05	-0.03	-0.10***	-0.02
	(0.173)	(0.460)	(0.003)	(0.809)
Inflation	7.19**	8.79**	0.12	-1.49
	(0.031)	(0.018)	(0.925)	(0.366)
Investment-to-GDP growth	-0.85**	-0.84**	-0.66***	-1.40***
	(0.012)	(0.021)	(0.003)	(0.000)
Credit-to-GDP growth	1.76**	1.51**	0.19	0.36
	(0.017)	(0.044)	(0.667)	(0.504)
Bank FE	Yes	Yes	Yes	Yes
No. of banks	1,264	1,263	1,264	1,101
No. of obs.	165,149	157,910	156,468	102,066
Adj. R^2	0.827	0.829	0.880	0.884
Adj. R^2 within	0.120	0.106	0.127	0.194

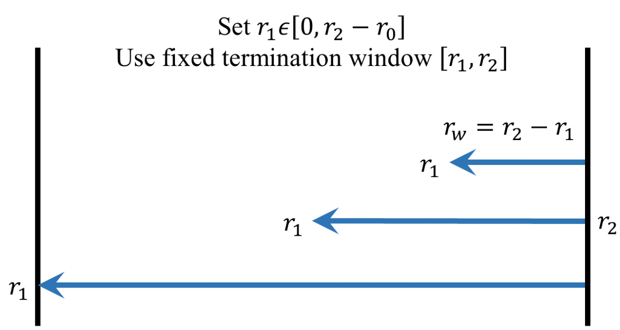
A Estimation of bubble episodes

The BSADF approach applies sequences of ADF tests to systematically changing fractions of a sample to identify episodes of explosive processes in price data. We follow the estimation strategy proposed by Phillips, Shi, and Yu (2015a). To fix notation, let r_1 denote some starting fraction of the sample and r_2 some ending fraction, implying $r_1 < r_2$. The fraction of the corresponding subsample is given by $r_w = r_2 - r_1$. Furthermore, let r_0 denote the fractional threshold that ensures that any analyzed subsample is large enough for the test to be efficient. The threshold is chosen according to $r_0 = 0.01 + 1.8\sqrt{T}$, where T refers to the number of observations in the sample.

The BSADF statistic (as opposed to the approach) for sample fraction r_2 is given by the supremum of all values of the test statistics of ADF tests performed while holding the ending fraction of the sample fixed at r_2 and varying the starting fraction from 0 to $r_2 - r_0$. Figure A.1 illustrates the idea. Formally, the BSADF statistic is thus given by

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \{BADF_{r_1}^{r_2}\} \ . \tag{A.1}$$

Figure A.1: Recursive nature of the BSADF test



Source: Phillips, Shi, and Yu (2015a, p. 1052)

The identification of bubble episodes relies on a sequence of BSADF statistics resulting from varying ending fraction r_2. Let the fraction of the sample at which the bubble starts be denoted by r_e, the fraction of the sample at which it ends by r_f, and the estimators of both by $\hat{r}_e$ and $\hat{r}_f$, respectively. The starting fraction r_e is estimated by the earliest point in time for which the BSADF test rejects the null hypothesis of no bubble existing. Similarly, the estimator for ending fraction r_f

is given by the earliest point in time after the emergence of the bubble and some minimum bubble length $\delta log(T)$ for which the BSADF test does not reject the null. Formally,

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} [r_2 : BSADF_{r_2}(r_0) > scv^{\beta}_{r_2}] \tag{A.2}$$

$$\text{and } \hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta log(T),1]} [r_2 : BSADF_{r_2}(r_0) < scv^{\beta}_{r_2}] \ , \tag{A.3}$$

where T is the number of observations of the analyzed time series and $scv^{\beta}_{r_2}$ is the critical value of the BSADF statistic based on $\lfloor Tr_2 \rfloor$ observations and confidence level β. $\lfloor Tr_2 \rfloor$ refers to the largest integer smaller than or equal to Tr_2. Critical values are obtained by Monte Carlo simulations based on 2,000 repetitions. The parameter δ is to be chosen freely according to one's beliefs about what minimum duration should be required in order to call surging prices a bubble. The minimum length requirement excludes short blips from being identified as bubbles and prevents estimating an overly early termination date of bubbles taking off slowly. We choose δ such that the minimum length of bubbles equals 6 months. The test identifies a few instances of bust-boom cycles that might be interpreted as "negative bubbles." Unfortunately, their number is too low to be included as a separate category in the main analyses. As the dynamics during such bust-boom cycles are likely to be quite different from those during customary bubble episodes, we disregard these bust-boom episodes when constructing the bubble indicators.

B Estimation of ΔCoVaR

We obtain daily information on the number of outstanding shares, unpadded unadjusted prices of common equity in national currency, and the corresponding market capitalization in US Dollar from Thomson Reuters Datastream for all listed institutions located in the 17 countries in our sample. To exclude public offerings, repurchases of shares and similar activities from biasing the results, observations for which the number of outstanding shares changed compared to the previous day are dropped. The daily observations are then collapsed to weekly frequency. As we additionally need balance sheet data in the main analyses, we include only those listed institutions for which such data is reported in the form of consolidated statements in Bankscope.

We calculate the weekly return losses on equity (X) of institution i and those of the financial system:

$$X^i_{t+1} = -\frac{P^i_{t+1}N^i_{t+1} - P^i_t N^i_t}{P^i_t N^i_t} \text{ and} \tag{B.1}$$

$$X^{system}_{t+1} = \sum_i \frac{MV^i_t}{\sum_i MV^i_t} X^i_{t+1} \ , \tag{B.2}$$

where P^i_t is the price of common equity of institution i at time t in national currency, N refers to the number of outstanding shares and MV is the market value in US Dollar. We use national currencies to compute the return losses in Equation (B.1) to prevent exchange rate fluctuations from biasing our results. To clarify the relevance of the currency, suppose return losses of Eurozone banks were calculated in US dollar. Further suppose, the euro would depreciate vis-à-vis the US dollar. Then, all other things equal, all banks in the Eurozone would simultaneously experience return losses which would lead to increases in ΔCoVaR. When calculating market shares of each institution (the ratio in Equation (B.2)), we have to rely on a uniform currency, which is why we use the market values in US dollar there. While exchange rate fluctuations introduce noise into the calculation of system return losses, they do not bias the results. Note that we calculate the system returns including the returns of institution i. One might suspect this to introduce a bias into the subsequent estimations as it should increase the correlation between system returns and institution-specific returns. Given the large number of institutions in our sample, such a bias should be negligible. We assess the robustness of the estimations by defining a separate system for each financial institution by excluding the corresponding institution from the calculation of the returns of its system. As in Adrian and Brunnermeier (2016), the results are highly robust to this alternative specification.

The sample is restricted to institutions with at least 260 weeks of non-missing return losses to ensure convergence of the quantile regressions (Equations (4) and (5)). The return losses are merged with variables capturing general risk factors. Adrian and Brunnermeier (2016) use the following state variables:

- the change in the three-month yield calculated from the three-month T-Bill rate published with the Federal Reserve Board's H.15 release;
- the change in the slope of the yield curve as captured by the yield spread between the ten-year treasury rate (FRB H.15) and the three-month T-Bill rate;
- the TED spread, measured as the difference between the three-month Libor rate (FRED database) and the three-month secondary market bill rate (FRB H.15);
- the change in the credit spread between the bonds obtaining a Baa rating from Moody's (FRB H.15) and the ten-year treasury rate;
- the weekly market returns of the S&P 500;
- the equity volatility calculated as a 22-day rolling window standard deviation of the daily CRSP equity market return;
- the difference between the weekly real estate sector return (companies with a SIC code between 65 and 66) and the weekly financial system return (all financial companies in the sample).

As usual for the estimation of ΔCoVaR outside the US, we do not include the spread between the real estate sector return and the financial system return.[11] Since we estimate ΔCoVaR in a multi-country setting, we assign each financial institution to one of the following four financial systems: North America, Europe, Japan or Australia. The association with a system is based on the location of an institution's headquarter. We use a distinct set of state variables for each system. Table B.1 provides an overview of the data used to construct the system-specific control variables.

We estimate ΔCoVaR at weekly frequency. To merge them with all other variables included in our main analyses, we collapse the resulting estimates to monthly frequency by taking averages.

[11] See, e. g., López-Espinosa, Moreno, Rubia, and Valderrama (2012); Barth and Schnabel (2013).

Table B.1: System-specific data

The 10-year government bond rates for Germany, Japan and Australia are only available at monthly frequency. In these instances, we use cubic spline interpolations to obtain the weekly observations required for the quantile regressions.

Adrian and Brunnermeier 2016	**Data used instead**			
	North America	**Europe**	**Japan**	**Australia**
10Y treasury rate	US 10Y treasury rate (FRED)	German 10Y govt. bond rate (OECD)	Japanese 10Y govt. bond rate (OECD)	Australian 10Y govt. bond rate (OECD)
3M T-Bill rate	US 3M T-Bill rate (FRED)	German 3M govt. bond rate (Bloomberg, FRED)	Japanese 3M govt. bond rate (Bloomberg, FRED)	Australian 3M govt. bond rate (Bloomberg, FRED)
3M Libor rate	3M Libor rate (FRED)	3M Fibor and 3M Euribor rate (Datastream)	3M Japanese Libor rate (FRED)	Australian 3M interbank rate (Datastream)
Moody's Baa rated bonds	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)
S&P500	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)
CRSP equity market index	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)

C Additional tables

Table C.1: Variable definitions and data sources

Detailed information on the variables' construction is provided in Sections 3 and 5.3, as well as Appendices A and B.

Variable name	Description
Dependent variable	
ΔCoVaR	Change in the conditional value at risk; estimation strategy provided in Section 3.2 and Appendix B. Source of market equity data: Datastream. Sources of control variables: see Table B.1.
Rolling ΔCoVaR	Rolling window version of ΔCoVaR (see above); estimation strategy provided in Section 6.1.
System-specific CoVaR variables	
Equity market returns	Weekly market returns of system-specific MSCI indices. Data sources: see Table B.1.
Equity market volatility	22-day rolling window standard deviation of the daily system-specific MSCI indices. Data sources: see Table B.1.
Change in the 3M yield	The change in three-month government bond rates. Data sources: see Table B.1.
Change in the slope of the yield curve	The change in the yield spread between ten-year and three-month government bond rates. Data sources: see Table B.1.
TED spread	The difference between three-month Libor rates and three-month government bond rates. Data sources: see Table B.1.
Credit spread	The difference between Moody's Baa rated bonds and ten-year government bond rates. Data sources: see Table B.1.
Bubble indicators	
Real estate boom	Country-specific binary indicator; equals one during the boom phase of a real estate bubble; estimated based on the BSADF approach (cf. Section 3.2 and Appendix B). Data source of real estate date: OECD.
Real estate bust	Country-specific binary indicator; equals one during the bust phase of a real estate bubble; estimated based on the BSADF approach (cf. Section 3.2 and Appendix B). Data source of real estate date: OECD.
Stock market boom	Country-specific binary indicator; equals one during the boom phase of a stock market bubble; estimated based on the BSADF approach (cf. Section 3.2 and Appendix B). Data source of stock market indeces: Datastream.
Stock market bust	Country-specific binary indicator; equals one during the bust phase of a stock market bubble; estimated based on the BSADF approach (cf. Section 3.2 and Appendix B). Data source of stock market indeces: Datastream.

(*table continued on next page*)

Table C.1 - *continued*

Variable name	Description
Bubble characteristics	
Length	Four country-specific variables (length of real estate boom, real estate bust, stock market boom, stock market bust); number of months since the beginning or climax of the respective bubble phase and episode; equals zero outside of the respective bubble phase and episode (cf. Section 5.3). Sources of the underlying data: OECD and Datastream.
Size	Four country-specific variables (size of real estate boom, real estate bust, stock market boom, stock market bust); size of an emerging bubble or size of its collapse; equals zero outside of bubble episodes (cf. Section 5.3). Sources of the underlying data: OECD and Datastream.
Bank characteristics	
Bank size	log(total assets); winsorized at 1%/99%. Source: Bankscope.
Loan growth	Δlog(total loans); monthly growth rate of total loans excluding interbank lending; winsorized at 1%/99%. Source: Bankscope.
Leverage	Total assets/equity; winsorized at 1%/99%. Source: Bankscope.
Maturity mismatch (MM)	(Total deposits, money market and short-term funding – loans and advances to banks – cash and due from banks)/total assets; winsorized at 1%/99%. Source: Bankscope.
Macroeconomic variables	
GDP growth	Δlog(real GDP); monthly growth rate. Source: OECD.
Interest rate	log(10-year government bond rate); Source: OECD. For a robustness check: log(policy rate); Sources: OECD, Datastream, National Central Banks.
Inflation	Δlog(CPI); monthly rate. Source: OECD.
Investment-to-GDP growth	Δlog(investment/GDP); monthly rate. Source: OECD.
Credit-go-GDP growth	Δlog(private non-financial credit/GDP); monthly rate. Source: BIS.

Table C.2: Sample coverage

The choice of countries is entirely determined by data availability. See Section 6.2 for robustness checks confirming that the results are not driven by a single country.

	Full sample			Large banks			Small banks		
Country	Banks	# Obs.	% Obs.	Banks	# Obs.	% Obs.	Banks	# Obs.	% Obs.
Australia	16	2,732	2	9	1,605	6	7	1,127	1
Belgium	5	597	0	3	514	2	2	83	0
Canada	14	1,976	1	9	1,662	6	5	314	0
Denmark	19	2,981	2	3	440	2	16	2,541	2
Finland	4	696	0	2	114	0	2	582	0
France	48	6,515	4	10	1,776	6	38	4,739	3
Germany	24	3,581	2	15	1,960	7	9	1,621	1
Italy	36	5,917	4	22	2,498	9	14	3,419	3
Japan	112	6,210	4	66	3,652	13	46	2,558	2
Netherlands	9	1,198	1	3	283	1	6	915	1
Norway	24	3,369	2	3	283	1	21	3,086	2
Portugal	7	969	1	3	341	1	4	628	0
Spain	14	2,724	2	10	1,588	6	4	1,136	1
Sweden	6	1,192	1	4	1,084	4	2	108	0
Switzerland	23	3,609	2	10	786	3	13	2,823	2
UK	20	3,633	2	12	2,233	8	8	1,400	1
US	883	117,250	71	59	7,493	26	824	109,757	80
Total	1,264	165,149	100	243	28,312	100	1,021	136,837	100

Table C.3: Bubble characteristics

Dependent variable: systemic risk estimated by ΔCoVaR. "... boom" and "... bust" indicate the respective bubble phases estimated based on the BSADF approach. "Length" and "size" capture bubble characteristics. Variable definitions are provided in Table C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)
Stock market boom	0.335***	0.313***	0.340***
	(0.000)	(0.000)	(0.000)
Length (Stock market boom)		0.015***	
		(0.000)	
Size (Stock market boom)			0.423***
			(0.000)
Stock market bust	0.364***	0.337***	0.360***
	(0.000)	(0.000)	(0.000)
Length (Stock market bust)		-0.022***	
		(0.005)	
Size (Stock market bust)			-1.077
			(0.152)
Real estate boom	0.005	-0.067	-0.046
	(0.935)	(0.331)	(0.497)
Length (Real estate boom)		-0.002**	
		(0.023)	
Size (Real estate boom)			-0.123
			(0.259)
Real estate bust	0.244*	0.155	0.178
	(0.055)	(0.253)	(0.198)
Length (Real estate bust)		-0.009***	
		(0.008)	
Size (Real estate bust)			-1.679**
			(0.032)

(*table continued on next page*)

Table C - *continued*

	(1)	(2)	(3)
log(Bank size)	0.266***	0.273***	0.267***
	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	0.002	-0.001	0.002
	(0.895)	(0.951)	(0.890)
log(Bank size) · Real estate bust	0.154***	0.177***	0.166***
	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock market boom	0.047***	0.069***	0.064***
	(0.007)	(0.000)	(0.001)
log(Bank size) · Stock market bust	0.113***	0.113***	0.112***
	(0.000)	(0.000)	(0.000)
Loan growth	-4.384***	-3.224***	-3.526***
	(0.000)	(0.000)	(0.000)
Loan growth · Real estate boom	4.384***	2.882***	3.298***
	(0.000)	(0.000)	(0.000)
Loan growth · Real estate bust	7.952***	6.136***	6.594***
	(0.000)	(0.000)	(0.000)
Loan growth · Stock market boom	3.256***	1.900***	2.222***
	(0.000)	(0.010)	(0.004)
Loan growth · Stock market bust	3.923***	3.238***	3.380***
	(0.000)	(0.000)	(0.000)
Leverage	0.006***	0.005**	0.005**
	(0.005)	(0.012)	(0.013)
Leverage · Real estate boom	0.008**	0.007*	0.008**
	(0.030)	(0.054)	(0.033)
Leverage · Real estate bust	-0.009	-0.012	-0.010
	(0.196)	(0.108)	(0.173)
Leverage · Stock market boom	-0.014***	-0.013***	-0.015***
	(0.001)	(0.001)	(0.000)
Leverage · Stock market bust	-0.020***	-0.021***	-0.020***
	(0.000)	(0.000)	(0.000)

(*table continued on next page*)

Table C - *continued*

	(1)	(2)	(3)
Maturity mismatch	-0.682***	-0.710***	-0.680***
	(0.000)	(0.000)	(0.000)
Maturity mismatch · Real estate boom	0.271***	0.224**	0.169*
	(0.006)	(0.020)	(0.081)
Maturity mismatch · Real estate bust	0.447**	0.385*	0.443**
	(0.034)	(0.060)	(0.036)
Maturity mismatch · Stock market boom	0.669***	0.350***	0.472***
	(0.000)	(0.002)	(0.000)
Maturity mismatch · Stock market bust	0.377***	0.277*	0.390***
	(0.007)	(0.057)	(0.005)
GDP growth	-3.784***	-4.989***	-5.046***
	(0.004)	(0.000)	(0.000)
log(Interest rate)	-0.052	-0.059	-0.052
	(0.173)	(0.102)	(0.144)
Inflation	7.190**	8.537**	8.439**
	(0.031)	(0.013)	(0.014)
Investment-to-GDP growth	-0.854**	-0.623*	-0.665**
	(0.012)	(0.051)	(0.034)
Credit-to-GDP growth	1.763**	2.043**	1.943**
	(0.017)	(0.013)	(0.014)
Bank FE	Yes	Yes	Yes
No. of banks	1,264	1,264	1,264
No. of obs.	165,149	165,149	165,149
Adj. R^2	0.827	0.831	0.829
Adj. R^2 within	0.120	0.142	0.134