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Asset Price Bubbles and Systemic Risk

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Abstract

We analyze the relationship between asset price bubbles and systemic risk, using bank-level data covering almost thirty years. Systemic risk of banks rises already during a bubble's build-up phase, and even more so during its bust. The increase differs strongly across banks and bubble episodes. It depends on bank characteristics (especially bank size) and bubble characteristics, and it can become very large: In a median real estate bust, systemic risk increases by almost 70 percent of the median for banks with unfavorable characteristics. These results emphasize the importance of bank-level factors for the build-up of financial fragility during bubble episodes.

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

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

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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 without any wider macroeconomic consequences.

Historical evidence suggests that the severity of crises after the burst of a bubble depends on the state of the financial system. 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 may be amplified through the financial sector. For example, the US subprime mortgage market accounted for only 4 percent of the total US mortgage market at the time of the burst of the subprime bubble (Brunnermeier and Oehmke, 2013, p. 1223). Yet, this burst gave rise to one of the largest financial crises in history, because the initial shock was amplified by the imbalances that had built up in the financial sector.

While the impact of asset price bubbles on macroeconomic variables is well-documented (Jordà, Schularick, and Taylor, 2013, 2015a,b), little is known about the role of individual financial institutions in the build-up of systemic risk during asset price bubbles. However, this knowledge is crucial to understand the channels through which asset price bubbles affect systemic risk and to design appropriate policy responses. Moreover, a single systemically important financial institution can play a critical role in a financial crisis, just like Lehman Brothers did in the Global Financial Crisis. Hence, not only the overall size of financial sector imbalances during asset price bubbles matters but also the allocation of risks across banks.

We fill this gap in the literature by empirically analyzing the relationship between asset price bubbles and systemic risk at bank level. Our analysis covers 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. Moreover, we analyze the role of bubble characteristics, namely their length and size.

Measuring systemic risk at bank level yields additional insights compared to employing a binary indicator of financial crises for three reasons. First, it allows us to analyze the changes in systemic risk across banks during asset price bubbles in addition to the aggregate level of systemic risk. This is important because financial crises are often not merely the result of macroeconomic shocks but are reinforced by contagion effects within the financial sector, for which a small number of banks often play an important role. Second, using continuous measures of systemic risk raises the statistical power of our estimates due to their variation over time and across banks, whereas banking crises are rare events. Third, systemic risk measures are useful from a conceptual perspective. Unlike a financial crisis dummy, they also account for episodes of high financial fragility that did not result in a crisis. In fact, increased systemic risk predicts future declines in real activity (Allen, Bali, and Tang, 2012; Engle, Jondeau, and Rockinger, 2015; Giglio, Kelly, and Pruitt, 2016; Brownlees and Engle, 2017), which points towards costs of financial fragility independent of whether the risks materialize. Hence, regulation should care about episodes of high systemic risk due to their crisis potential and the real effects of financial fragility.[1]

Our analysis is based on a broad, bank-level dataset spanning the time period from 1987 to 2015. The dataset contains monthly observations on 1,264 financial institutions. The empirical analysis models banks' contributions to systemic risk, or banks' exposures to systemic risk, as a function of financial bubbles as well as bank- and country-level characteristics. Our analysis distinguishes between the boom and bust phases of bubble episodes to analyze both the build-up of asset price bubbles as well as their bursting. We allow the effect of bubbles to depend on bank characteristics (bank size, loan growth, leverage, maturity mismatch) and on bubble characteristics (boom and bust length and size) to account for the heterogeneity across banks and bubble episodes.

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, however, lead us to overestimate the relationship between asset price bubbles and systemic risk. To prevent this sample selection bias, we instead estimate bubble episodes by applying the Backward Sup Augmented Dickey-Fuller

[1]Moreover, the estimation of the systemic risk measures applied in this paper is based on equity return losses, which also capture the intensity of financial crises (Baron, Verner, and Xiong, 2018).

(BSADF) approach introduced by Phillips, Shi, and Yu (2015a,b). This approach identifies bubble episodes based on episodes of non-stationary behavior in price data. We also consider price-to-rent and price-to-dividend data to account for fundamentals. Additionally, we apply an alternative bubble identification approach proposed by Jordà, Schularick, and Taylor (2015b), which relies on price deviations from trends.

The second challenge lies in the quantification of systemic risk at bank level. We apply ΔCoVaR (conditional value at risk) introduced by Adrian and Brunnermeier (2016) and the marginal expected shortfall (MES) proposed by Acharya, Pedersen, Philippon, and Richardson (2017). Both measures quantify systemic risk at bank level, while taking a complementary perspective. ΔCoVaR 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. Hence, this measure thinks of banks as *risk inducers*. Contrary to this perspective, MES treats banks as *risk recipients* by calculating the equity losses of a bank conditional on the financial system experiencing distress.

Our results are in line with the common conjecture that asset price bubbles pose a threat to financial stability. As summarized in Figure 1, asset price bubbles of median length and size go along with a significant increase in systemic risk for banks of median size, loan growth, leverage, and maturity mismatch (light blue bars). This increase in systemic risk is not limited to the turmoil following the burst of a bubble, but exists already during its build-up phase. Policies aimed at preventing financial fragility 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.

[Figure 1 about here]

Moreover, the increase in systemic risk depends strongly on bank characteristics (grey bars) and somewhat less on bubble characteristics (dark blue bars). During the bust phase of a bubble with median bust size and length, the systemic risk contribution of a bank with unfavorable bank characteristics increases by 54 percent of the median of ΔCoVaR. Bank size is the most important determinant of this increase, underlining large banks' potential to propagate and amplify shocks from a bursting asset price bubble when getting under distress. High loan growth and a large maturity mismatch also contribute to a larger increase in systemic risk, but to a smaller extent. The findings regarding leverage are mixed and economically small. With respect to bubble characteristics, we find longer and larger bubbles to be associated with larger increases in systemic risk during the boom phase. During the bust phase, the increase in systemic risk is smaller the more time has passed since the burst and the more the bubble has deflated already. This points towards a fading out of the effects of bursting bubbles.

The increase in systemic risk is largest during real estate busts, especially in case of unfavorable balance sheet characteristics: The 95^{th} percentile of the increase in systemic risk in dependence of balance sheet characteristics amounts to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent. To further put the size of the effect into perspective, consider the most prominent example of a single bank's distress translating into a worldwide systemic financial crisis, namely the collapse of Lehman Brothers. Shortly before its collapse during the bust phase of the US subprime housing bubble in 2008, our estimates imply that systemic risk associated with Lehman getting under distress would have been 40 percent lower if there had not been a bubble. While the risks associated with stock market bubbles are smaller, the estimated increase in systemic risk during these episodes suggests that stock market bubbles should not be disregarded either as a potential source of financial fragility.

In order to check the robustness of our results, we apply different measures of asset price bubbles and systemic risk. Specifically, we normalize price series by rents and dividends, respectively, in the BSADF test. Alternatively, we identify bubble episodes based on deviations of prices from trends. As a second measure of systemic risk, we use MES to capture banks' exposures to systemic risk. The robustness checks confirm the rise of systemic risk in bubble episodes (although the result on real estate bubbles is weakened for the trend-deviation approach) and the important role played by bank and bubble characteristics. For MES, the relationship to specific bank characteristics is different from ΔCoVaR due to the conceptual differences, but the overall relationship between bubbles and systemic risk is again similar, with a strong role for bubble and bank characteristics, especially bank size.

We additionally account for a potentially mechanical correlation between our bubble and systemic risk measures and find that systemic risk increases less during stock market bubbles in some specifications. When distinguishing between banks of different sizes, we show that both small and large banks are affected to a similar extent. Moreover, neither a certain country nor a specific time period is driving our main result that increases in systemic risk differ systematically across banks and bubble episodes. Finally, accounting better for business cycles does not affect our main results.

Overall, our results suggest that strengthening the resilience of the financial system at the bank level may significantly decrease the system's vulnerability to asset price bubbles. Moreover, it may not be sufficient to "clean up the mess" after a bubble has burst as a longer and larger bubble tends to increase the build-up of systemic risk. It rather seems advisable to try to prevent the build-up of risk in the first place.

The paper proceeds as follows. We start with a brief discussion of the related literature and our contribution in Section 2. Section 3 elaborates on the data, the identification of bubble episodes, the estimation of systemic risk measures, as well as the empirical model. Section 4 contains our baseline results, followed by a discussion of the results using alternative measures in Section 5. Section 6 presents further robustness checks. We conclude with a discussion of policy implications in Section 7. The Appendix provides further details on the data, estimation procedures, as well as additional figures and tables.

2 Contribution to the literature

Our paper contributes to the strands of literature in macroeconomics and finance studying asset price bubbles, systemic risk, and financial crises. Financial crises are frequently accompanied by a boom and bust of asset prices in both developed and developing economies. Although the corresponding narrative has been known for a long time (Minsky, 1982), the relationship between asset price bubbles and systemic risk has hardly been analyzed empirically. 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). Our paper speaks to this literature by analyzing a large number of asset price bubbles, based on a broad set of countries and a time period of almost thirty years. It thus complements this literature with an econometric perspective.

The notion of systemic risk as a concept for financial stability appeared only in the late 1990s and early 2000s, which has given rise to a large literature attempting to measure systemic risk at bank and system level, including Acharya, Engle, and Richardson (2012), Adrian and Brunnermeier (2016), Brownlees and Engle (2017), as well as Acharya, Pedersen, Philippon, and Richardson (2017). An early literature review of the concepts of systemic risk is provided by de Bandt and Hartmann (2000). Bisias, Flood, Lo, and Valavanis (2012) provide a taxonomy and discuss the advantages and drawbacks of different approaches. Allen, Babus, and Carletti (2012) as well as Brunnermeier and Oehmke (2013) provide comprehensive reviews, also including the theoretical literature. We draw upon this literature by applying established measures of systemic risk and by analyzing asset price bubbles as a new driver of these measures. We also shed light on the interplays between asset price bubbles and bank characteristics that have been shown to be linked to systemic risk, such as bank size, leverage, and maturity mismatch.

Similarly, we build on the literature dealing with the identification of asset price bubbles by applying some of the most prominent approaches. Many strategies are built around tests for non-stationary behavior in price data (Kim, 2000; Kim and Amador, 2002; Busetti and Taylor, 2004; Breitung and Homm, 2012).[2] One of the most prominent estimation procedures is the Backward Sup Augmented Dickey-Fuller (BSADF) approach introduced by Phillips, Shi, and Yu (2015a,b) and developed further by Phillips and Shi (2018). The quantitative procedures allow to objectify the classifications. This reduces the selection bias inherent in historical accounts of bubbles and financial crises, which tend to focus on the most severe events, because these were most likely to be reported. We contribute to this literature by contrasting the results of the applications of several conceptually different measures and by analyzing the relationship between the identified bubble episodes and systemic risk.

[2]Early contributions were Shiller (1981), 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.

We also draw upon the theoretical literature suggesting channels through which asset price bubbles may give rise to financial instability. Bursting asset price bubbles can set in motion loss and liquidity spirals, forcing distressed institutions to sell assets, thereby further depressing prices and forcing additional 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 make risk 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).[3] However, asset price bubbles may not only trigger the materialization of financial imbalances. They can also cause the build-up of these imbalances in the first place. 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 financial institutions' risk. To capture the role of asset price bubbles both in the build-up and in the realization of financial risks, we consider the emergence of systemic risk in the boom phase as well as the materialization of risk in the bust phase of the bubble.

The comparably small literature looking specifically at the relationship between asset price bubbles and systemic risk has largely taken a macroeconomic perspective. Gertler and Gilchrist (2018) describe how the recent theoretical and empirical literature can explain the developments during the Great Recession. They also provide an empirical analysis, emphasizing the importance of the disruption of financial intermediation relative to other contributing factors. Schularick and

[3] Empirical evidence on such spirals is provided, for example, by Schnabel and Shin (2004), Adrian and Shin (2010), and Gorton and Metrick (2012).

Taylor (2012) and Jordà, Schularick, and Taylor (2013, 2015a,b) provide econometric analyses 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). By analyzing the role of bank characteristics for the relationship between asset price bubbles and systemic risk, this paper takes the analysis of bubbles from the macroeconomic to the microeconomic level while maintaining a systemic perspective through its approach to the measurement of risk. This yields new insights on the transmission channels between asset price bubbles and systemic risk and highlights the heterogeneity of the increase in systemic risk across banks.

3 Data and empirical model

3.1 Data sources and sample

Our analysis relies on a number of data sources listed in Table C1, which also provides variable definitions. The estimation of real estate bubbles is based on real house prices and rents provided by the OECD. Stock market bubbles are estimated using country-specific MSCI price indices and, in some cases, dividends recovered from MSCI return indices from Thomson Reuters' Datastream. These indices were chosen due to their broad coverage (85% of each country's total stock market capitalization) and the unified methodological framework, which makes them comparable across countries.

For the estimation of systemic risk, we obtain daily information on the number of outstanding shares, stock prices of common equity, and market capitalization from Thomson Reuters' Datastream for all listed institutions. The control variables used in the estimation of ΔCoVaR are listed in Table B1 in Appendix B. Bank balance sheet characteristics are taken from Bureau von Dijk's Bankscope. Finally, we use a large number of macroeconomic control variables.

The sample includes all countries for which we have data on both real estate and stock markets. We keep all banks for which balance sheet information and sufficient return data for the estimation of systemic risk contributions are available.[4] The final sample contains monthly observations on 1,264 financial institutions located in 17 countries, yielding a total of 165,149 observations.[5]

3.2 Measuring asset price bubbles

In order to identify asset price bubbles, we rely on the Backward Sup Augmented Dickey-Fuller (BSADF) approach by Phillips, Shi, and Yu (2015a,b) and updated by Phillips and Shi (2018), which is well established in the literature.[6] It outperforms comparable approaches in terms of size and power if multiple bubble episodes occur within a dataset, as is shown by the simulations in Breitung and Homm (2012) and Phillips, Shi, and Yu (2015a). This property is valuable for our study as the analyzed sample typically covers more than one bubble episode per price series. The BSADF approach applies backward-expanding sequences of Augmented Dickey-Fuller (ADF) tests to subsamples of price data.

Figure 2 shows the recent Spanish housing bubble for illustration. The test 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). It thus signals that the price data (black line) is on an explosive trajectory. The end of a bubble episode is reached once the test statistics fall back below their critical values. Appendix A provides a detailed description of the estimation procedure.

In alternative specifications, we apply the approach by Jordà, Schularick, and Taylor (2015b) who define a bubble as an episode in which prices are elevated relative to their trend and exhibit a large price correction. Specifically, this approach first identifies episodes of price elevation whenever log real asset prices exceed their Hodrick-Prescott filtered trend by more than one standard deviation. Afterwards, a price correction signal is defined to equal one whenever prices drop by

[4]We exclude all institutions with fewer than 260 weeks of non-missing equity return losses to ensure convergence of the quantile regressions used during the estimation of systemic risk contributions.

[5]As shown in Table C2 in the Appendix, the number of banks differs widely across countries. The number of US banks is comparably large due to the high number of small publicly traded banks. This does not drive our results as shown in the robustness check in Section 6.2, where we explore differences between large and small banks.

[6]Applications can be found, e. g., in Gutierrez (2013); Bohl, Kaufmann, and Stephan (2013); Etienne, Irwin, and Garcia (2014); Jiang, Phillips, and Yu (2015).

more than 15% within three years. Finally, a bubble is any episode of price elevation during which the price correction signal equals one at least once.

We distinguish between the boom and the bust phases of a bubble (see the blue and grey shaded areas in Figure 2) based on the global peak of the price series during each bubble episode. Hence, we construct four binary variables for each country, indicating episodes in which a real estate or stock market bubble builds up or collapses, in order to capture differences across the phases of the asset price cycle.[7]

[Figure 2 about here]

We apply the BSADF test to quarterly real house price data covering the period 1976 to 2016 and monthly observations of stock price indices covering the period 1973 to 2016. The data used to estimate the bubble episodes go back further than the data used in the main analysis, which improves the size and power of the BSADF test.[8] 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.[9]

Asset price bubbles are often thought of as price deviations from fundamental values. To account for this property, we additionally apply the BSADF approach to normalized price series, i. e., real house prices divided by rents and stock prices divided by dividends. Unfortunately, the availability of rent and dividend data is limited in the time dimension. The advantage of using the normalized price series thus comes at the cost of lower size and power. Our main analyses therefore rely on the BSADF estimates based on non-normalized price series.[10]

The dataset used in the regressions spans 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,

[7] Unlike the trend-deviation approach, the BSADF approach is entirely backward-looking. The boom-bust distinction introduces a forward-looking component. Our main results are robust towards dropping the boom-bust distinction (see Table C3).

[8] 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).

[9] The results are robust towards using quarterly data (see Table C4).

[10] The results are virtually the same when using estimates based on the normalized price series (see Section 5.1).

but also many other bubble episodes, such as the dotcom stock market boom and bust around 2000, or the real estate boom and bust cycles around 1990 in several countries.[11] Table 1 provides an overview of the number of bubble episodes resulting from the three different estimation strategies. According to the BSADF approach, our sample comprises 33 real estate booms and 26 busts, while it contains 45 stock market booms and 47 busts.[12] On average, countries experienced 1.9 real estate booms, 1.5 real estate busts, 2.6 stock market booms, and 2.8 stock market busts. The two alternative bubble identification strategies also find stock market bubbles to occur more frequently than real estate bubbles. Using normalized data, the BSADF approach finds a lower average number of stock market booms and busts per country (2.1 and 1.6) and an almost identical average number of real estate booms and busts (1.9 and 1.6). The trend-deviation approach finds fewer real estate booms and busts per country (1.2 and 1.3) and significantly more stock market booms and busts (4.2 and 3.8).

[Table 1 about here]

Figure 3 displays the occurrence of booms and busts per country for our baseline bubble estimates. Many stock market bubble episodes occur around the run-up to the global financial crisis, the dotcom bubble, as well as the mid-1980s.[13] Real estate bubbles appear to be much more persistent, especially since the 2000s when most countries experienced a real estate bubble. According to our estimates, real estate booms last on average five years, while the bust lasts 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. With the exception of the stock market bubbles between 2006 and 2008, the bubble episodes relying on normalized data generally identify similar yet shorter periods. The stock market bubble episodes estimated using deviations from trend are again similar to those

[11] 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.

[12] The number of booms and busts differs if a bubble is already in the bust phase at the beginning of our sample period, or if a bubble is still in the boom phase at the end of the sample used in the main analysis. We can estimate these bubble episodes since the data used for bubble identification covers a significantly longer period than the data used in the main analyses.

[13] The results are not driven by episodes during which a lot of countries simultaneously experience a stock market bubble (see Table C5).

identified by the BSADF approach. The largest differences are found for real estate bubbles in the second half of the sample. These occur less frequently and are less persistent compared to the bubbles estimated with the BSADF approach (see Figures C1 and C2 in the Appendix).

[Figure 3 about here]

On the basis of the estimated bubble episodes, we calculate the bubble characteristics *length* and *size*. *Length* counts the number of months 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 equal to zero.

Table 2 displays summary statistics of bubble characteristics during bubble episodes (i. e., conditioning on a bubble being identified). The general patterns are consistent across bubble identification approaches. Real estate bubbles have on average been present for a longer time than stock market bubbles, and booms are more persistent than busts. Stock market booms and busts are on average larger than real estate booms and busts. Finally, the average size of a boom is larger than the average size of a bust. Specifically, prices are on average 78% above the initial value during a stock market boom, but only 38% during a real estate boom according to our baseline BSADF approach. 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.[14]

[Table 2 about here]

3.3 Measuring systemic risk

Our goal is to analyze the link between asset price bubbles and systemic risk at bank level. There exists no single "correct" approach to quantify systemic risk at the micro level. In this paper,

[14] Interestingly, the average bust size is very similar between our baseline BASDF estimates and the trend-deviation approach even though the BSADF approach does not explicitly incorporate a bust criterion.

we rely on two prominent measures, ΔCoVaR (Adrian and Brunnermeier, 2016) and marginal expected shortfall (MES) (Acharya, Pedersen, Philippon, and Richardson, 2017).[15] The combination of both measures is appealing due to their complementary perspectives. ΔCoVaR regards banks as "risk inducers" and quantifies the contribution of a financial institution to the system's level of systemic risk by estimating the additional value at risk (VaR) of the entire financial system associated with this institution experiencing distress. Contrary to this perspective, MES treats banks as "risk recipients" and calculates the equity losses of a bank conditional on the financial system experiencing distress.

In accordance with the above definition, ΔCoVaR can be written as

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=VaR_{50}^i} \ , \tag{1}$$

where X_i denotes the return loss of institution i and q refers to a percentile of the loss distribution. The VaR is implicitly defined by $Pr(X^i \leq VaR_q^i) = q\%$, and CoVaR is implicitly defined by $Pr(X^{system} \leq CoVaR_q^{system|C(X^i)}|C(X^i)) = q\%$. Following Adrian and Brunnermeier (2016), we estimate ΔCoVaR using quantile regressions.[16] The estimation procedure is described in detail in Appendix B.

MES is calculated as the average bank return during the 5% days during which the financial system exhibited the worst losses during the past year. We use overlapping windows to obtain monthly estimates. Denoting the set of trading days with the 5% worst system returns during the past 12 months at month t as $\mathbb{Z}_t^{system}$, MES can be expressed as

$$MES_t^i = \frac{1}{\text{\# of days in } \mathbb{Z}_t} \sum_{\tau \in \mathbb{Z}_t^{system}} X_\tau^i \ . \tag{2}$$

[15] 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), realized systemic risk beta (Hautsch, Schaumburg, and Schienle, 2015), and SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2017).

[16] 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.

Both measures are based on tail correlations of equity returns. As for most other systemic risk measures, the quantified relationship is non-causal. While the measures pick up causal spillovers from one financial institution to the system (or vice versa in case of MES), they also capture correlated shocks that affect many banks at the same time, for example, small banks being "systemic as part of a herd". The common idea underlying tail-correlation measures is that the functioning of the financial system is likely to be impaired if a large number of banks experience distress at the same time. Given this definition of systemic risk, banks' common exposures to shocks are equally relevant for financial stability as spillover risks. The ability of systemic risk measures to capture both sources of systemic risk should hence be considered a virtue rather than a bug.

Table 3 provides summary statistics for ΔCoVaR and MES. 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 of 1.96 percentage points based on weekly returns. The mean of MES equals 1.34, meaning that, on average, a bank's daily equity return was –1.34 percent on days during which the financial system suffered severe market equity value losses. Figure 4 displays the evolution of the average ΔCoVaR and MES in the four considered financial systems (North America, Europe, Japan, and Australia) over time. Both measures evolve similarly. However, ΔCoVaR leads MES due to the use of a rolling window in the estimation of MES. Therefore, in some regressions with MES, we lag all explanatory variables by 6 months. All four financial systems show a marked peak in ΔCoVaR and MES at the time of the global financial crisis.[17] 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 episode is hardly reflected in the series.

[Table 3 about here]

[Figure 4 about here]

3.4 Bank-level variables and macroeconomic controls

We include bank characteristics in our analysis that have been shown to drive an institution's systemic risk contribution, such as size (the logarithm of total assets), leverage (total assets divided

[17] Despite its prominence, this crisis does not drive our results (see Section 6.3).

by equity), and maturity mismatch (short-term liabilities minus short-term assets, divided by total assets). Additionally, we consider the role of loan growth (Δlog(loans)), as credit-fueled bubbles have been shown to be particularly harmful (Jordà, Schularick, and Taylor, 2015b; Brunnermeier and Schnabel, 2016).[18] We apply cubic spline interpolations to obtain monthly observations. The bank-level variables enter the regressions winsorized at the 1 and 99-percent level to deal, for example, with extreme leverage of defaulting institutions and high loan growth of institutions starting from a very low loan level.

The median bank in our sample is small with total assets of around 1.9 billion US dollar, and size varies greatly (Table 3).[19] Average and median 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 12 and a median maturity mismatch of 0.75, again with a wide variation.

With respect to macroeconomic control variables, we observe a banking crisis during 36 percent of observations. Median real GDP growth and inflation are 2.3 and 2.1 percent. The median 10-year government bond rate is 4.5 percent and median investment-to-GDP growth is slightly positive. Looking at the 5^{th} and 95^{th} percentile of the distribution, we can see that the sample includes severe recessions as well as strong booms, mirroring the diverse macroeconomic developments of the 17 countries over the sample period of almost thirty years.

3.5 Empirical model

We regress systemic risk (measured by ΔCoVaR or MES) of institution i at time t on bank fixed effects (α_i), the four binary variables indicating booms and busts in stock and real estate markets ($I_{c,t}^{Bubble}$) in country c at time t, lagged bank characteristics, the interaction terms of the bubble indicators with bank and bubble characteristics, and the lagged country-specific macroeco-

[18] The literature suggests that bank activities not related to lending may also be relevant (see, e. g., Brunnermeier, Dong, and Palia, 2012). Therefore, we also included the ratio of non-interest rate income to interest rate income in our regressions. However, this variable and its interactions with the bubble indicators are not significant in any regression (see Table C6) and do not change any coefficient of the other variables significantly. Therefore, we disregard this variable in the remainder of this paper.

[19] In Section 6.2, we check 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.

nomic control variables ($C_{c,t-1}$). We do not need to include non-interacted bubble characteristics as they are zero outside of bubble episodes.

$$\begin{aligned} Systemic\ risk_{i,t} = \alpha_i &+ \beta_1 \cdot I^{Bubble}_{c,t} + \gamma \cdot Bank\ characteristics_{i,t-1} \\ &+ \beta_2 \cdot I^{Bubble}_{c,t} \cdot Bank\ characteristics_{i,t-1} \\ &+ \beta_3 \cdot I^{Bubble}_{c,t} \cdot Bubble\ characteristics_{c,t} + \lambda \cdot C_{c,t-1} + u_{i,t}\ . \end{aligned} \tag{3}$$

Larger values of ΔCoVaR (MES) correspond to a higher systemic risk contribution (exposure). Hence, we expect a positive sign for all coefficients included in β, corresponding to an increase in systemic risk during asset price bubbles. The relationship between bubbles and systemic risk is likely to depend on an institution's balance sheet characteristics, which is captured by the interaction terms. We expect a stronger relationship between bubbles and systemic risk for banks with unfavorable bank characteristics. For instance, if a bubble is financed by loans, higher loan growth raises a bank's exposure to the bubble and should thus also raise its systemic risk contribution. Similarly, the relationship may depend on bubble characteristics. For example, an emerging asset price bubble might be more harmful the longer it has lasted already because it 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 fades out.

We do not include time fixed effects in the baseline regressions because these would absorb part of the variation that we are interested in. To clarify the argument, suppose we had only two countries in the sample that exhibit a bubble at the same time and banks experience the same increase in systemic risk. With time fixed effects, the coefficients of the bubble indicators would capture the change in systemic risk relative to the average of the two countries. Then, the coefficients on the bubble indicators would suggest no change in systemic risk during asset price bubbles (relative to the global average). In Section 6.1, we analyze the robustness of our results with respect to time and country-time fixed effects and find that most results continue to hold.

We subtract the median from all bank-level variables and bubble characteristics such that the coefficients on the bubble indicators can be interpreted as the change in systemic risk contributions (or exposures) of a bank of *median* size, loan growth, leverage, and maturity mismatch during a boom or bust of *median* size and length.

On country level, we include a banking crisis dummy, real GDP growth to capture national business cycles, and inflation, which has been identified as a factor contributing to the occurrence of financial crises (Demirgüç-Kunt and Detragiache, 1998).[20] The 10-year government bond rates (in logs) account for the nexus between sovereigns and banks. In a robustness check (not reported), we use 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).[21] Our results are robust to the choice of the interest rate. Growth of investment to GDP is included to control for the use of credit for investment versus consumption (see Schularick and Taylor, 2012).

One concern in our empirical model could be reverse causality. This problem appears less severe than in analyses at macroeconomic level because systemic risk contributions at bank level are less likely to impact asset price bubbles than aggregate systemic risk. Nevertheless, it is plausible that banks themselves play a role in the creation of asset price bubbles. Cheap financing during a credit boom may lead to large real estate investments which may culminate in, or reinforce, a real estate bubble. Since we explicitly control for banks' loan growth, this would not bias our results. To further alleviate the concern of reserve causality, we also control for a number of other bank characteristics and, in some specifications, further lags of the explanatory variables.[22] These precautions make it less likely that our estimates suffer from reverse causality. In another robustness check, we estimate simple linear probability models and run Granger causality tests to check whether ΔCoVaR or MES predict asset price bubbles. We do not find any indication of reverse causality in these tests (see Tables C8 and C9). Nevertheless, we are conservative in the interpretation of our results and speak of an increase in systemic risk *during* rather than *due to* asset price bubbles throughout the paper.

[20] In Section 6.4, we account for business cycles more extensively, but find our results to be highly robust.
[21] Also see the discussion in the context of the recent financial crisis in Deutsche Bundesbank (2014).
[22] Table C7 demonstrates that our results are also robust to using different lag structures.

Standard errors are clustered at bank and time level. The clustering at bank level accounts for autocorrelation, including that introduced by interpolation of the data. The clustering at time level allows error terms to be correlated across banks in all countries, which is important in light of several countries experiencing asset price bubbles at similar times. Since the precise timing of asset price booms and busts differs across countries, the bubble indicators show, however, variation in the cross-sectional dimension even for those countries that experience asset price bubbles in similar periods. The results are robust to alternative clustering of standard errors (see Table C10).

4 Results

4.1 Asset price bubbles and systemic risk in booms and busts

We start by illustrating the underlying conditional correlations without allowing for heterogeneous effects across banks. To this end, we regress ΔCoVaR on the bubble indicators, macroeconomic control variables, and bank fixed effects. The coefficients of all four bubble indicators are positive and highly significant (Table 4, column 1). Overall, asset price bubbles are associated with a significant increase in systemic risk, which is in line with our hypothesis. The strongest relationship is found for real estate busts.

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.[23] Hence, the underlying correlation is pervasive in our sample and not driven by individual countries.

[Table 4 about here]

When adding bank-level variables, the coefficients of the bubble indicators change, but the signs and significance prevail (Table 4, column 2). The coefficients of real estate booms and busts

[23] The negative correlation is found for 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 for each asset class.

decrease, while those on stock market booms and busts increase slightly. This may hint at a larger relevance of bank characteristics during real estate bubbles compared to stock market bubbles, which is explored further in the subsequent section.

The signs of the coefficients of macroeconomic control variables are largely in line with expectations. Systemic risk is significantly elevated during banking crises and decreases in real GDP growth. Higher investment-to-GDP growth is negatively related to systemic risk. The positive coefficient of inflation is insignificant, but points in the expected direction. The 10-year government bond rate is negative and insignificant when bank controls are included. 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.[24] Only the coefficient of loan growth is insignificant.

4.2 The role of bank and bubble characteristics

The results presented above provide first evidence of higher systemic risk during bubble episodes and underline the importance of bank-level characteristics for banks' systemic risk contributions. We go one step further and ask what is the role of bank and bubble characteristics for the relationship between asset price bubbles and systemic risk.

Columns 1 to 4 of Table 5 report regression results including one bank-level variable at a time and the respective interactions with the bubble indicators. In Column 5, all four bank-level variables and their interactions with the bubble indicators are included jointly. In columns 6 and 7, we add the two bubble characteristics, leading to our baseline regression in Equation (3).

[Table 5 about here]

The inclusion of interaction terms leaves the coefficients of the bubble indicators qualitatively unchanged. However, it alters their interpretation as they now refer to a bank with median bank (and bubble) characteristics. The interpretation of the coefficients of bank characteristics changes as well. They now refer to normal times, i. e., outside of bubble episodes.

[24] 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 that paper.

The estimated coefficients of bank characteristics during non-bubble times are similar to those in previous regressions. While larger bank size and leverage go along with higher systemic risk, maturity mismatch is associated with lower systemic risk, regardless of whether we include only one of the bank characteristics (columns 1 to 4) or all four at the same time (column 5). Loan growth is highly significant with a negative sign, implying that higher loan growth goes along with lower systemic risk in normal times. This finding, which proves to be very robust throughout the analysis, is suggestive of healthy loan growth outside of bubble periods.

Interestingly, the relationship between bank characteristics and systemic risk contributions changes markedly during bubble episodes. For example, size is associated with larger increases in systemic risk contributions during real estate and stock market busts and, to a lesser extent, also during stock market booms (column 5). Hence, large banks' contributions to systemic risk appear to be particularly large during asset price bubbles, as would have been expected due to their greater power to spread risks throughout the financial system. Loan growth is less benign in bubble episodes than in normal times. While the relationship between loan growth and systemic risk is negative in normal times, this relationship vanishes during bubble episodes. During real estate busts, systemic risk contributions even increase in lending growth, as the sum of the coefficients of loan growth and its interaction with the bust indicators becomes positive and statistically significant (column 5, test not reported). This stresses the dangers for financial stability of high lending growth during bubble episodes when rising prices induce unhealthy lending, the risks of which materialize in the bust. Similarly, the regressions show a significantly less negative relationship between maturity mismatch and systemic risk during all types of bubble episodes when all bank characteristics are included (column 5). Hence, higher maturity mismatch appears more problematic during bubble episodes. The results on leverage are more mixed as its interaction has a significantly positive coefficient only during real estate booms, while it is not statistically significant during real estate busts and significantly negative during stock market bubbles (column 5). Overall, these regressions strongly support the relevance of banks' balance sheet characteristics for the relationship between asset price bubbles and systemic risk.

When adding bubble length and bubble size to our analysis (columns 6 and 7), these results regarding bank characteristics during and outside of bubble episodes remain almost identical. For bubble characteristics, we find that during stock market booms the coefficients of *length* and *size* are positive and significant. This is plausible as longer booms are likely to lead to a larger build-up of imbalances in the financial system and larger booms have the potential for a more pronounced bust after the burst. Since *length* and *size* are highly correlated during the emergence of stock market bubbles (0.97), it is impossible to distinguish their effects empirically. The coefficients of size and length are insignificant during real estate booms. The increase in systemic risk during these episodes appears to depend more on bank than on bubble characteristics. During both real estate and stock market busts, the coefficients of the two bubble characteristics are negative and, with the exception of bubble size during stock market busts, statistically significant. This could be explained by a fading out of the initial shock of the burst and policy interventions alleviating the consequences of the burst at later stages of the bust.

4.3 Economic significance

We now analyze the economic significance of the observed increase in systemic risk during bubble episodes and discuss the quantitative importance of bank and bubble characteristics. During a stock market boom or bust with median bubble characteristics, ΔCoVaR increases by around 0.37 percentage points relative to normal times for a bank of median size, loan growth, leverage, and maturity mismatch (average of columns 6 and 7 in Table 5). This corresponds to 22 percent (=0.37/1.68) of the median level of ΔCoVaR. The corresponding increases associated with the boom and bust of real estate bubbles amount to 6 and 15 percent, respectively.

From a financial stability perspective, we are more concerned about extreme events, i. e., about a bank like Lehman Brothers during the US subprime housing bubble rather than some average bank during a median bubble. To account for this heterogeneity, we quantify the dependence of the systemic risk increase on bank and bubble characteristics. The boxplots in Figure 5 illustrate the distribution of the increase in systemic risk relative to the median of ΔCoVaR. Specifically, it depicts the median increase (white horizontal line in each box), the 75^{th} and 25^{th} percentile (upper and lower end of each box), and the 95^{th} and 5^{th} percentile of the increase in systemic risk (whiskers) in dependence of bank and bubble characteristics. Note that there is no reason to expect the largest bank to also exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics. Moreover, as bubble length and size are highly correlated, their effects do not add up. Since we cannot simultaneously include bubble length and size due to the high correlation of both variables, the figure is based on the average of the estimated coefficients in our two baseline regressions (Table 5, columns 6 and 7).

The boxplots yield some interesting insights. It is striking that, with the exception of stock market booms, the increase in systemic risk depends much more on bank than on bubble characteristics. This corresponds well to the narrative of the rather small shock from the US subprime housing bubble that was amplified due to imbalances in the financial sector. Comparing boom and bust phases, the bust phases exhibit a larger median increase in systemic risk, but also a larger range of the increase. Hence, an emerging asset price bubble goes along with increased financial fragility, yet it is only during the bust phase that the full risk associated with the bubble materializes. During real estate busts, the 95^{th} percentile of the increase in systemic risk in dependence of balance sheet characteristics amounts to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent. For stock market busts, the corresponding increases are 46 and 56 percent, respectively.

The most important factor driving the heterogeneity of effects during bubble episodes is bank size, especially during bust phases. This is plausible as a large bank under distress due to the burst of an asset price bubble has a much higher potential to transmit this distress to the rest of the financial system. The systemic risk contribution of a bank with bank size at the 95^{th} percentile of the size distribution increases by approximately 70 percent of the median of ΔCoVaR during real estate busts and by almost 60 percent during stock market busts.

To put these estimates further into perspective, we predict ΔCoVaR for Lehman Brothers once with the actual values of all variables and once assuming no bubble had been present. According to our estimation, at the time of the burst of the US subprime housing bubble, the systemic risk posed by Lehman Brothers would have been 40 percent lower if the bubble had not existed.

These results do not support the view that real estate bubbles are generally more harmful than their stock market counterparts. Instead, the ordering depends on bank characteristics. While, for example, stock market busts appear to be more harmful than real estate busts at median bank characteristics, the latter are more harmful at sufficiently unfavorable bank characteristics. Moreover, our results support the view that developments within the financial sector are more relevant than a bubble's asset class, as has already been argued by Brunnermeier and Schnabel (2016).

[Figure 5 about here]

5 Results for alternative measures

Our baseline results are based on regressions using one identification procedure for asset price bubbles and one specific measure of systemic risk. While the measures we rely on are widely used, others constitute reasonable alternatives. Therefore, we repeat our regressions using alternative measures of asset price bubbles and systemic risk.

5.1 Results using alternative bubble measures

We first repeat our main analyses using the alternative bubble measures, applying the BSADF approach to price-to-rent and price-to-dividend data, or the trend-deviation approach (see Section 3.2). Table 6 restates our two baseline regressions alongside estimates obtained from an identical specification, but using the alternative bubble measures.

Compared to the baseline results (columns 1 and 2), the regressions using bubbles identified through the BSADF test applied to normalized price data (columns 3 and 4) confirm most of our previous findings, with slightly lower significance levels. Again, all bubble episodes are associated with increased systemic risk at median bank and bubble characteristics. Moreover, systemic risk contributions increase in bank size, decrease in maturity mismatch, and do not significantly differ in leverage during normal times. The coefficients of loan growth remain negative but turn insignificant. During bubble episodes, we once more see that the increase in systemic risk during real estate busts and stock market booms and busts is more pronounced for larger banks. Only during real estate boom phases, it is still less pronounced, but it now turns significant. The relationship between loan growth and systemic risk during bubble episodes remains positive but becomes less significant during real estate bubbles and more significant during stock market booms. In economic terms, however, the relationship remains small (see Figure C3). The results on leverage remain mixed. For maturity mismatch, there is no significantly different relationship during real estate bubbles anymore, while results on stock market bubbles are unchanged.

The results on bubble characteristics are again similar. Some bubble characteristics lose significance, suggesting a higher relevance of bank characteristics. Only the coefficient on the size of real estate busts changes its sign, a finding that only appears in this particular specification. As before, bust phases of the bubble exhibit a higher level and a higher range of the systemic risk increase compared to the boom phases. Bank size remains the most relevant driver of the increase in systemic risk contributions (see Figure C3).

The results based on bubbles estimated with the trend-deviation approach are very similar to those using the normalized price series, with one important exception. The increase in systemic risk during real estate bubbles is much smaller. At median bank and bubble characteristics, real estate bubbles are not associated with increased systemic risk. This could be driven by the much smaller number of observations for real estate bubbles (see Figure C2). In fact, standard errors are now much larger, while coefficients are not that much smaller. Moreover, as argued before, extreme cases are more relevant than average bubble episodes. In case of unfavorable bubble characteristics, the results again show a significant increase in ΔCoVaR by 53 percent of its median (see Figure C4).

[Table 6 about here]

Hence, despite some quantitative differences, the regressions with the alternative bubble measures support the finding that systemic risk increases during asset price bubbles, especially for unfavorable bank characteristics. As before, bank size stands out, while the results on bubble characteristics are slightly weaker than before, at least for real estate bubbles.

5.2 Results using MES as an alternative systemic risk measure

To assess whether the results depend on the choice of systemic risk measure, we repeat our baseline regressions using MES instead of ΔCoVaR. In the interpretation, one has to keep in mind the conceptual differences between the two measures. MES quantifies the average return loss of a financial institution during the 5 percent days with the worst financial system returns during the past year. Hence, a higher MES signals a larger systemic risk *exposure* of a bank. In contrast, a higher ΔCoVaR stands for a larger systemic risk *contribution* of a bank. Based on the similar evolution of ΔCoVaR and MES in the aggregate (see Figure 4), we expect MES to also increase during bubble episodes. In contrast, due to the conceptual differences, there is no reason to expect the same relationships with bank characteristics. In fact, ΔCoVaR has been shown to react more to the size of banks, while other measures are driven more by leverage (see, e. g., Benoit, Colletaz, Hurlin, and Pérignon, 2013).

Table 7 displays the results from re-running our baseline regressions with MES instead of ΔCoVaR as dependent variable. As in our baseline regressions, systemic risk increases during stock market bubbles at median bank and bubble characteristics. For real estate bubbles, the increase in systemic risk is significant only for the bust phase and only when lagged data series are used, but then with a very large coefficient.

The coefficients on bank characteristics in normal times are also similar to before. As ΔCoVaR, MES increases in bank size and decreases in loan growth and maturity mismatch outside of bubble episodes. Leverage now has a significantly negative effect in columns 1 and 2 suggesting a higher systemic risk exposure for better capitalized banks. This may reflect the fact that better capitalized banks can afford to be riskier and therefore take higher asset risk.

Again, the relationship between asset price bubbles and systemic risk depends on bank characteristics but in different ways than before. Large banks now show a smaller systemic risk exposure during real estate booms. This is plausible as large banks are often less active in mortgage lending than smaller banks. In contrast, large banks are highly exposed during stock market busts, which is consistent with a higher share of market-based activities. Hence, while large banks are typically greater risk spreaders during bubble episodes, their exposure to systemic risk may actually be smaller in some cases.

Unlike for ΔCoVaR, the relationship between loan growth and MES during asset price bubbles is not statistically different from normal times. Hence, loan growth during asset price bubbles appears to increase banks' potential to contribute risk to the financial system but not their exposure to systemic risk. The results on leverage point more strongly in a risk-increasing direction. Higher leverage is associated with a higher risk exposure especially during real estate booms, suggesting that poorly capitalized banks become highly vulnerable in such periods. Somewhat surprisingly, the sign reverses during stock market busts. The findings regarding the interactions between maturity mismatch and the bubble indicators show another noteworthy difference. The corresponding interactions with real estate booms and busts are still significantly positive or insignificant. The interactions with stock market booms and busts, however, are now negative and significant. This could reflect the fact that banks with a stronger focus on the traditional banking business involving higher maturity transformation are less susceptible to market risk especially during stock market bubbles. If the overall effect of maturity mismatch during bubble episodes is considered (i. e., the sum of the single and the interaction term), the relationship between the maturity mismatch and systemic risk is negative or insignificant for both MES and ΔCoVaR.

Looking at bubble characteristics, the results are very similar to before. During a stock market boom, MES increases in bubble size and length, pointing towards the potential for a more pronounced bust. MES decreases in bubble size and length during the bust phase of stock market and real estate bubbles. Hence, we again see a fading impact of the burst, potentially due to policy measures alleviating financial sector distress.

Considering economic significance, the results are very similar (see Figure C5). As before, the boxplots corresponding to the regression results show a larger dependence of the increase in systemic risk on bank than on bubble characteristics . For MES, this ordering also applies during stock market booms. Bust phases exhibit larger increases in systemic risk. And bank size is a dominant factor driving the heterogeneity of effects. Hence, while the specific interpretation of the interaction terms differs due to the different interpretations of the two measures, the main finding regarding the important role of bank characteristics is highly robust.

[Table 7 about here]

6 Further robustness checks

In this section, we assess the robustness of our baseline results in several directions. First, we account for ΔCoVaR's variation coming from developments at macro level by considering additional control variables, additional fixed effects, 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. Third, we evaluate whether the results are driven by particular episodes such as the global financial crisis, which stands out due to its spike in systemic risk.

6.1 Controlling for additional variation at macro level

In this subsection we check whether the results in the regressions using ΔCoVaR depend on the specific properties of this measure, in particular the inclusion of macroeconomic variables in the estimation. The motivation for these additional analyses becomes apparent when writing ΔCoVaR as

$$\Delta CoVaR^i_{q,t} = \sigma^i_q + \omega^i_q M_{t-1} \ , \tag{4}$$

where $\sigma^i_q = \hat{\beta}^{system|i}_q (\hat{\alpha}^i_q - \hat{\alpha}^i_{50})$ and $\omega^i_q = \hat{\beta}^{system|i}_q (\hat{\gamma}^i_q - \hat{\gamma}^i_{50})$.[25] 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 (4)). These variables vary over time at the financial system level (see Appendix B). While none of these variables are directly related to real estate price dynamics, the variables include stock market returns and volatility. This may not be a concern during stock market booms, as ΔCoVaR relies on conditional correlations in the left tail of the return distributions of the financial system and individual banks. It may, however, raise concerns regarding our estimates on stock market busts. In this robustness check, we therefore want to exclude that the results are driven by a mechanical correlation due to stock market returns and volatilities being included in both the systemic risk estimation and the bubble estimation.

[25] The expression can be derived by substituting Equation (B3) in Equation (B6) (see Appendix B).

Columns 1 and 2 of Table 8 restate our baseline results from Table 5 (columns 6 and 7). In columns 3 and 4 of this table, we add the stock market return and volatility included in M_{t-1} as additional controls to absorb the corresponding variation (coefficients of controls not displayed). The coefficients of the real estate bubble indicators prove to be fully robust. However, the coefficient of the stock market boom indicator becomes smaller, and the one on stock market busts even insignificant. Hence, it cannot be ruled out that the estimated increase in systemic risk during stock market bubbles is partly driven by the involvement of the stock market return and volatility during the estimation of the systemic risk measure. At the same time, the coefficients of all bank characteristics and their interactions with the bubble indicators are remarkably robust. The coefficients of the variables capturing bubble characteristics are also similar but become smaller in absolute terms. This further supports the larger relevance of bank characteristics compared to bubble characteristics for the increase in systemic risk. As before, real estate busts go along with a larger increase in systemic risk than stock market busts for unfavorable bank characteristics. In this robustness check, this ordering also applies for the bust phases at median bank characteristics.

Next, we add country-time fixed effects to our baseline regression instead of the stock-price related financial system variables. In this specification (column 5 of Table 8), the bubble indicators, bubble characteristics, and macroeconomic control variables drop out as they vary only at 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 findings.

[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 (see Equation (B3)). This estimated VaR introduces ΔCoVaR's dependence on financial system variables (see Equation (4)). 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

$$\Delta CoVaR^{i}_{q,t} = \hat{\beta}^{system|i}_{q}(VaR^{i}_{q,t} - VaR^{i}_{50,t}) \ , \tag{5}$$

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 (see Equation (B4)).

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 before, there is a pronounced peak at the time of the global financial crisis. The euro area crisis and the Japanese banking crisis at the beginning of the 1990s show spikes, while the dotcom bubble is hardly recognizable in the US series (see Figure C6).

We re-estimate our baseline regression with the rolling ΔCoVaR as dependent variable. As shown in columns 6 and 7 of Table 8, there is a significant increase in systemic risk in all bubble episodes, as in our baseline regressions. The magnitudes are higher for real estate bubbles and slightly lower for stock market bubbles. While some of the further variables experience changes in their significance levels, the overall results are again robust.

We also run regressions with time fixed effects to account for global factors (Table C11, columns 3 and 4). As expected, the increase in systemic risk during bust episodes turns insignificant at the median level of bank and bubble characteristics, as the bust phases are generally shorter and often show up simultaneously to bust phases in other countries such that the remaining variation is highly limited (see Figure 3). All other main results, particulary the significant increase in systemic risk for unfavorable bank characteristics, are confirmed. This also applies when we consider the full bubble episodes without distinguishing between boom and bust phases (see Table C3, column 2).

6.2 Large and small banks

In a next step, we analyze whether the results differ between large and small banks. 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 C2). Small US banks are much more frequently listed than, e. g., small European banks. Therefore, this robustness check can also rule out that our results are driven by small US banks. 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 may be rather strong. A focus on small, locally active banks allows us to address this potential concern because for them the assumption is more appropriate. Third, small and large banks display different business models and dynamics, which might not be fully captured by bank fixed effects and the bank size variable.

For the analyses, 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 to 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). In these regressions, we use the logarithm of ΔCoVaR as dependent variable in order to make the size of the estimated coefficients comparable across bank groups.

Columns 1 and 2 of Table 9 display the results for large banks, columns 3 and 4 those for small banks. We find that the results for both bank groups are very similar to each other and to our baseline estimates. There is, however, one interesting exception. The increase in systemic risk during real estate booms is statistically significant only for the group of small banks. This may be due to mortgage lending being a core activity of small banks while large banks' business models are more diversified. While some of the other coefficients lose significance, which may be due to the strongly reduced sample size, the results for both bank groups are very similar to our baseline regression. We can thus exclude that our results are driven by small banks or by the large number of US observations. Moreover, our previous results do not appear to be driven by asset price bubbles emerging outside of their home country, as they equally apply to small banks, which are only locally active.

As a further robustness check, we re-run our baseline regressions including the full sample of banks, weighting each bank's observations with their mean bank size relative to the size of their financial system. Thereby, we simultaneously limit the relevance of observations of small banks and eliminate the US bias in our sample. The results are reported in columns 5 and 6 of Table 9. While the increase in systemic risk during real estate booms again turns insignificant at median bank and bubble characteristics (similar to columns 1 and 2), the general results are once more well in line with our previous findings. Overall, our results do not seem to be driven by banks of particular size.

[Table 9 about here]

6.3 Choice of sample period

We then re-estimate our baseline regressions for different sample periods to exclude that the results are driven by particular bubble episodes. First, we run the regressions excluding observations before 1995, as the number of banks is relatively small in the beginning of our sample, which may make this period less representative. As shown in Table 10, the results are highly robust to the exclusion of the initial period of our sample (columns 3 and 4). While the relationship between systemic risk and real estate booms turns insignificant at median bank and bubble characteristics, the signs and significance levels of all other coefficients are almost always identical to the baseline regression shown in columns 1 and 2.

Second, one may worry that the results are unduly affected by the global financial crisis. Moreover, real estate bubbles are more frequent during the second half of our sample. One might be concerned about a structural break leading to both the occurrence of real estate bubbles and increased systemic risk. A visual inspection of Figure 4, which displays the development of ΔCoVaR over time, does not reveal a general increase in systemic risk when abstracting from the financial crisis. Excluding the global financial crisis yields an even stronger relationship between systemic risk and real estate busts (Table 10, columns 5 and 6). The remaining results are again highly robust. Consequently, none of our results appears to be driven by particular bubble episodes.

[Table 10 about here]

6.4 Business cycles

In a final robustness check, we attempt to better account for business cycles. In our regressions, we take account of the development of the real economy by controlling for GDP growth. However, this variable may not fully capture business cycles. While parts of the recent literature have argued that business cycles and financial cycles have become less connected in recent years (e. g., Drehmann, Borio, and Tsatsaronis, 2012), this may not be true for our entire sample. Therefore, we use data on turning points of business cycles provided by the OECD to construct an indicator variable that equals one during the boom phase of the business cycle, and zero otherwise.

We plot business cycles alongside bubble boom and bust episodes. The visual inspection reveals no significant synchronization between business and financial cycles (see Figure C7). In fact, business cycle booms exhibit a small negative correlation with stock market and real estate booms in our sample (see Table C12, columns 1 and 3). As an additional check, we re-estimate our baseline regressions including the business cycle boom indicator. Only few coefficients change their significance levels, and all main results continue to hold, which confirms our previous findings (see Table 11).

[Table 11 about here]

7 Conclusion

Employing a broad sample of banks in 17 OECD countries over the period 1987 to 2015, this paper empirically analyzes the relationship between asset price bubbles and systemic risk. While most of the previous empirical literature has approached this question at macroeconomic level, we provide evidence on the relationship between asset price bubbles and systemic risk at the level of individual financial institutions. This allows us to assess the allocation of risks across banks, which is crucial for detecting the sources of financial fragility.

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 exists already during its emergence. We find that the increase in systemic risk depends strongly on bank characteristics. Higher loan growth, a stronger maturity mismatch, and especially larger bank size tend to make financial institutions, and hence the financial system, vulnerable to asset price bubbles. The size and length of asset price booms and busts matter as well, albeit to a lesser extent. The increase in systemic risk is largest during real estate busts, especially for unfavorable balance sheet characteristics: The 95^{th} percentile of the increase in systemic risk in dependence of balance sheet characteristics is equal to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent.

To put the economic significance of the increase in systemic risk further into perspective, a back of the envelope calculation for the time of the burst of the US subprime housing bubble shows that the systemic risk posed by the distress of Lehman Brothers would have been 40 percent lower if the bubble had not existed. Overall, the highest increases in systemic risk are found in real estate busts for banks with unfavorable balance sheet characteristics.

The main results are robust across different bubble and systemic risk measures. While real estate bubbles appear less problematic at median bank and bubble characteristics when using a trend-deviation approach, all types of bubbles show sharp increases in systemic risk for unfavorable balance sheet characteristics. When using MES instead of ΔCoVaR as a measure of systemic risk, the specific relationship with bank characteristics changes in line with the conceptual differences between the two measures. But as with ΔCoVaR, busts show larger increases in systemic risk than booms, and the increases are strongly related to banks' characteristics, especially bank size. When accounting for the systemic risk measures' dependence on aggregate equity market returns and volatilities, the increase in systemic risk during stock market busts becomes smaller. Our results are not driven by particular episodes, such as the US subprime housing bubble and the following global financial crisis, or by business cycle effects. Neither are they specific to certain countries or a particular group of banks. Hence, the results appear to be robust across a broad range of robustness checks.

While we do not explicitly analyze the role of financial regulation, our results suggest a number of important policy implications from a financial stability perspective. First, and most importantly, our results suggest that policies at macroeconomic level are insufficient to deal with asset price bubbles, because an important part of the vulnerability stems from the differences across banks. According to our analysis, the adverse effects of bubbles may be mitigated substantially by strengthening the resilience of financial institutions. Large banks deserve particular attention. The strong relationship between bank size and increases in systemic risk during bubble episodes may justify bank structural reforms trying to contain bank size. Second, policies focusing on managing the turmoil after the burst of a bubble ("cleaning up the mess") may be insufficient. Systemic risk rises already in the boom phase and it appears well-advisable to counteract such a build-up of systemic risk early on in order to avoid a harmful collapse at later stages. In fact, bubble size and length play a noticeable role in the build-up of systemic risk, especially in stock market booms. However, such policy measures are much harder to implement because they require identifying asset price bubbles in real time. Finally, stock market bubbles cannot entirely be dismissed as a source of financial instability because their fallout may be substantial as well, especially for weak bank characteristics. While causal relationships are hard to establish in a clear-cut way, our analysis is highly suggestive that policies focusing on the resilience of financial institutions starting preferably already in the boom phase carry the promise of substantially contributing to a more stable financial system.

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Figures and tables

Figure 1: The increase in systemic risk during bubble episodes

The figure illustrates the increase in systemic risk during bubble episodes in dependence of bank and bubble characteristics. "Unfavorable characteristics" refers to the 95^{th} percentile of this increase based on the distribution of bank or bubble characteristics as indicated in the legend. The pattern is robust to the choice of the percentile. The figure relies on regression results provided and discussed in Section 4.

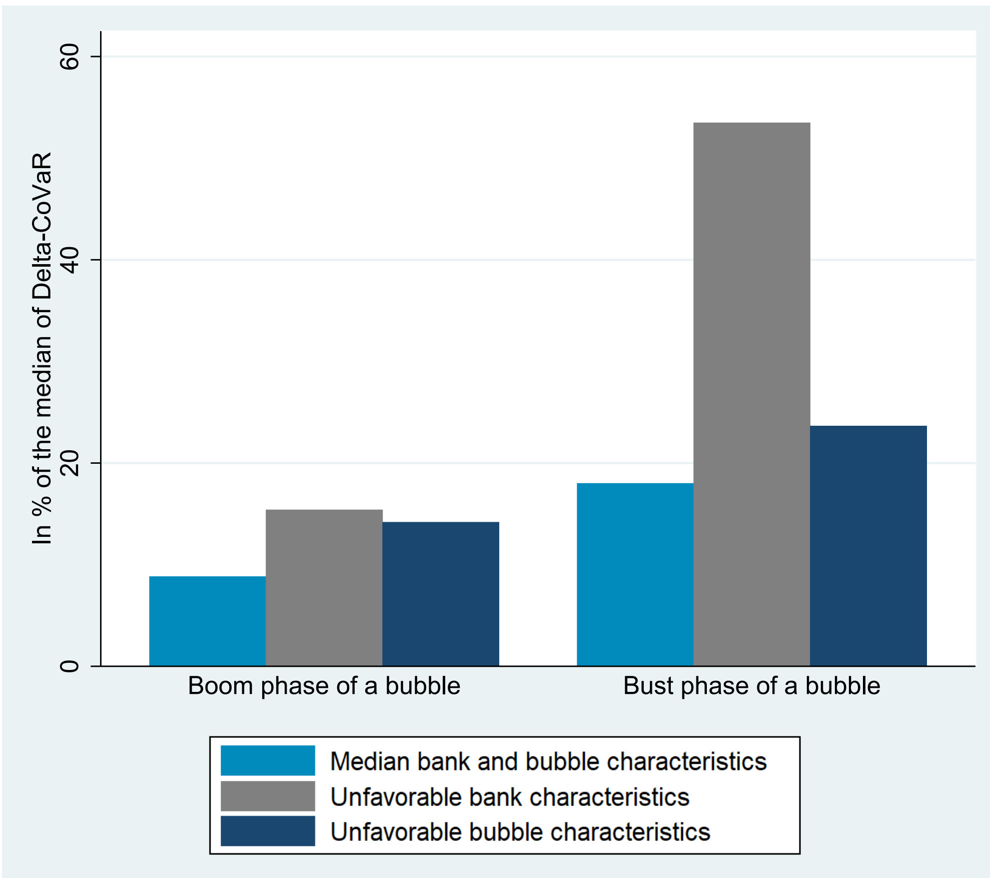


Figure 2: Construction of the bubble indicators

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 3.2 and Appendix A.

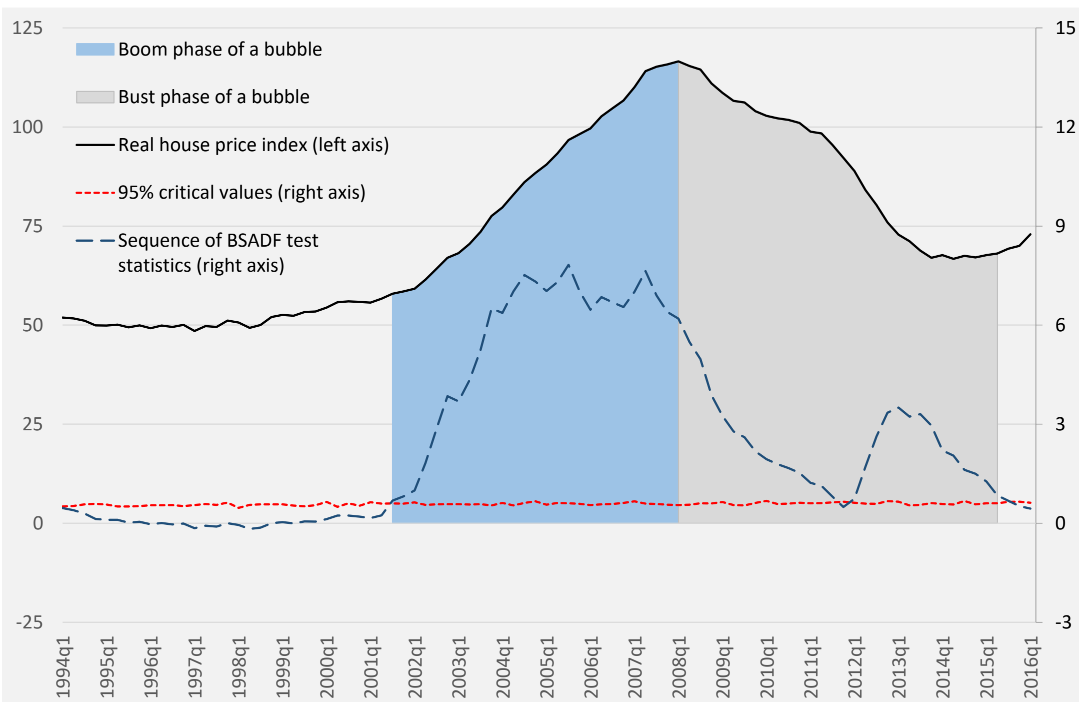
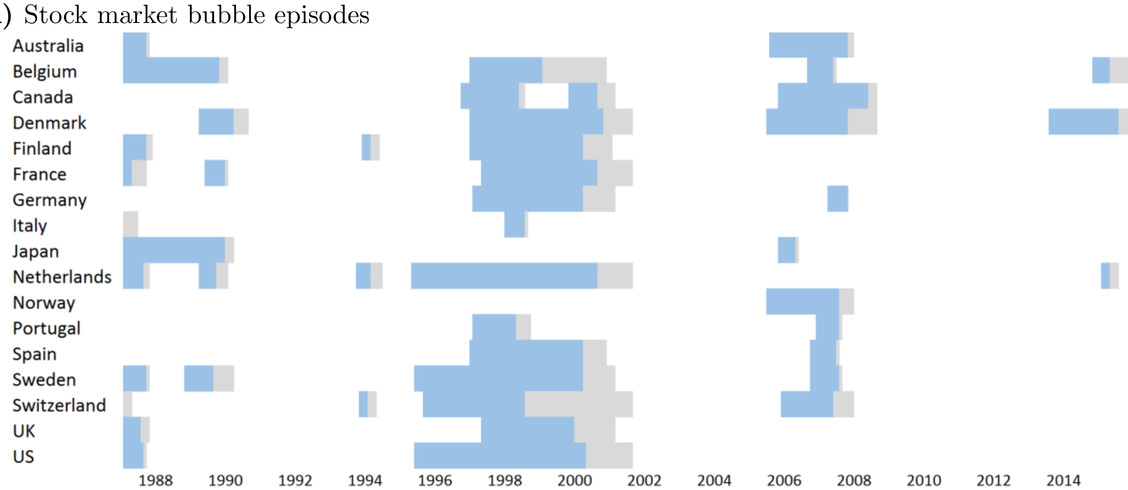


Figure 3: Bubble episodes by country and asset class

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated based on the BSADF approach. For details on the estimation procedure see Section 3.2 and Appendix A. The timelines based on the BSADF approach applied to data normalized by fundamentals and the timeline based on the trend-deviation approach are provided in Figures C1 and C2.

(a) Stock market bubble episodes



(b) Real estate bubble episodes

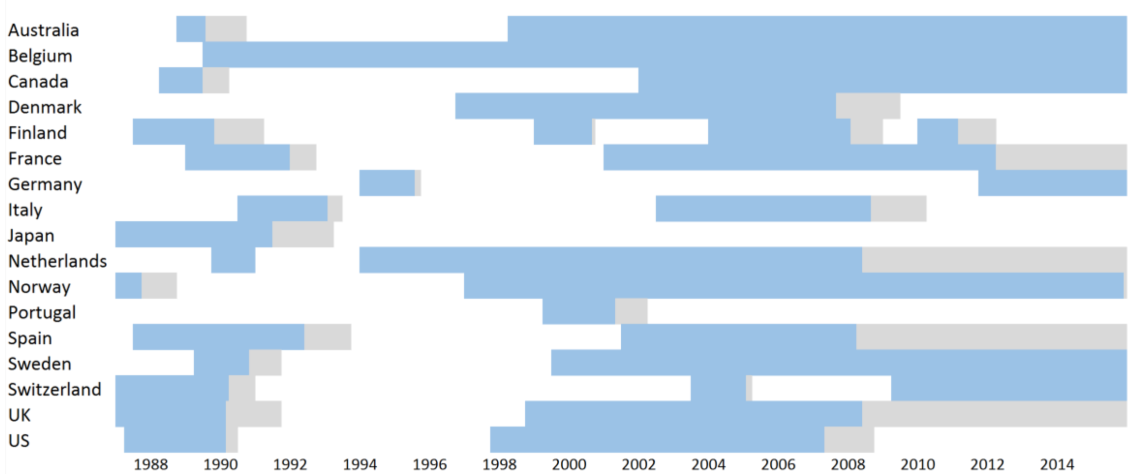


Figure 4: Evolution of ΔCoVaR and MES over time

The figure displays the unweighted means of ΔCoVaR and MES in weekly percentage points and daily percent for the four financial systems in our sample: North America, Europe, Japan, and Australia. Details on the estimation procedure of ΔCoVaR and MES are provided in Section 3.3 and Appendix B.

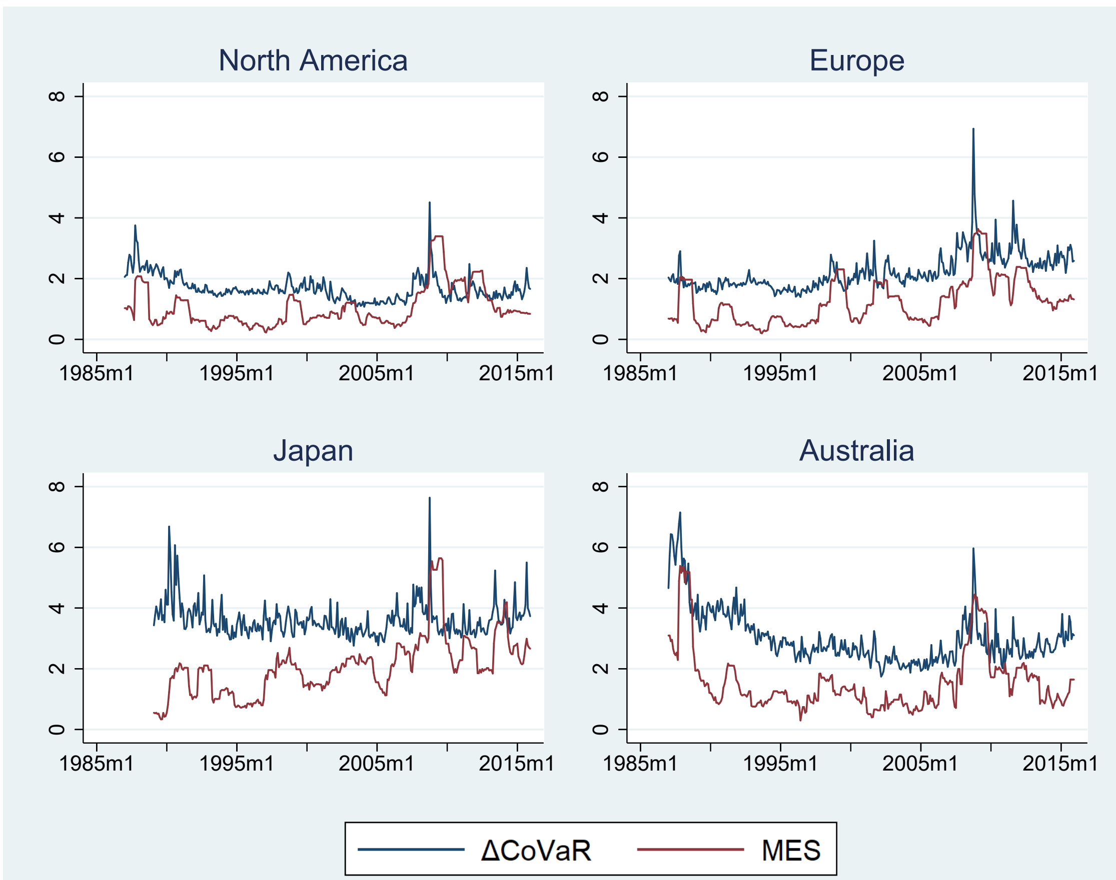


Figure 5: Systemic risk during bubble episodes in dependence of bank and bubble characteristics

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. All results rely on the average of the estimated coefficients in our two baseline regressions (Table 5, columns (6) and (7)). The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

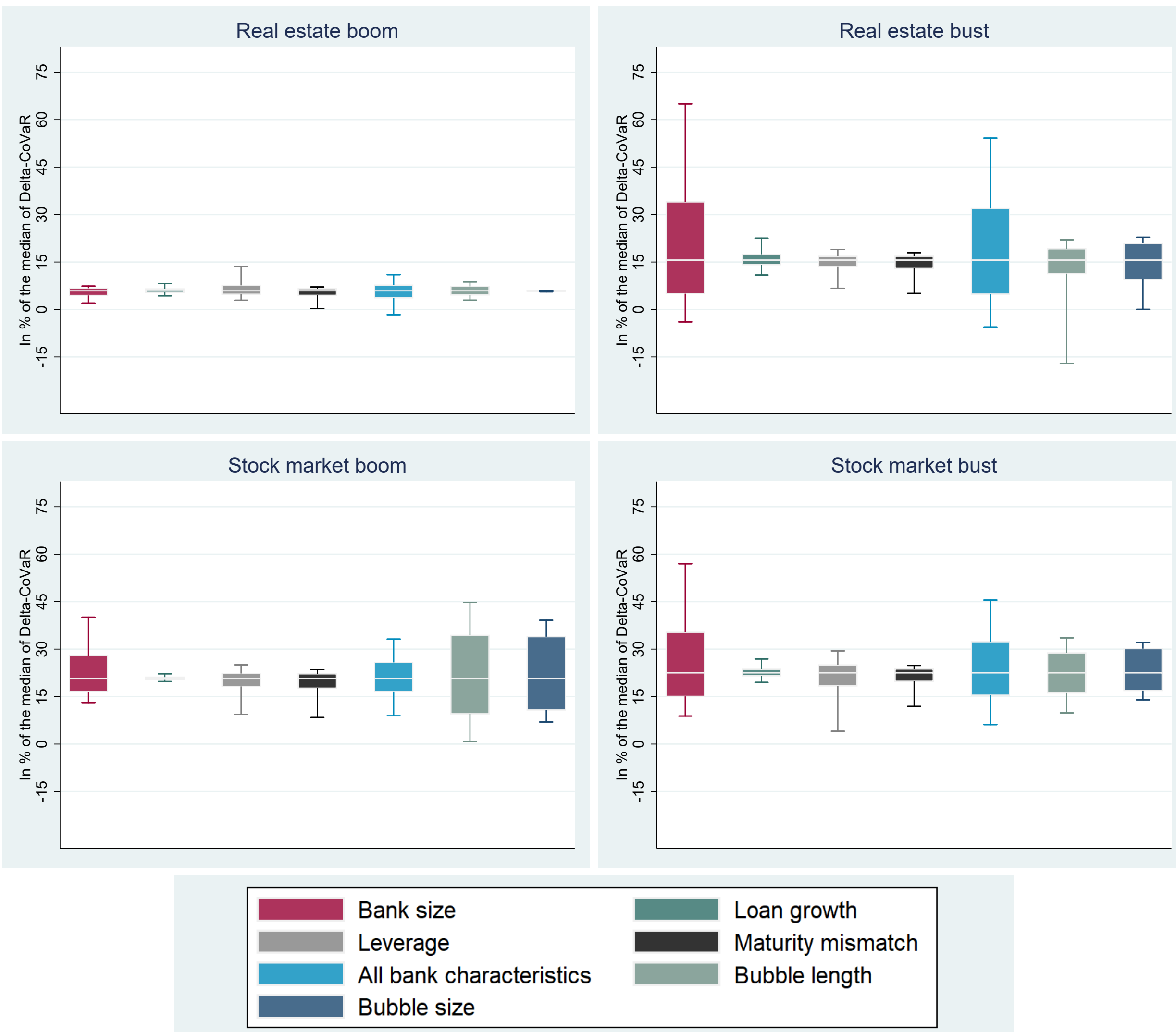


Table 1: Number of bubble episodes per country

The estimation approaches are described in Sections 3.2 and Appendix A. The statistics are computed for the dataset used in the baseline regression. Figures 3, C1, and C2 provide 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. We can estimate these bubble episodes since the data used for bubble identification covers a significantly longer time period than the data used in the main analyses.

	Real estate		**Stock market**	
	Boom	**Bust**	**Boom**	**Bust**
BSADF approach				
Average per country	1.9	1.5	2.6	2.8
Min per country	1	0	1	1
Max per country	4	4	5	5
Total	33	26	45	47
BSADF approach: price-to-rent and price-to-dividend data				
Average per country	1.9	1.6	2.1	1.6
Min per country	0	0	1	0
Max per country	4	4	5	4
Total	33	27	35	27
Trend-deviation approach				
Average per country	1.2	1.3	4.2	3.8
Min per country	0	0	2	2
Max per country	2	2	8	7
Total	21	22	71	64

Table 2: Descriptive statistics on bubble characteristics during bubble episodes

The statistics are computed for the dataset used in the baseline regression and 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 79% price increase relative to the pre-bubble level according to estimates building on the BSADF approach. Variable definitions are provided in Table C1. The estimation approaches are described in Sections 3.2 and Appendix A.

Variable	Mean	Median	Std. Dev.	5%	95%
BSADF approach					
Real estate boom length	69	68	40.1	10	128
Real estate bust length	15	10	16.8	1	56
Stock market boom length	29	28	17.8	3	58
Stock market bust length	8	8	5.5	1	16
Real estate boom size	38	33	29.3	3	99
Real estate bust size	6	5	7	0	15
Stock market boom size	78	72	54.5	8	156
Stock market bust size	12	13	8.3	1	24
BSADF approach: price-to-rent and price-to-dividend data					
Real estate boom length	55	52	36.3	8	116
Real estate bust length	15	13	12.0	2	38
Stock market boom length	20	20	13.6	2	41
Stock market bust length	5	5	3	1	10
Real estate boom size	26	18	24.7	3	80
Real estate bust size	4	2	3.2	0	10
Stock market boom size	43	45	27.3	6	87
Stock market bust size	6	6	4.1	0	13
Trend-deviation approach					
Real estate boom length	34	33	18.9	4	62
Real estate bust length	13	11	11.9	2	36
Stock market boom length	15	13	11.3	1	35
Stock market bust length	9	8	6	1	18
Real estate boom size	19	19	11.7	3	36
Real estate bust size	7	6	5.2	0	15
Stock market boom size	39	33	28.7	3	82
Stock market bust size	13	13	9.4	1	26

Table 3: Descriptive statistics

The statistics are computed for the dataset used in the baseline regression. “Size” and “Interest rate” enter the regressions in logs. “Interest rate” refers to 10-year government bond rates. For descriptive statistics on bubble characteristics see Table 2. Variable definitions are provided in Table C1.

Variable	**Mean**	**Median**	**Std. Dev.**	**5%**	**95%**
Dependent variable					
ΔCoVaR	1.96	1.68	1.65	-0.11	4.91
MES	1.34	1.06	1.94	-1.11	4.92
Bank characteristics					
Bank size [billion USD]	64.58	1.88	260.79	0.25	316.73
log(bank size)	1.22	0.63	2.19	-1.40	5.76
Loan growth	0.008	0.006	0.015	-0.012	0.032
Leverage	13.43	11.70	7.14	5.92	27.02
Maturity mismatch	0.69	0.75	0.19	0.27	0.86
Macroeconomic variables					
Banking crisis	0.36	0	0.48	0	1
Real GDP growth	0.021	0.023	0.020	-0.024	0.045
Interest rate	4.70	4.50	1.62	2.52	7.46
log(interest rate)	1.33	1.44	0.51	0.43	1.96
Inflation	0.022	0.021	0.013	-0.002	0.041
Investment-to-GDP growth	-0.004	0.010	0.061	-0.119	0.066

Table 4: Systemic risk during booms and busts of asset price bubbles

Bubble estimates are based on the BSADF approach. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)
Dependent variable:	ΔCoVaR	
Real estate boom	0.20***	0.15***
	(0.000)	(0.001)
Real estate bust	0.46***	0.35***
	(0.000)	(0.002)
Stock boom	0.30***	0.37***
	(0.000)	(0.000)
Stock bust	0.35***	0.38***
	(0.000)	(0.000)
log(Bank size)		0.28***
		(0.000)
Loan growth		-0.13
		(0.765)
Leverage		0.00**
		(0.019)
Maturity mismatch		-0.43***
		(0.001)
Banking crisis	0.27***	0.23***
	(0.000)	(0.000)
GDP growth	-4.22**	-3.00*
	(0.019)	(0.074)
log(Interest rate)	-0.22***	-0.02
	(0.000)	(0.684)
Inflation	4.81	5.57
	(0.237)	(0.170)
Investment-to-GDP growth	-0.40	-0.62*
	(0.198)	(0.061)
Bank FE	Yes	Yes
No. of obs.	165,149	165,149
Adj. R^2	0.819	0.824
Adj. R^2 within	0.082	0.106

Table 5: The role of bank and bubble characteristics

Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:				ΔCoVaR			
Real estate boom	0.16***	0.19***	0.19***	0.20***	0.15***	0.09**	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.031)	(0.004)
Real estate bust	0.26**	0.46***	0.45***	0.42***	0.27**	0.25**	0.27**
	(0.021)	(0.000)	(0.000)	(0.000)	(0.019)	(0.036)	(0.018)
Stock boom	0.37***	0.29***	0.31***	0.33***	0.38***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.35***	0.34***	0.35***	0.35***	0.37***	0.38***	0.38***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.27***				0.27***	0.26***	0.25***
	(0.000)				(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.00				-0.01	-0.01	-0.01
	(0.898)				(0.533)	(0.490)	(0.492)
log(Bank size) · Real estate bust	0.12***				0.14***	0.17***	0.16***
	(0.000)				(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.00				0.05**	0.07***	0.06***
	(0.888)				(0.018)	(0.002)	(0.003)
log(Bank size) · Stock bust	0.07***				0.11***	0.11***	0.11***
	(0.000)				(0.000)	(0.000)	(0.000)
Loan growth		-2.77***			-2.28***	-1.49**	-1.59**
		(0.000)			(0.001)	(0.020)	(0.014)
Loan growth · Real estate boom		2.75***			2.51***	1.43**	1.58**
		(0.001)			(0.001)	(0.044)	(0.026)
Loan growth · Real estate bust		5.16***			6.19***	4.47***	4.58***
		(0.009)			(0.000)	(0.003)	(0.002)
Loan growth · Stock boom		2.01***			1.89**	0.86	1.03
		(0.004)			(0.011)	(0.202)	(0.140)
Loan growth · Stock bust		2.33**			3.55***	2.81***	2.94***
		(0.023)			(0.001)	(0.001)	(0.001)
Leverage			0.00*		0.00*	0.00*	0.00
			(0.058)		(0.061)	(0.097)	(0.107)
Leverage · Real estate boom			0.00		0.01**	0.01**	0.01**
			(0.116)		(0.021)	(0.028)	(0.020)
Leverage · Real estate bust			0.01		-0.01	-0.01	-0.01
			(0.150)		(0.254)	(0.123)	(0.206)
Leverage · Stock boom			-0.01**		-0.01***	-0.01***	-0.01***
			(0.021)		(0.001)	(0.002)	(0.001)
Leverage · Stock bust			0.00		-0.02***	-0.02***	-0.02***
			(0.891)		(0.000)	(0.000)	(0.000)
Maturity mismatch				-0.62***	-0.66***	-0.65***	-0.62***
				(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom				0.26***	0.27***	0.21**	0.18*
				(0.009)	(0.004)	(0.024)	(0.051)
MM · Real estate bust				-0.40	0.40*	0.33	0.41*
				(0.129)	(0.072)	(0.122)	(0.063)
MM · Stock boom				0.48***	0.65***	0.38***	0.48***
				(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust				-0.01	0.40***	0.31**	0.43***
				(0.951)	(0.001)	(0.020)	(0.000)
Real estate boom length						-0.00	
						(0.224)	
Real estate boom size							-0.00
							(0.937)
Real estate bust length						-0.01***	
						(0.000)	
Real estate bust size							-0.03***
							(0.009)
Stock boom length						0.01***	
						(0.000)	
Stock boom size							0.00***
							(0.000)
Stock bust length						-0.03***	
						(0.001)	
Stock bust size							-0.01
							(0.112)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149	165,149	165,149	165,149
Adj. R^2	0.826	0.819	0.820	0.820	0.827	0.831	0.830
Adj. R^2 within	0.115	0.083	0.084	0.087	0.123	0.141	0.135

Table 6: The role of bank and bubble characteristics: alternative bubble measures

Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Bubble estimation approach:	BSADF		BSADF normalized		Trend deviations	
Real estate boom	0.09**	0.11***	0.08**	0.08**	-0.04	-0.04
	(0.031)	(0.004)	(0.027)	(0.037)	(0.474)	(0.383)
Real estate bust	0.25**	0.27**	0.20***	0.14**	0.14	0.13
	(0.036)	(0.018)	(0.001)	(0.010)	(0.266)	(0.273)
Stock boom	0.34***	0.36***	0.45***	0.46***	0.38***	0.38***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.50***	0.51***	0.40***	0.37***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.26***	0.29***	0.30***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.04**	-0.04**	-0.09***	-0.08***
	(0.490)	(0.492)	(0.011)	(0.019)	(0.000)	(0.000)
log(Bank size) · Real estate bust	0.17***	0.16***	0.09***	0.08***	0.15***	0.14***
	(0.000)	(0.000)	(0.001)	(0.005)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.09***	0.09***	0.05**	0.06***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.022)	(0.009)
log(Bank size) · Stock bust	0.11***	0.11***	0.16***	0.16***	0.08***	0.08***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Loan growth	-1.49**	-1.59**	-0.52	-0.80	-1.15*	-1.12
	(0.020)	(0.014)	(0.407)	(0.204)	(0.095)	(0.113)
Loan growth · Real estate boom	1.43**	1.58**	0.44	0.76	0.82	0.85
	(0.044)	(0.026)	(0.578)	(0.331)	(0.291)	(0.265)
Loan growth · Real estate bust	4.47***	4.58***	1.22	2.36**	1.66	1.65
	(0.003)	(0.002)	(0.275)	(0.034)	(0.155)	(0.152)
Loan growth · Stock boom	0.86	1.03	1.78**	2.25**	1.54*	1.74**
	(0.202)	(0.140)	(0.041)	(0.016)	(0.067)	(0.041)
Loan growth · Stock bust	2.81***	2.94***	3.39***	3.70***	3.27***	3.15***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Leverage	0.00*	0.00	0.00	0.00	0.00	0.00*
	(0.097)	(0.107)	(0.481)	(0.459)	(0.103)	(0.098)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01***	0.02***	0.02***
	(0.028)	(0.020)	(0.001)	(0.001)	(0.000)	(0.000)
Leverage · Real estate bust	-0.01	-0.01	0.01	0.01	-0.01	-0.01
	(0.123)	(0.206)	(0.279)	(0.254)	(0.112)	(0.114)
Leverage · Stock boom	-0.01***	-0.01***	-0.01**	-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)	(0.012)	(0.010)	(0.001)	(0.000)
Leverage · Stock bust	-0.02***	-0.02***	-0.03***	-0.03***	-0.01***	-0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.007)
Maturity mismatch	-0.65***	-0.62***	-0.58***	-0.58***	-0.60***	-0.62***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.12	0.11	0.00	-0.04
	(0.024)	(0.051)	(0.213)	(0.225)	(0.977)	(0.729)
MM · Real estate bust	0.33	0.41*	-0.02	-0.02	0.12	0.14
	(0.122)	(0.063)	(0.882)	(0.911)	(0.600)	(0.538)
MM · Stock boom	0.38***	0.48***	0.31***	0.36***	0.64***	0.64***
	(0.000)	(0.000)	(0.007)	(0.002)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.47***	0.47***	0.33**	0.38***
	(0.020)	(0.000)	(0.010)	(0.005)	(0.018)	(0.005)
Real estate boom length	-0.00		-0.00		-0.00	
	(0.224)		(0.103)		(0.258)	
Real estate boom size		-0.00		-0.00		-0.00
		(0.937)		(0.259)		(0.228)
Real estate bust length	-0.01***		0.00		-0.00	
	(0.000)		(0.768)		(0.317)	
Real estate bust size		-0.03***		0.04***		-0.01
		(0.009)		(0.002)		(0.672)
Stock boom length	0.01***		0.01***		0.02***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.01***		0.01***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.03***		-0.02		-0.03***	
	(0.001)		(0.263)		(0.000)	
Stock bust size		-0.01		0.00		-0.01**
		(0.112)		(0.975)		(0.027)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,134	165,134	144,771	144,771
Adj. R^2	0.831	0.830	0.829	0.829	0.823	0.822
Adj. R^2 within	0.141	0.135	0.131	0.132	0.160	0.156

Table 7: The role of bank and bubble characteristics: alternative systemic risk measure

Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Columns 3 and 4 report regressions with all explanatory variables lagged by an additional 6 months. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Real estate boom	0.04	0.06	0.05	0.05
	(0.421)	(0.249)	(0.353)	(0.352)
Real estate bust	0.01	0.03	0.47***	0.53***
	(0.910)	(0.757)	(0.000)	(0.000)
Stock boom	0.10*	0.11*	0.16**	0.16**
	(0.078)	(0.062)	(0.017)	(0.021)
Stock bust	0.25***	0.25***	0.21***	0.21***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.66***	0.66***	0.76***	0.74***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.20***	-0.20***	-0.17***	-0.17***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate bust	-0.01	-0.04	0.14**	0.11*
	(0.814)	(0.458)	(0.011)	(0.072)
log(Bank size) · Stock boom	-0.00	-0.01	0.06*	0.06*
	(0.923)	(0.820)	(0.066)	(0.054)
log(Bank size) · Stock bust	0.09***	0.09***	0.12***	0.12***
	(0.004)	(0.004)	(0.000)	(0.000)
Loan growth	-6.08***	-6.07***	-3.10*	-3.15*
	(0.000)	(0.000)	(0.078)	(0.071)
Loan growth · Real estate boom	2.02	2.09	0.35	0.37
	(0.255)	(0.237)	(0.848)	(0.842)
Loan growth · Real estate bust	2.52	2.98	2.99	4.38
	(0.418)	(0.360)	(0.370)	(0.210)
Loan growth · Stock boom	0.76	0.81	1.36	1.31
	(0.671)	(0.656)	(0.461)	(0.471)
Loan growth · Stock bust	3.19	3.08	2.15	2.17
	(0.208)	(0.229)	(0.351)	(0.346)
Leverage	-0.01**	-0.01**	-0.00	-0.00
	(0.048)	(0.045)	(0.784)	(0.712)
Leverage · Real estate boom	0.03***	0.03***	0.02***	0.02***
	(0.000)	(0.000)	(0.005)	(0.002)
Leverage · Real estate bust	0.02**	0.03***	-0.01	-0.00
	(0.015)	(0.006)	(0.467)	(0.754)
Leverage · Stock boom	0.01	0.01	0.00	0.00
	(0.136)	(0.231)	(0.819)	(0.914)
Leverage · Stock bust	-0.03***	-0.02***	-0.02***	-0.02**
	(0.000)	(0.001)	(0.009)	(0.017)
Maturity mismatch	-0.86***	-0.85***	-1.10***	-1.05***
	(0.005)	(0.006)	(0.000)	(0.001)
MM · Real estate boom	0.06	-0.01	0.21	0.08
	(0.789)	(0.972)	(0.365)	(0.723)
MM · Real estate bust	0.32	0.44	1.19***	1.30***
	(0.368)	(0.219)	(0.003)	(0.001)
MM · Stock boom	-1.14***	-1.05***	-1.22***	-1.23***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	-0.73***	-0.60**	-0.84***	-0.73***
	(0.007)	(0.022)	(0.001)	(0.003)
Real estate boom length	-0.00		-0.00	
	(0.131)		(0.110)	
Real estate boom size		-0.00		0.00
		(0.328)		(0.873)
Real estate bust length	-0.02***		-0.03***	
	(0.000)		(0.000)	
Real estate bust size		-0.03***		-0.02**
		(0.000)		(0.040)
Stock boom length	0.02***		0.01***	
	(0.000)		(0.000)	
Stock boom size		0.01***		0.00***
		(0.000)		(0.000)
Stock bust length	-0.03***		-0.03***	
	(0.000)		(0.000)	
Stock bust size		-0.02***		-0.01***
		(0.000)		(0.006)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
No. of obs.	162,092	162,092	160,980	160,980
Adj. R^2	0.472	0.470	0.454	0.452
Adj. R^2 within	0.218	0.216	0.194	0.191

Table 8: Controlling for additional variation at the macro level

Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. The additional macroeconomic variables in columns 3 and 4 are the stock price returns and volatilities used during the estimation of ΔCoVaR (see Appendix B). Column 5 estimates our baseline regression with country-time fixed effects. The estimation strategy of the rolling ΔCoVaR is described in Section 6.1. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:			ΔCoVaR			Rolling ΔCoVaR	
Real estate boom	0.09**	0.11***	0.13***	0.14***		0.24***	0.24***
	(0.031)	(0.004)	(0.000)	(0.000)		(0.000)	(0.000)
Real estate bust	0.25**	0.27**	0.28***	0.29***		0.38***	0.36***
	(0.036)	(0.018)	(0.000)	(0.000)		(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.18***	0.18***		0.26***	0.28***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.08	0.07		0.37***	0.37***
	(0.000)	(0.000)	(0.137)	(0.181)		(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.10***	0.09***	0.01	0.26***	0.25***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.812)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.02	-0.02	-0.04	-0.15***	-0.15***
	(0.490)	(0.492)	(0.373)	(0.336)	(0.108)	(0.000)	(0.000)
log(Bank size) · Real estate bust	0.17***	0.16***	0.16***	0.16***	0.20***	0.13***	0.09*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.056)
log(Bank size) · Stock boom	0.07***	0.06***	0.07***	0.07***	0.07***	0.06**	0.05**
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.049)	(0.047)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.12***	0.14***	0.17***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-1.77***	-1.79***	-2.02***	-4.79***	-4.95***
	(0.020)	(0.014)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
Loan growth · Real estate boom	1.43**	1.58**	2.25***	2.22***	2.23***	1.60	1.84
	(0.044)	(0.026)	(0.001)	(0.001)	(0.001)	(0.234)	(0.172)
Loan growth · Real estate bust	4.47***	4.58***	4.24***	4.36***	3.18**	3.78	5.32
	(0.003)	(0.002)	(0.003)	(0.002)	(0.012)	(0.221)	(0.104)
Loan growth · Stock boom	0.86	1.03	0.90	0.93	0.70	3.41**	3.51**
	(0.202)	(0.140)	(0.142)	(0.139)	(0.193)	(0.017)	(0.013)
Loan growth · Stock bust	2.81***	2.94***	1.38*	1.24*	1.15*	3.68	3.49
	(0.001)	(0.001)	(0.068)	(0.100)	(0.075)	(0.102)	(0.136)
Leverage	0.00*	0.00	0.00**	0.00**	0.00**	0.01***	0.01***
	(0.097)	(0.107)	(0.031)	(0.030)	(0.044)	(0.000)	(0.000)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**	0.01***	0.01*	0.01*
	(0.028)	(0.020)	(0.011)	(0.010)	(0.000)	(0.086)	(0.056)
Leverage · Real estate bust	-0.01	-0.01	-0.01**	-0.01*	-0.01***	0.01	0.02
	(0.123)	(0.206)	(0.040)	(0.062)	(0.005)	(0.495)	(0.400)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	0.00	-0.00
	(0.002)	(0.001)	(0.000)	(0.000)	(0.003)	(0.879)	(0.907)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)
Maturity mismatch	-0.65***	-0.62***	-0.47***	-0.46***	-0.33***	-1.04***	-1.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.20**	0.20***	0.18**	0.40**	0.29*
	(0.024)	(0.051)	(0.014)	(0.010)	(0.025)	(0.025)	(0.089)
MM · Real estate bust	0.33	0.41*	0.42**	0.46**	-0.13	1.14***	1.24***
	(0.122)	(0.063)	(0.024)	(0.016)	(0.455)	(0.000)	(0.000)
MM · Stock boom	0.38***	0.48***	0.46***	0.48***	0.03	0.19	0.24
	(0.000)	(0.000)	(0.000)	(0.000)	(0.735)	(0.225)	(0.136)
MM · Stock bust	0.31**	0.43***	0.21**	0.27***	-0.02	0.19	0.30
	(0.020)	(0.000)	(0.023)	(0.005)	(0.790)	(0.364)	(0.147)
Real estate boom length	-0.00		0.00*			-0.00***	
	(0.224)		(0.076)			(0.007)	
Real estate boom size		-0.00		0.00***			-0.00
		(0.937)		(0.006)			(0.183)
Real estate bust length	-0.01***		-0.01***			-0.02***	
	(0.000)		(0.001)			(0.001)	
Real estate bust size		-0.03***		-0.01**			-0.01
		(0.009)		(0.018)			(0.359)
Stock boom length	0.01***		0.00			0.01***	
	(0.000)		(0.141)			(0.000)	
Stock boom size		0.00***		0.00			0.00***
		(0.000)		(0.258)			(0.000)
Stock bust length	-0.03***		-0.01***			-0.02**	
	(0.001)		(0.006)			(0.016)	
Stock bust size		-0.01		-0.01***			-0.02***
		(0.112)		(0.001)			(0.000)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CoVaR controls	No	No	Yes	Yes	No	No	No
Country-time FE	No	No	No	No	Yes	No	No
No. of obs.	165,149	165,149	165,149	165,149	164,934	162,776	162,776
Adj. R^2	0.831	0.830	0.865	0.865	0.891	0.674	0.672
Adj. R^2 within	0.141	0.135	0.313	0.313	0.044	0.161	0.156

Table 9: Large and small banks

Bubble estimates are based on the BSADF approach. Columns 1 to 4 provide estimates of our baseline regressions for small and large banks separately. We eliminate the US bias in the sample of small banks by excluding the smallest US banks. See Table C2 for an overview of the number of banks and observations per country. Columns 5 and 6 provide estimates from regressions with each bank's observations weighted by their mean bank size relative to the size of their financial system (North America, Europe, Japan, or Australia). Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Large banks		Small banks		Weighted by size	
Dependent variable:	log(ΔCoVaR)		log(ΔCoVaR)		log(ΔCoVaR)	
Real estate boom	0.01	0.03	0.04**	0.05***	-0.01	0.01
	(0.470)	(0.101)	(0.044)	(0.008)	(0.645)	(0.578)
Real estate bust	0.15***	0.15***	0.13***	0.14***	0.13***	0.13***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock boom	0.17***	0.16***	0.11***	0.09***	0.15***	0.14***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.22***	0.21***	0.17***	0.17***	0.19***	0.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.13***	0.13***	0.12***	0.11***	0.12***	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.03**	-0.03***	-0.00	-0.00	-0.01	-0.01
	(0.018)	(0.008)	(0.782)	(0.809)	(0.363)	(0.108)
log(Bank size) · Real estate bust	0.02	0.01	-0.01	-0.01	0.04**	0.04**
	(0.198)	(0.498)	(0.752)	(0.710)	(0.012)	(0.033)
log(Bank size) · Stock boom	0.01	0.02	0.06***	0.07***	0.01	0.01*
	(0.337)	(0.157)	(0.000)	(0.000)	(0.188)	(0.071)
log(Bank size) · Stock bust	0.02*	0.02*	0.01	0.01	0.01	0.01*
	(0.061)	(0.096)	(0.227)	(0.268)	(0.164)	(0.098)
Loan growth	-1.73***	-1.80***	-0.53*	-0.60*	-1.43***	-1.49***
	(0.000)	(0.000)	(0.089)	(0.055)	(0.003)	(0.002)
Loan growth · Real estate boom	0.72	0.80	0.74*	0.80**	1.03*	1.27**
	(0.143)	(0.112)	(0.070)	(0.049)	(0.070)	(0.034)
Loan growth · Real estate bust	3.84***	4.14***	1.42*	1.25*	3.12***	3.46***
	(0.000)	(0.000)	(0.059)	(0.080)	(0.003)	(0.001)
Loan growth · Stock boom	0.77*	0.73	0.39	0.40	0.07	0.08
	(0.096)	(0.113)	(0.446)	(0.445)	(0.878)	(0.871)
Loan growth · Stock bust	1.22*	1.47**	0.64	0.64	0.76	0.73
	(0.072)	(0.024)	(0.328)	(0.358)	(0.274)	(0.300)
Leverage	0.00**	0.00**	0.00	0.00	0.00*	0.00
	(0.042)	(0.043)	(0.669)	(0.459)	(0.075)	(0.131)
Leverage · Real estate boom	0.00	0.00	-0.00	-0.00	0.00*	0.01**
	(0.563)	(0.395)	(0.272)	(0.181)	(0.065)	(0.012)
Leverage · Real estate bust	-0.01***	-0.01**	0.01*	0.01*	-0.00	-0.00
	(0.005)	(0.015)	(0.072)	(0.079)	(0.446)	(0.693)
Leverage · Stock boom	-0.00**	-0.00***	-0.00	-0.00*	-0.00	-0.00**
	(0.023)	(0.004)	(0.151)	(0.061)	(0.122)	(0.022)
Leverage · Stock bust	-0.01***	-0.01***	-0.00	-0.00	-0.00**	-0.00**
	(0.000)	(0.000)	(0.876)	(0.810)	(0.017)	(0.018)
Maturity mismatch	-0.16	-0.15	-0.22***	-0.23***	-0.18**	-0.21**
	(0.106)	(0.120)	(0.003)	(0.002)	(0.034)	(0.017)
MM · Real estate boom	0.04	0.06	0.16***	0.17***	0.12	0.13
	(0.604)	(0.424)	(0.009)	(0.004)	(0.265)	(0.194)
MM · Real estate bust	0.10	0.13	0.15	0.17*	0.06	0.09
	(0.418)	(0.314)	(0.119)	(0.080)	(0.630)	(0.502)
MM · Stock boom	0.17*	0.20**	-0.14*	-0.11	0.14	0.14*
	(0.070)	(0.041)	(0.096)	(0.205)	(0.137)	(0.094)
MM · Stock bust	0.11	0.13*	0.02	0.04	0.08	0.12
	(0.108)	(0.068)	(0.816)	(0.570)	(0.395)	(0.245)
Real estate boom length	-0.00		0.00		-0.00***	
	(0.655)		(0.606)		(0.006)	
Real estate boom size		0.00		0.00		-0.00
		(0.537)		(0.118)		(0.160)
Real estate bust length	-0.00***		-0.00***		-0.00**	
	(0.000)		(0.003)		(0.021)	
Real estate bust size		-0.01***		-0.01**		-0.00**
		(0.000)		(0.017)		(0.012)
Stock boom length	0.01***		0.00***		0.01***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.00***		0.00***
		(0.000)		(0.007)		(0.000)
Stock bust length	-0.01**		-0.00*		-0.01	
	(0.023)		(0.082)		(0.152)	
Stock bust size		-0.00		-0.00		-0.00
		(0.397)		(1.000)		(0.719)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	28,844	28,844	30,502	30,502	155,222	155,222
Adj. R^2	0.770	0.767	0.916	0.915	0.828	0.826
Adj. R^2 within	0.238	0.229	0.179	0.174	0.237	0.228

Table 10: Choice of sample period

Columns 1 and 2 restate the baseline regression results from Table 5, columns 6 and 7. Columns 3 to 6 restrict the sample period as indicated. Bubble estimates are based on the BSADF approach. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Full sample		>1995m1		≠2008	
Dependent variable:			ΔCoVaR			
Real estate boom	0.09**	0.11***	0.03	0.06	0.12***	0.14***
	(0.031)	(0.004)	(0.455)	(0.139)	(0.000)	(0.000)
Real estate bust	0.25**	0.27**	0.22*	0.25**	0.39***	0.40***
	(0.036)	(0.018)	(0.084)	(0.045)	(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.30***	0.33***	0.30***	0.31***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.36***	0.35***	0.43***	0.42***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.22***	0.22***	0.17***	0.16***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.02	-0.02	0.01	0.01
	(0.490)	(0.492)	(0.287)	(0.280)	(0.644)	(0.634)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.16***	0.13***	0.12***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.06**	0.05**	0.08***	0.07***
	(0.002)	(0.003)	(0.012)	(0.021)	(0.000)	(0.000)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.11***	0.12***	0.12***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-1.24*	-1.34**	-1.67***	-1.83***
	(0.020)	(0.014)	(0.066)	(0.049)	(0.000)	(0.000)
Loan growth · Real estate boom	1.43**	1.58**	1.40*	1.55**	0.87	1.09*
	(0.044)	(0.026)	(0.062)	(0.041)	(0.108)	(0.050)
Loan growth · Real estate bust	4.47***	4.58***	4.79***	4.89***	5.25***	5.58***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.006)	(0.003)
Loan growth · Stock boom	0.86	1.03	0.78	0.93	1.29**	1.48**
	(0.202)	(0.140)	(0.243)	(0.183)	(0.033)	(0.018)
Loan growth · Stock bust	2.81***	2.94***	2.45***	2.66***	2.98***	3.11***
	(0.001)	(0.001)	(0.005)	(0.003)	(0.001)	(0.000)
Leverage	0.00*	0.00	0.00	0.00	0.00*	0.00**
	(0.097)	(0.107)	(0.147)	(0.166)	(0.054)	(0.047)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01***	0.01*	0.01*
	(0.028)	(0.020)	(0.010)	(0.007)	(0.075)	(0.063)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.00	-0.01	-0.01
	(0.123)	(0.206)	(0.431)	(0.644)	(0.134)	(0.190)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)	(0.006)	(0.002)	(0.002)	(0.001)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.55***	-0.52***	-0.55***	-0.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.11	0.07	0.22***	0.22**
	(0.024)	(0.051)	(0.215)	(0.414)	(0.009)	(0.010)
MM · Real estate bust	0.33	0.41*	0.26	0.35	0.52**	0.58**
	(0.122)	(0.063)	(0.245)	(0.122)	(0.017)	(0.011)
MM · Stock boom	0.38***	0.48***	0.32***	0.43***	0.35***	0.46***
	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.29**	0.43***	0.34***	0.43***
	(0.020)	(0.000)	(0.030)	(0.001)	(0.005)	(0.000)
Real estate boom length	-0.00		-0.00		-0.00	
	(0.224)		(0.318)		(0.509)	
Real estate boom size		-0.00		0.00		0.00
		(0.937)		(0.849)		(0.940)
Real estate bust length	-0.01***		-0.01***		-0.01**	
	(0.000)		(0.000)		(0.017)	
Real estate bust size		-0.03***		-0.03***		-0.01**
		(0.009)		(0.004)		(0.036)
Stock boom length	0.01***		0.02***		0.01***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.00***		0.00***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.03***		-0.03***		-0.02***	
	(0.001)		(0.000)		(0.003)	
Stock bust size		-0.01		-0.01*		-0.01
		(0.112)		(0.092)		(0.196)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	157,910	157,910	156,468	156,468
Adj. R^2	0.831	0.830	0.834	0.833	0.884	0.883
Adj. R^2 within	0.141	0.135	0.132	0.125	0.153	0.144

Table 11: The role of bank and bubble characteristics: additionally controlling for business cycles

Columns 1 and 2 restate the baseline regression results from Table 5, columns 6 and 7. Columns 3 and 4 additionally include a business cycle indicator. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:		ΔCoVaR		
Real estate boom	0.09**	0.11***	0.11***	0.13***
	(0.031)	(0.004)	(0.003)	(0.000)
Real estate bust	0.25**	0.27**	0.22*	0.25**
	(0.036)	(0.018)	(0.069)	(0.037)
Stock boom	0.34***	0.36***	0.38***	0.40***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.29***	0.28***
	(0.000)	(0.000)	(0.000)	(0.001)
log(Bank size)	0.26***	0.25***	0.27***	0.27***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.01	-0.01
	(0.490)	(0.492)	(0.494)	(0.465)
log(Bank size) · Real estate bust	0.17***	0.16***	0.18***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.06***	0.06***
	(0.002)	(0.003)	(0.002)	(0.004)
log(Bank size) · Stock bust	0.11***	0.11***	0.12***	0.12***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-1.78***	-1.87***
	(0.020)	(0.014)	(0.005)	(0.003)
Loan growth · Real estate boom	1.43**	1.58**	2.02***	2.12***
	(0.044)	(0.026)	(0.005)	(0.003)
Loan growth · Real estate bust	4.47***	4.58***	4.61***	4.59***
	(0.003)	(0.002)	(0.002)	(0.002)
Loan growth · Stock boom	0.86	1.03	0.86	1.01
	(0.202)	(0.140)	(0.206)	(0.155)
Loan growth · Stock bust	2.81***	2.94***	2.74***	2.90***
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.00*	0.00	0.00*	0.00*
	(0.097)	(0.107)	(0.072)	(0.071)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**
	(0.028)	(0.020)	(0.030)	(0.028)
Leverage · Real estate bust	-0.01	-0.01	-0.01*	-0.01
	(0.123)	(0.206)	(0.083)	(0.135)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)	(0.003)	(0.001)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.60***	-0.59***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.19**	0.18**
	(0.024)	(0.051)	(0.044)	(0.049)
MM · Real estate bust	0.33	0.41*	0.26	0.34
	(0.122)	(0.063)	(0.226)	(0.121)
MM · Stock boom	0.38***	0.48***	0.39***	0.49***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.21	0.32**
	(0.020)	(0.000)	(0.137)	(0.015)
Real estate boom length	-0.00		0.00	
	(0.224)		(0.922)	
Real estate boom size		-0.00		0.00
		(0.937)		(0.300)
Real estate bust length	-0.01***		-0.01***	
	(0.000)		(0.000)	
Real estate bust size		-0.03***		-0.03***
		(0.009)		(0.005)
Stock boom length	0.01***		0.01***	
	(0.000)		(0.000)	
Stock boom size		0.00***		0.00***
		(0.000)		(0.000)
Stock bust length	-0.03***		-0.03***	
	(0.001)		(0.001)	
Stock bust size		-0.01		-0.01
		(0.112)		(0.120)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
Business Cycle	No	No	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149
Adj. R^2	0.831	0.830	0.833	0.832
Adj. R^2 within	0.141	0.135	0.153	0.148

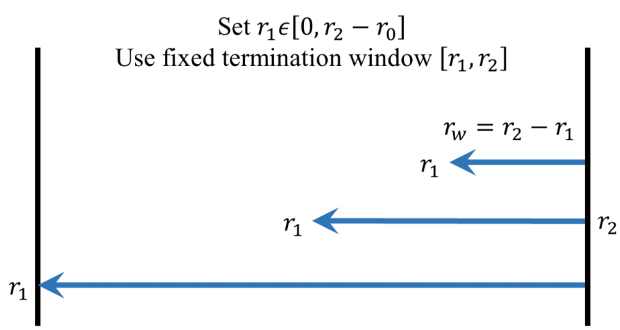
Appendix A Estimation of bubble episodes

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 A1 illustrates the idea. Formally, the BSADF statistic is thus given by

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} . \tag{A1}$$

Figure A1: 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,

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} [r_2 : BSADF_{r_2}(r_0) > scv^{\beta}_{r_2}] \tag{A2}$$

$$\text{and } \hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta log(T),1]} [r_2 : BSADF_{r_2}(r_0) < scv^{\beta}_{r_2}] \ , \tag{A3}$$

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.

Appendix B Estimation of ∆CoVaR

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. 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.

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

$$X_{t+1}^{i} = -\frac{P_{t+1}^{i} N_{t+1}^{i} - P_{t}^{i} N_{t}^{i}}{P_{t}^{i} N_{t}^{i}} \text{ and} \tag{B1}$$

$$X_{t+1}^{system} = \sum_{i} \frac{MV_{t}^{i}}{\sum_{i} MV_{t}^{i}} X_{t+1}^{i} \ , \tag{B2}$$

where P_t^i 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 (B1) to prevent exchange rate fluctuations from biasing our results.[26] When calculating market shares of each institution (the ratio in Equation (B2)), 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.

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;

[26] 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.

- 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.[27] 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 B1 provides an overview of the data used to construct the system-specific control variables.

The estimation procedure starts by estimating the VaR and the relationship between institution-specific losses and system losses as

$$\widehat{VaR}^{i}_{q,t} = \hat{X}^{i}_{q,t} = \hat{\alpha}^{i}_{q} + \hat{\gamma}^{i}_{q} M_{t-1} \ , \tag{B3}$$

$$\hat{X}^{system|i}_{q,t} = \hat{\alpha}^{system|i}_{q} + \hat{\gamma}^{system|i}_{q} M_{t-1} + \hat{\beta}^{system|i}_{q} X^{i}_{t} \ . \tag{B4}$$

M_{t-1} is a vector of the macroeconomic control variables. We apply a stress level of $q = 98\%$ in all regressions. The conditional value at risk is calculated by combining estimates from the two previous regressions:

$$CoVaR^{i}_{q,t} = \hat{\alpha}^{system|i}_{q} + \hat{\gamma}^{system|i}_{q} M_{t-1} + \hat{\beta}^{system|i}_{q} \widehat{VaR}^{i}_{q,t} \ . \tag{B5}$$

Following the definition provided in Equation (1), the time series of ΔCoVaR is calculated as

$$\Delta CoVaR^{i}_{q,t} = \hat{\beta}^{system|i}_{q} (\widehat{VaR}^{i}_{q,t} - \widehat{VaR}^{i}_{50,t}) \ . \tag{B6}$$

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

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.

Table B1: 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)

Appendix C Additional figures and tables

Figure C1: Bubble episodes by country and asset class

BSADF approach with price-to-rent and price-to-dividend data

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated based on the BSADF approach using price-to-dividend and price-to-rent data. For details on the estimation procedure see Section 3.2 and Appendix A.

(a) Stock market bubble episodes

(b) Real estate bubble episodes

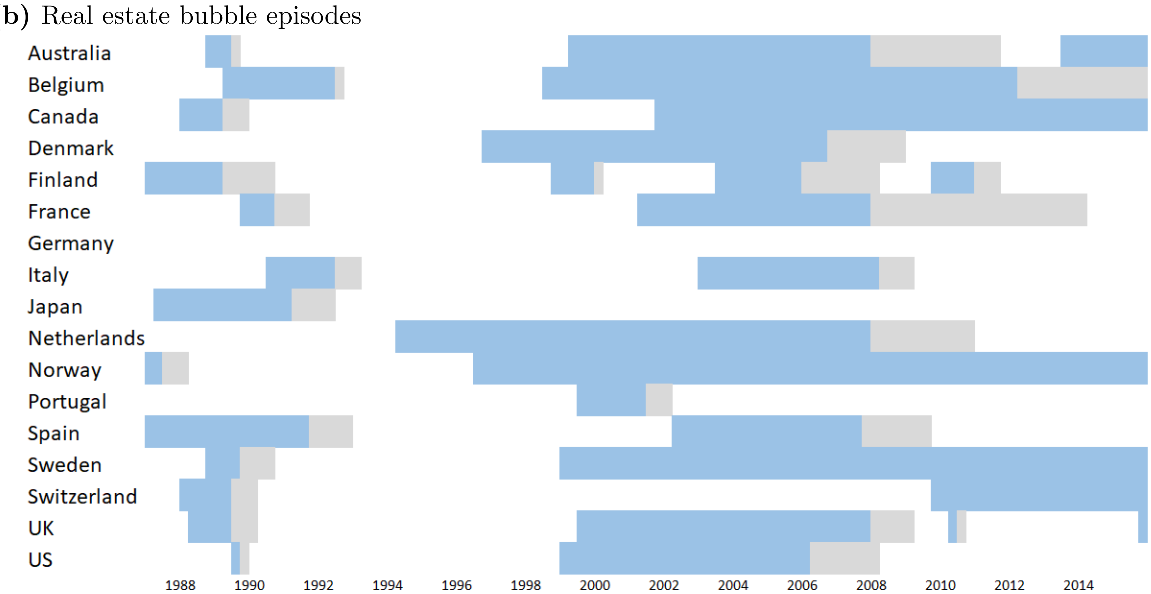
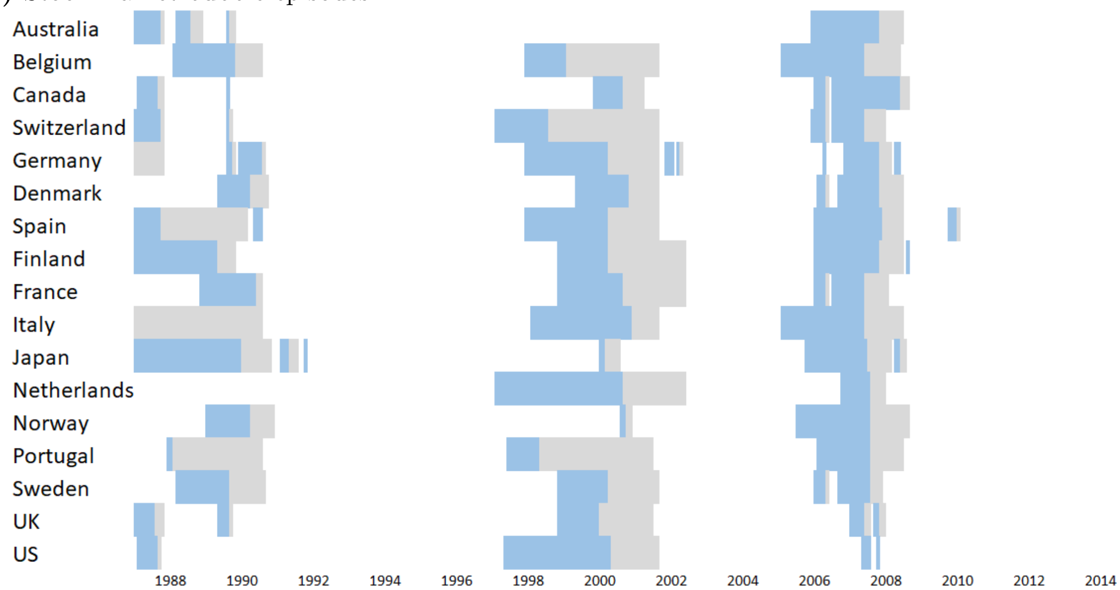


Figure C2: Bubble episodes by country and asset class

Trend-deviation approach

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated following the strategy in Jordà, Schularick, and Taylor (2015b). For details on the estimation procedure see Section 3.2.

(a) Stock market bubble episodes



(b) Real estate bubble episodes

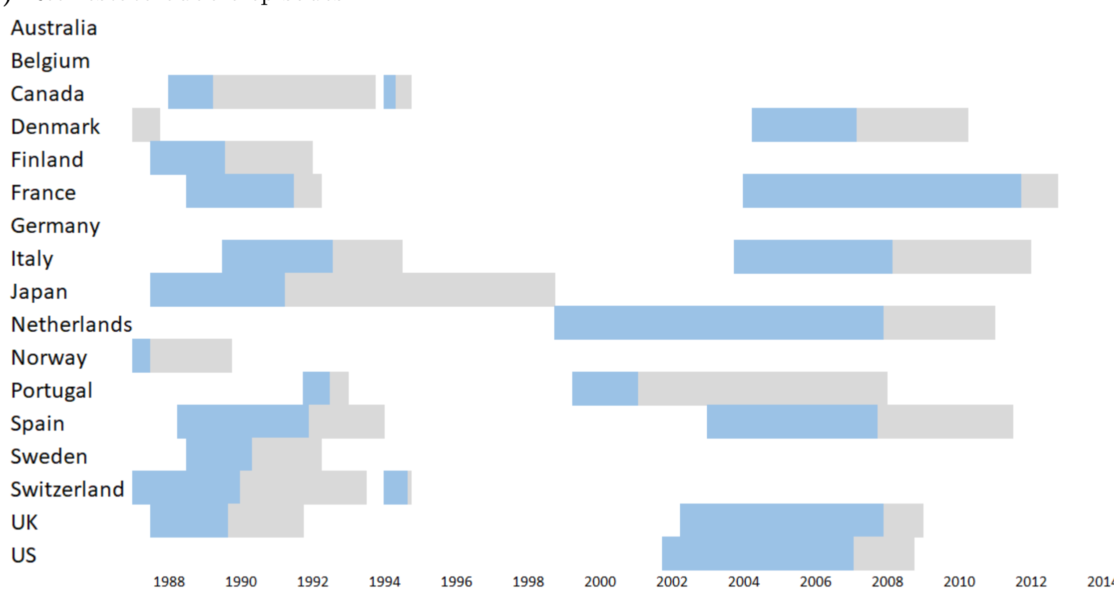


Figure C3: Systemic risk during bubble episodes in dependence of bank and bubble characteristics

Alternative bubble measure: BSADF approach with price-to-rent and price-to-dividend data

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 6, columns 3 and 4. The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

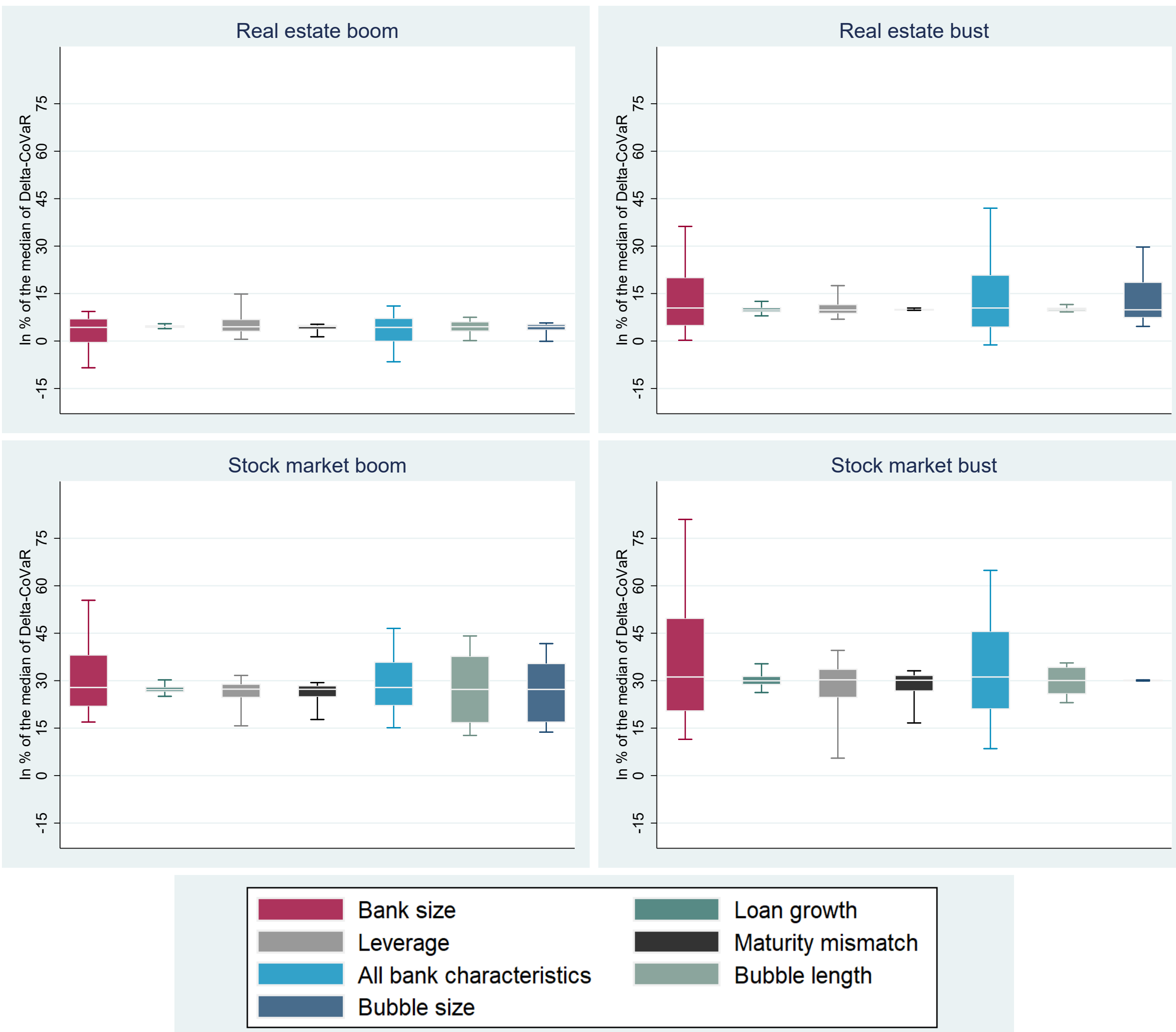


Figure C4: Systemic risk during bubble episodes in dependence of bank and bubble characteristics

Alternative bubble measure: trend-deviation approach

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 6, columns 5 and 6. The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

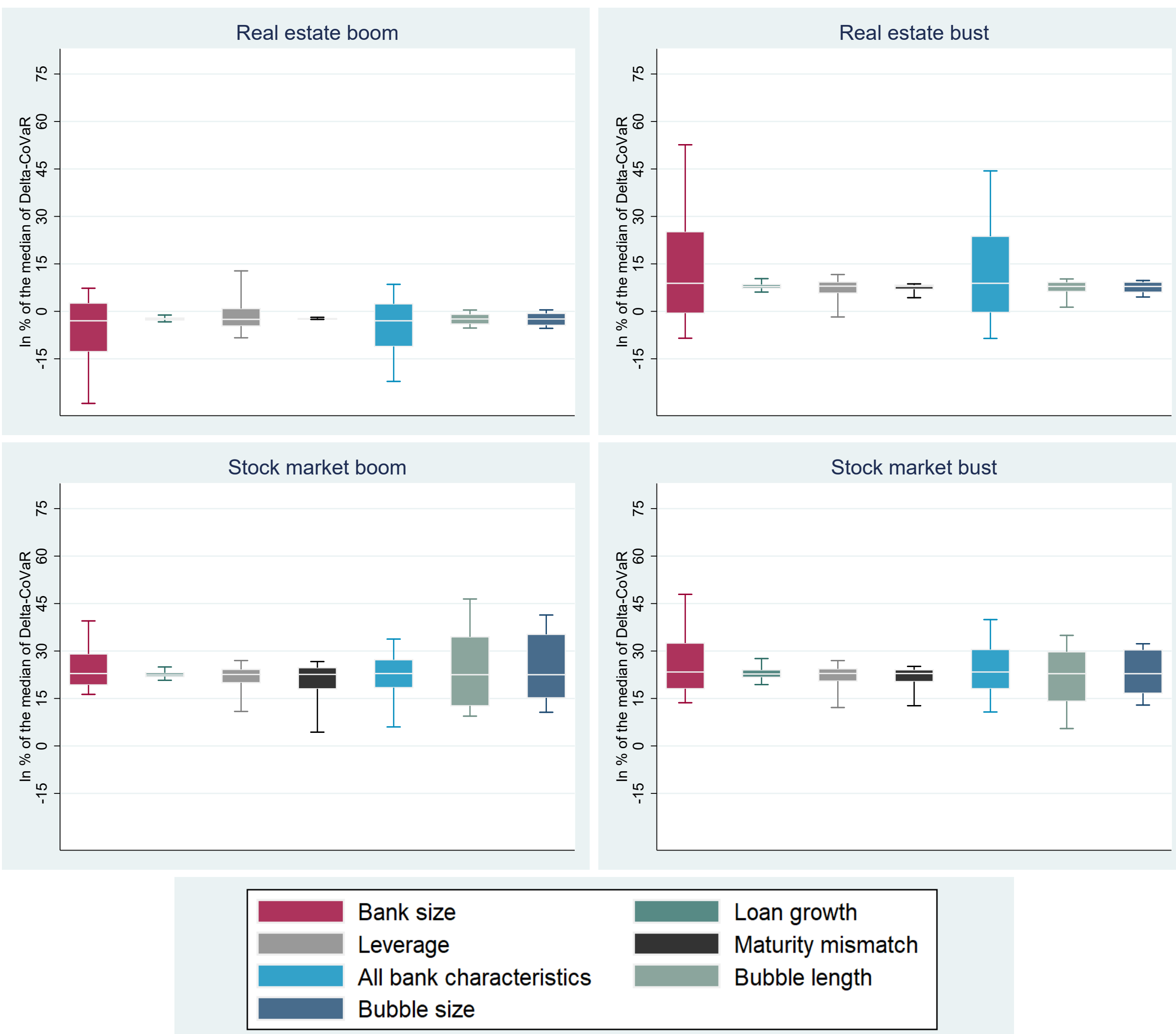


Figure C5: Systemic risk during bubble episodes in dependence of bank and bubble characteristics

Alternative systemic risk measure

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔMES. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 7, columns 6 and 7. The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

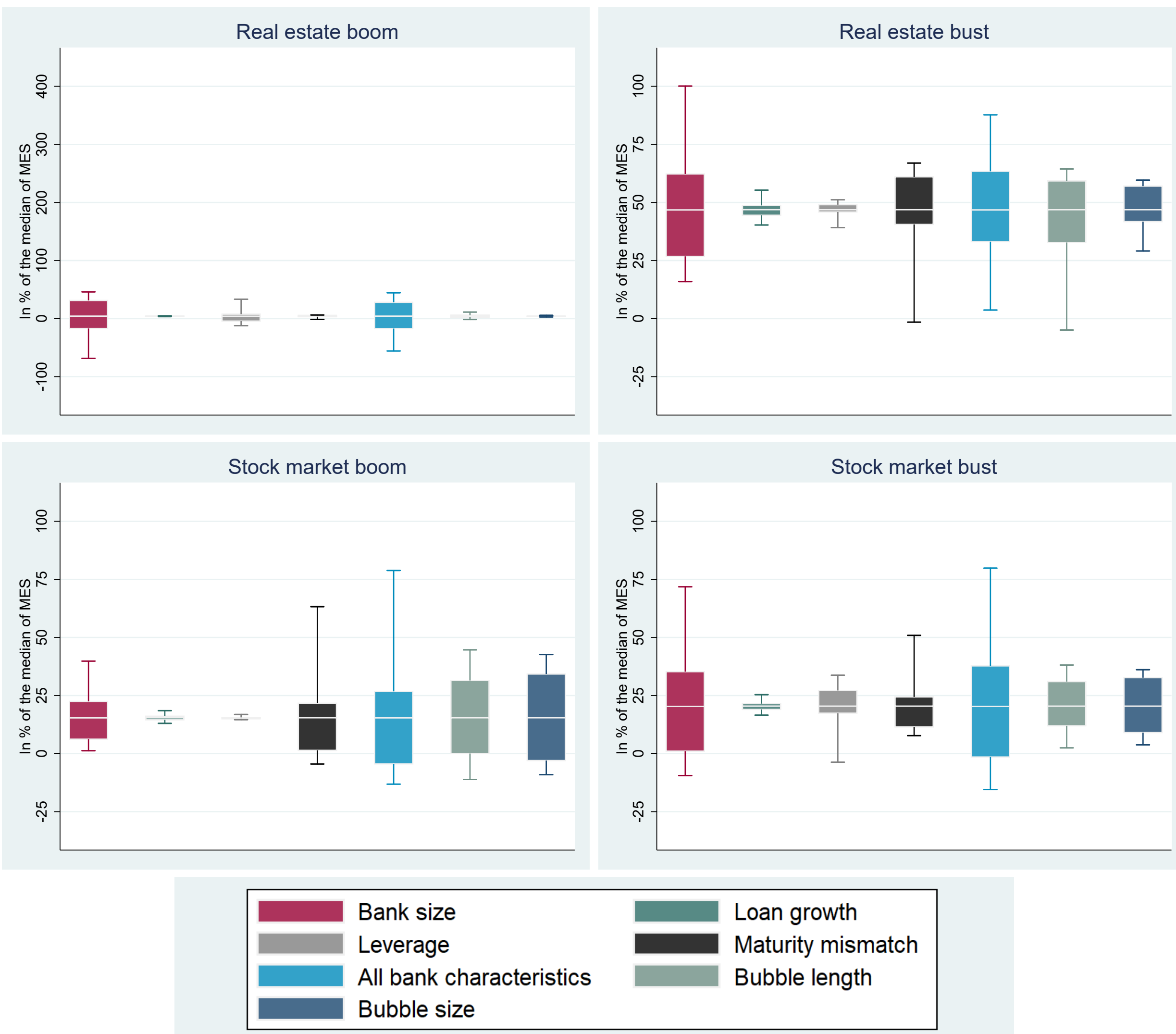


Figure C6: Evolution of ΔCoVaR and rolling ΔCoVaR over time

The figure displays the unweighted means of ΔCoVaR and the rolling ΔCoVaR in weekly percentage points for the four financial systems in our sample: North America, Europe, Japan, and Australia. Details on the estimation procedure of ΔCoVaR are provided in Section 3.3 and Appendix B. The estimation procedure of the rolling ΔCoVaR is described in Section 6.1.

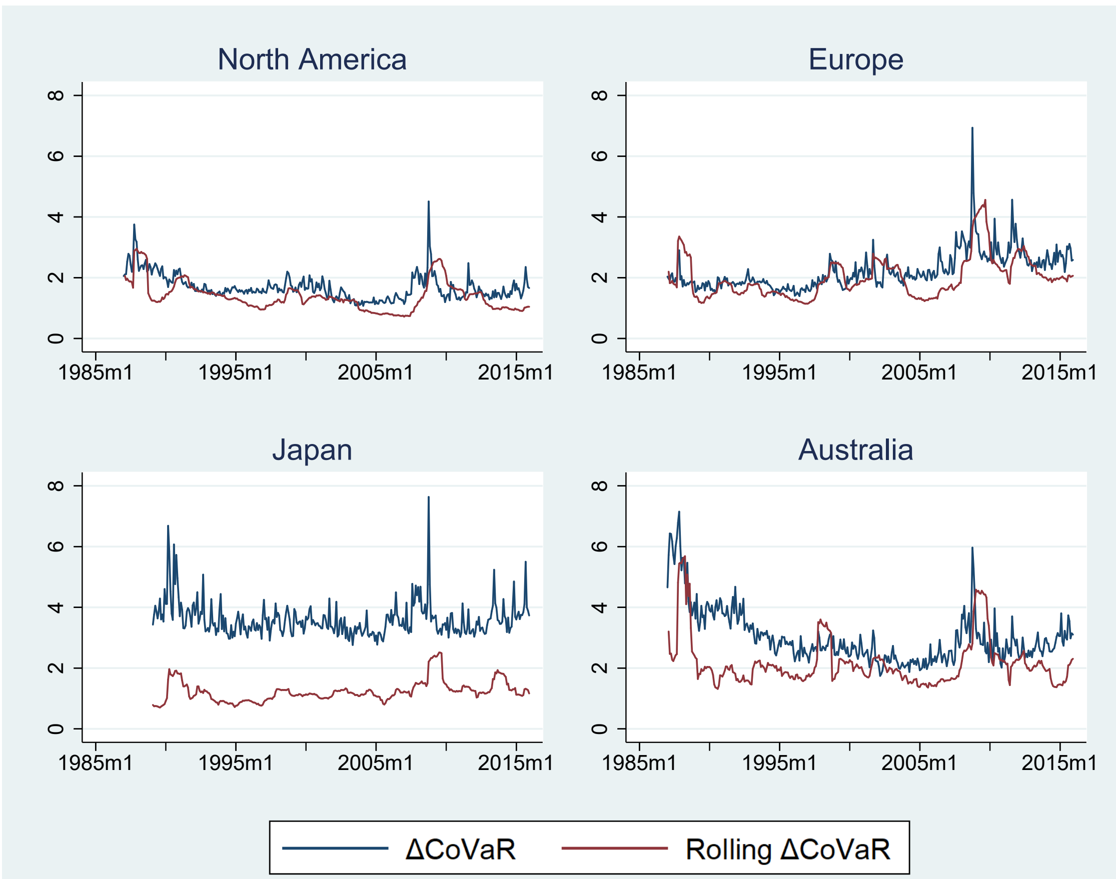
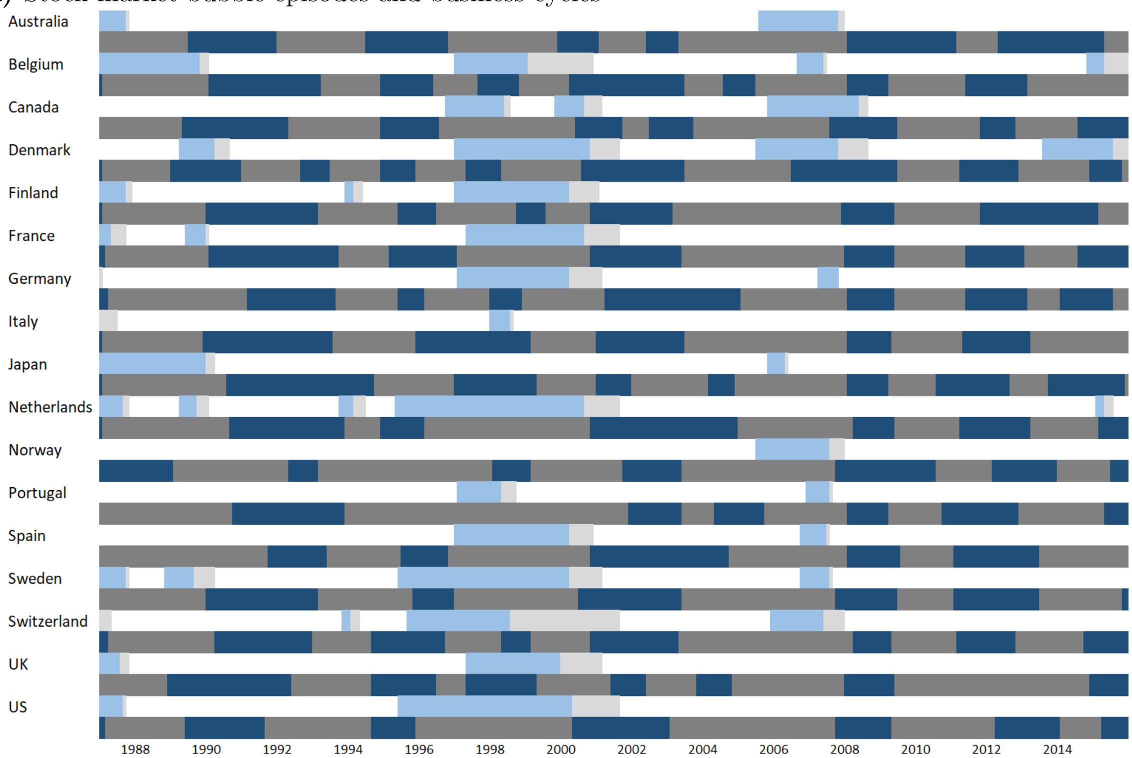


Figure C7: Bubble episodes by country and asset class: business cycles

Periods colored in light blue and light grey represent the boom and bust phase of asset price bubbles. Periods colored in dark blue and dark grey represent the boom and bust phase of the business cycle. Bubble episodes are estimated based on the BSADF approach. For details on the estimation procedure see Section 3.2 and Appendix A.

(a) Stock market bubble episodes and business cycles



(b) Real estate bubble episodes and business cycles

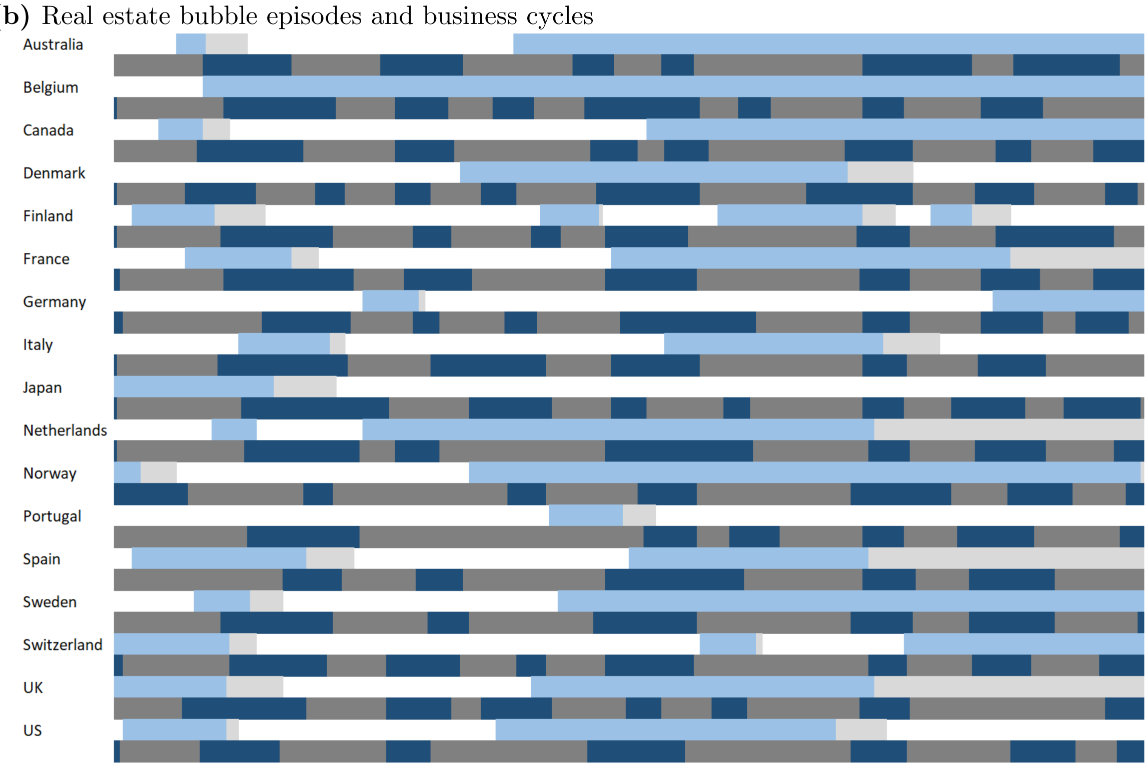


Table C1: Variable definitions and data sources

Detailed information on the variables' construction is provided in Sections 3, Appendix A, and Appendix B.

Variable name	Description
Dependent variable	
ΔCoVaR	Change in the conditional value at risk; estimation strategy provided in Section 3.3 and Appendix B. Source of market equity data: Datastream. Sources of control variables: see Table B1.
MES	Marginal expected shortfall; estimation strategy provided in Section 3.3 Source of market equity data: Datastream.
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 B1.
Equity market volatility	22-day rolling window standard deviation of the daily system-specific MSCI indices. Data sources: see Table B1.
Change in the 3M yield	The change in three-month government bond rates. Data sources: see Table B1.
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 B1.
TED spread	The difference between three-month Libor rates and three-month government bond rates. Data sources: see Table B1.
Credit spread	The difference between Moody's Baa rated bonds and ten-year government bond rates. Data sources: see Table B1.
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 or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.2). 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 or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.2). 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 or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.2). 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 or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.2). Source of stock market indeces: Datastream.

(*table continued on next page*)

Table C1 - *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 (Section 3.2). 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 (Section 3.2). 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	
Banking crisis	Country-specific binary indicator; equals one during a banking crisis; Source: Laeven and Valencia (2012), updated.
GDP growth	Δlog(real GDP); monthly growth rate. Source: OECD.
Interest rate	log(10-year government bond rate); Source: OECD.
Inflation	Δlog(CPI); monthly rate. Source: OECD.
Investment-to-GDP growth	Δlog(investment/GDP); monthly rate. Source: OECD.

Table C2: 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 C3: Baseline regression without boom-bust distinction

Re-esimate of the baseline regression from Table 5, column 5, but without the boom-bust distinction. Bubble characteristics are left out as they were defined in dependence of the switch from boom to bust. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)
Dependent variable:	ΔCoVaR	
Real estate bubble	0.17***	0.17***
	(0.001)	(0.002)
Stock market bubble	0.37***	0.19***
	(0.000)	(0.000)
log(Bank size)	0.28***	0.05*
	(0.000)	(0.086)
log(Bank size) · Real estate bubble	0.02	0.01
	(0.244)	(0.645)
log(Bank size) · Stock market bubble	0.05***	0.06***
	(0.001)	(0.001)
Loan growth	-1.98***	-2.29***
	(0.004)	(0.000)
Loan growth · Real estate bubble	2.37***	2.62***
	(0.004)	(0.000)
Loan growth · Stock market bubble	2.29***	1.22**
	(0.002)	(0.033)
Leverage	0.00*	0.01**
	(0.076)	(0.010)
Leverage · Real estate bubble	0.00	0.00
	(0.412)	(0.623)
Leverage · Stock market bubble	-0.01***	-0.01***
	(0.000)	(0.000)
Maturity mismatch	-0.67***	-0.57***
	(0.000)	(0.000)
MM · Real estate bubble	0.28***	0.18**
	(0.003)	(0.029)
MM · Stock market bubble	0.51***	0.54***
	(0.000)	(0.000)
Bank FE	Yes	Yes
Time FE	No	Yes
Macro Controls	Yes	Yes
No. of obs.	165,149	165,149
Adj. R^2	0.824	0.873
Adj. R^2 within	0.107	0.028

Table C4: The role of bank and bubble characteristics: use of interpolated data

Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. In columns 3 and 4, we estimate these regressions based on quarterly data to test the robustness of the results with regard to the interpolation of data. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	ΔCoVaR			
Frequency:	Monthly		Quarterly	
Real estate boom	0.09**	0.11***	0.15***	0.17***
	(0.031)	(0.004)	(0.001)	(0.000)
Real estate bust	0.25**	0.27**	0.42***	0.44***
	(0.036)	(0.018)	(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.27***	0.29***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.50***	0.51***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.21***	0.20***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	0.00	0.00
	(0.490)	(0.492)	(0.962)	(0.963)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.15***
	(0.000)	(0.000)	(0.001)	(0.002)
log(Bank size) · Stock boom	0.07***	0.06***	0.05*	0.04
	(0.002)	(0.003)	(0.090)	(0.103)
log(Bank size) · Stock bust	0.11***	0.11***	0.14***	0.14***
	(0.000)	(0.000)	(0.001)	(0.001)
Loan growth	-1.49**	-1.59**	-1.84***	-1.99***
	(0.020)	(0.014)	(0.009)	(0.005)
Loan growth · Real estate boom	1.43**	1.58**	1.72*	1.89**
	(0.044)	(0.026)	(0.071)	(0.050)
Loan growth · Real estate bust	4.47***	4.58***	4.73**	5.12***
	(0.003)	(0.002)	(0.010)	(0.005)
Loan growth · Stock boom	0.86	1.03	1.34*	1.54*
	(0.202)	(0.140)	(0.093)	(0.070)
Loan growth · Stock bust	2.81***	2.94***	3.58***	3.83***
	(0.001)	(0.001)	(0.003)	(0.001)
Leverage	0.00*	0.00	0.00*	0.00*
	(0.097)	(0.107)	(0.063)	(0.065)
Leverage · Real estate boom	0.01**	0.01**	0.01	0.01
	(0.028)	(0.020)	(0.163)	(0.131)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01
	(0.123)	(0.206)	(0.136)	(0.199)
Leverage · Stock boom	-0.01***	-0.01***	-0.01**	-0.01**
	(0.002)	(0.001)	(0.027)	(0.017)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.001)	(0.002)
Maturity mismatch	-0.65***	-0.62***	-0.60***	-0.58***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.26**	0.24*
	(0.024)	(0.051)	(0.042)	(0.050)
MM · Real estate bust	0.33	0.41*	0.46*	0.52*
	(0.122)	(0.063)	(0.096)	(0.078)
MM · Stock boom	0.38***	0.48***	0.41***	0.48***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.51**	0.60***
	(0.020)	(0.000)	(0.012)	(0.002)
Real estate boom length	-0.00		-0.00	
	(0.224)		(0.588)	
Real estate boom size		-0.00		0.00
		(0.937)		(0.608)
Real estate bust length	-0.01***		-0.01**	
	(0.000)		(0.011)	
Real estate bust size		-0.03***		-0.02
		(0.009)		(0.133)
Stock boom length	0.01***		0.01***	
	(0.000)		(0.000)	
Stock boom size		0.00***		0.00***
		(0.000)		(0.001)
Stock bust length	-0.03***		-0.02	
	(0.001)		(0.285)	
Stock bust size		-0.01		-0.00
		(0.112)		(0.766)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	55,128	55,128
Adj. R^2	0.831	0.830	0.851	0.850
Adj. R^2 within	0.141	0.135	0.151	0.144

Table C5: The role of bank and bubble characteristics: excluding episodes due to correlated bubbles

Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Exclude if at least x % of the countries experience a stock market bubble	Baseline		50%		33%	
Real estate boom	0.09**	0.11***	0.09*	0.08*	0.09*	0.09*
	(0.031)	(0.004)	(0.069)	(0.060)	(0.054)	(0.053)
Real estate bust	0.25**	0.27**	0.24*	0.26**	0.27*	0.30**
	(0.036)	(0.018)	(0.062)	(0.037)	(0.060)	(0.027)
Stock boom	0.34***	0.36***	0.34***	0.33***	0.48***	0.41***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.36***	0.37***	0.30**	0.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.004)
log(Bank size)	0.26***	0.25***	0.30***	0.28***	0.33***	0.30***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03
	(0.490)	(0.492)	(0.130)	(0.119)	(0.149)	(0.116)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.16***	0.18***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	-0.01	-0.00	-0.05*	-0.04
	(0.002)	(0.003)	(0.889)	(0.897)	(0.059)	(0.110)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.11***	0.10**	0.11**
	(0.000)	(0.000)	(0.002)	(0.001)	(0.033)	(0.037)
Loan growth	-1.49**	-1.59**	-1.46**	-1.35*	-1.61**	-1.41*
	(0.020)	(0.014)	(0.038)	(0.054)	(0.029)	(0.054)
Loan growth · Real estate boom	1.43**	1.58**	1.52*	1.25	1.89**	1.39
	(0.044)	(0.026)	(0.067)	(0.116)	(0.040)	(0.113)
Loan growth · Real estate bust	4.47***	4.58***	4.95***	4.83***	5.83***	5.54***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Loan growth · Stock boom	0.86	1.03	0.94	1.01	1.81	1.62
	(0.202)	(0.140)	(0.364)	(0.337)	(0.140)	(0.179)
Loan growth · Stock bust	2.81***	2.94***	3.68***	4.13***	3.73***	4.24***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.00*	0.00	0.00	0.00	0.00	0.00
	(0.097)	(0.107)	(0.409)	(0.543)	(0.489)	(0.638)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01***	0.01***	0.02***
	(0.028)	(0.020)	(0.006)	(0.002)	(0.007)	(0.003)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01	-0.01*	-0.01
	(0.123)	(0.206)	(0.147)	(0.265)	(0.096)	(0.190)
Leverage · Stock boom	-0.01***	-0.01***	0.00	0.00	0.01*	0.01**
	(0.002)	(0.001)	(0.761)	(0.704)	(0.071)	(0.039)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02**	-0.02**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.017)	(0.013)
Maturity mismatch	-0.65***	-0.62***	-0.58***	-0.52***	-0.57***	-0.50***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
MM · Real estate boom	0.21**	0.18*	0.13	0.05	0.12	0.07
	(0.024)	(0.051)	(0.239)	(0.611)	(0.313)	(0.562)
MM · Real estate bust	0.33	0.41*	0.31	0.36	0.35	0.42*
	(0.122)	(0.063)	(0.171)	(0.112)	(0.147)	(0.083)
MM · Stock boom	0.38***	0.48***	0.28**	0.31**	0.11	0.14
	(0.000)	(0.000)	(0.024)	(0.014)	(0.512)	(0.429)
MM · Stock bust	0.31**	0.43***	0.28*	0.45***	0.22	0.13
	(0.020)	(0.000)	(0.075)	(0.002)	(0.267)	(0.241)
Real estate boom length	-0.00		-0.00		-0.00	
	(0.224)		(0.267)		(0.664)	
Real estate boom size		-0.00		0.00		0.00*
		(0.937)		(0.463)		(0.089)
Real estate bust length	-0.01***		-0.01***		-0.01***	
	(0.000)		(0.000)		(0.000)	
Real estate bust size		-0.03***		-0.03***		-0.03***
		(0.009)		(0.004)		(0.001)
Stock boom length	0.01***		0.02***		0.02***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.01***		0.01***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.03***		-0.03***		-0.02**	
	(0.001)		(0.002)		(0.013)	
Stock bust size		-0.01		-0.01		0.01
		(0.112)		(0.148)		(0.653)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	143,877	143,877	129,193	129,193
Adj. R^2	0.831	0.830	0.824	0.823	0.817	0.817
Adj. R^2 within	0.141	0.135	0.141	0.138	0.141	0.141

Table C6: The share of non-interest rate income

Columns 1 and 2 restate the baseline regressions from Table 5, columns 6 and 7. Columns 3 to 6 consider the share of non-interest rate income in various specifications. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Real estate boom	0.09**	0.11***	0.20***	0.15***	0.08**	0.11***
	(0.031)	(0.004)	(0.000)	(0.000)	(0.037)	(0.005)
Real estate bust	0.25**	0.27**	0.45***	0.27**	0.25**	0.27**
	(0.036)	(0.018)	(0.000)	(0.020)	(0.038)	(0.020)
Stock boom	0.34***	0.36***	0.30***	0.38***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.34***	0.36***	0.38***	0.37***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***		0.26***	0.26***	0.25***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01		-0.01	-0.01	-0.01
	(0.490)	(0.492)		(0.564)	(0.522)	(0.525)
log(Bank size) · Real estate bust	0.17***	0.16***		0.14***	0.17***	0.16***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***		0.05**	0.07***	0.06***
	(0.002)	(0.003)		(0.016)	(0.001)	(0.002)
log(Bank size) · Stock bust	0.11***	0.11***		0.11***	0.11***	0.11***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**		-2.29***	-1.50**	-1.59**
	(0.020)	(0.014)		(0.001)	(0.022)	(0.016)
Loan growth · Real estate boom	1.43**	1.58**		2.50***	1.42*	1.56**
	(0.044)	(0.026)		(0.001)	(0.051)	(0.031)
Loan growth · Real estate bust	4.47***	4.58***		6.29***	4.50***	4.66***
	(0.003)	(0.002)		(0.000)	(0.003)	(0.002)
Loan growth · Stock boom	0.86	1.03		1.88**	0.91	1.05
	(0.202)	(0.140)		(0.011)	(0.175)	(0.130)
Loan growth · Stock bust	2.81***	2.94***		3.40***	2.64***	2.75***
	(0.001)	(0.001)		(0.001)	(0.002)	(0.002)
Leverage	0.00*	0.00		0.00*	0.00*	0.00
	(0.097)	(0.107)		(0.063)	(0.100)	(0.109)
Leverage · Real estate boom	0.01**	0.01**		0.01**	0.01**	0.01**
	(0.028)	(0.020)		(0.018)	(0.024)	(0.018)
Leverage · Real estate bust	-0.01	-0.01		-0.01	-0.01	-0.01
	(0.123)	(0.206)		(0.250)	(0.121)	(0.203)
Leverage · Stock boom	-0.01***	-0.01***		-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)		(0.001)	(0.002)	(0.001)
Leverage · Stock bust	-0.02***	-0.02***		-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)

(*table continued on next page*)

Table C6 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Maturity mismatch	-0.65***	-0.62***		-0.71***	-0.70***	-0.67***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*		0.31***	0.25**	0.22**
	(0.024)	(0.051)		(0.003)	(0.018)	(0.033)
MM · Real estate bust	0.33	0.41*		0.39*	0.33	0.40*
	(0.122)	(0.063)		(0.096)	(0.147)	(0.081)
MM · Stock boom	0.38***	0.48***		0.72***	0.42***	0.54***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***		0.45***	0.36**	0.50***
	(0.020)	(0.000)		(0.001)	(0.019)	(0.000)
Share of non-interest income			0.00	-0.00	0.00	0.00
			(0.253)	(0.989)	(0.737)	(0.856)
Share of non-interest income · Real estate boom			-0.00	0.00	0.00	0.00
			(0.255)	(0.383)	(0.697)	(0.549)
Share of non-interest income · Real estate bust			0.01	0.00	0.00	0.00
			(0.574)	(0.999)	(0.745)	(0.971)
Share of non-interest income · Stock boom			-0.01	0.01	0.00	0.01
			(0.307)	(0.204)	(0.540)	(0.310)
Share of non-interest income · Stock bust			0.01	0.00	0.00	0.01
			(0.159)	(0.240)	(0.335)	(0.159)
Real estate boom length	-0.00				-0.00	
	(0.224)				(0.228)	
Real estate boom size		-0.00				-0.00
		(0.937)				(0.926)
Real estate bust length	-0.01***				-0.01***	
	(0.000)				(0.000)	
Real estate bust size		-0.03***				-0.03***
		(0.009)				(0.009)
Stock boom length	0.01***				0.01***	
	(0.000)				(0.000)	
Stock boom size		0.00***				0.00***
		(0.000)				(0.000)
Stock bust length	-0.03***				-0.03***	
	(0.001)				(0.001)	
Stock bust size		-0.01				-0.01
		(0.112)				(0.111)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	164,840	164,840	164,840	164,840
Adj. R^2	0.831	0.830	0.819	0.827	0.831	0.830
Adj. R^2 within	0.141	0.135	0.082	0.124	0.141	0.135

Table C7: The role of bank and bubble characteristics: more pronounced lead-lag structures

Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Explanatory variables additionally lagged by	0 months		3 months		6 months	
Real estate boom	0.09**	0.11***	0.08***	0.08***	0.15***	0.15***
	(0.031)	(0.004)	(0.006)	(0.005)	(0.000)	(0.000)
Real estate bust	0.25**	0.27**	0.55***	0.55***	0.66***	0.67***
	(0.036)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.37***	0.38***	0.39***	0.39***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.37***	0.38***	0.30***	0.31***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.24***	0.23***	0.21***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	0.01	0.01	0.03**	0.02*
	(0.490)	(0.492)	(0.377)	(0.353)	(0.045)	(0.062)
log(Bank size) · Real estate bust	0.17***	0.16***	0.25***	0.23***	0.25***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.09***	0.09***	0.11***	0.11***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock bust	0.11***	0.11***	0.13***	0.13***	0.08***	0.09***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.004)
Loan growth	-1.49**	-1.59**	-1.16**	-1.33**	-0.84	-0.95
	(0.020)	(0.014)	(0.048)	(0.019)	(0.185)	(0.122)
Loan growth · Real estate boom	1.43**	1.58**	1.46**	1.55**	1.30*	1.24*
	(0.044)	(0.026)	(0.028)	(0.020)	(0.052)	(0.060)
Loan growth · Real estate bust	4.47***	4.58***	3.20	4.13**	3.97**	4.52**
	(0.003)	(0.002)	(0.117)	(0.037)	(0.047)	(0.027)
Loan growth · Stock boom	0.86	1.03	1.29*	1.40*	1.92**	1.95**
	(0.202)	(0.140)	(0.089)	(0.060)	(0.023)	(0.019)
Loan growth · Stock bust	2.81***	2.94***	2.68***	2.48***	3.03***	2.98***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Leverage	0.00*	0.00	0.00**	0.00*	0.01**	0.00**
	(0.097)	(0.107)	(0.044)	(0.051)	(0.026)	(0.030)
Leverage · Real estate boom	0.01**	0.01**	0.00	0.01	0.00	0.00
	(0.028)	(0.020)	(0.164)	(0.110)	(0.372)	(0.345)
Leverage · Real estate bust	-0.01	-0.01	-0.02***	-0.02***	-0.03***	-0.03***
	(0.123)	(0.206)	(0.001)	(0.003)	(0.001)	(0.001)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***	-0.01**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.010)	(0.013)
Maturity mismatch	-0.65***	-0.62***	-0.57***	-0.54***	-0.52***	-0.49***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.11	0.06	0.13	0.11
	(0.024)	(0.051)	(0.260)	(0.538)	(0.172)	(0.246)
MM · Real estate bust	0.33	0.41*	0.67**	0.72**	0.77**	0.81***
	(0.122)	(0.063)	(0.019)	(0.013)	(0.010)	(0.008)
MM · Stock boom	0.38***	0.48***	0.36***	0.41***	0.41***	0.44***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.38***	0.48***	0.34***	0.47***
	(0.020)	(0.000)	(0.002)	(0.000)	(0.006)	(0.000)
Real estate boom length	-0.00		-0.00		0.00*	
	(0.224)		(0.911)		(0.087)	
Real estate boom size		-0.00		0.00**		0.00***
		(0.937)		(0.026)		(0.002)
Real estate bust length	-0.01***		-0.01***		-0.02***	
	(0.000)		(0.000)		(0.000)	
Real estate bust size		-0.03***		-0.01		-0.02**
		(0.009)		(0.378)		(0.010)
Stock boom length	0.01***		0.01***		0.01***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.00***		0.00***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.03***		-0.02**		-0.02***	
	(0.001)		(0.027)		(0.000)	
Stock bust size		-0.01		-0.01***		-0.02**
		(0.112)		(0.001)		(0.016)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	164,467	164,467	163,436	163,436
Adj. R^2	0.831	0.830	0.840	0.839	0.838	0.837
Adj. R^2 within	0.141	0.135	0.184	0.179	0.172	0.170

Table C8: Do systemic risk measures predict asset price bubbles?

Variable definitions are provided in Table C1. 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)	(7)	(8)
Dependent variable:	Real estate bubble				Stock market bubble			
ΔCoVaR	0.05	0.03			0.03	0.02		
	(0.189)	(0.362)			(0.222)	(0.516)		
MES			0.01	-0.01			0.02	0.00
			(0.620)	(0.662)			(0.425)	(0.990)
log(Bank size)	0.09	0.10*	0.12**	0.12**	-0.07	-0.06	-0.05	-0.05
	(0.154)	(0.095)	(0.015)	(0.016)	(0.101)	(0.160)	(0.145)	(0.159)
Loan growth	3.96	5.07	4.31	5.13	5.08*	5.83**	5.40*	5.99*
	(0.123)	(0.118)	(0.110)	(0.110)	(0.062)	(0.042)	(0.066)	(0.052)
Leverage	-0.01	-0.01	-0.01	-0.01	0.01**	0.01**	0.01*	0.01**
	(0.201)	(0.188)	(0.128)	(0.167)	(0.027)	(0.038)	(0.056)	(0.049)
Maturity mismatch	-0.35	-0.37	-0.34	-0.39	-0.43	-0.44	-0.41	-0.44
	(0.351)	(0.307)	(0.385)	(0.300)	(0.184)	(0.153)	(0.210)	(0.166)
GDP growth	-0.09	0.56	-0.13	0.24	3.86***	4.30***	3.93***	4.19***
	(0.952)	(0.674)	(0.933)	(0.873)	(0.006)	(0.004)	(0.008)	(0.008)
log(Interest rate)	-0.19***	-0.15***	-0.19***	-0.15***	0.05	0.07**	0.05	0.07**
	(0.000)	(0.003)	(0.001)	(0.002)	(0.116)	(0.016)	(0.113)	(0.017)
Inflation	7.52***	7.21***	7.79***	7.45***	-7.55***	-7.76***	-7.38***	-7.63***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Investment-to-GDP growth	0.33	0.38	0.34	0.38	0.12	0.15	0.12	0.15
	(0.222)	(0.200)	(0.205)	(0.189)	(0.667)	(0.616)	(0.656)	(0.610)
Banking crisis	-0.21**		-0.20*		-0.14***		-0.14***	
	(0.049)		(0.057)		(0.002)		(0.005)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,400	4,400	4,397	4,397	4,400	4,400	4,397	4,397
Adj. R^2	0.371	0.355	0.367	0.354	0.236	0.225	0.234	0.225
Adj. R^2 within	0.178	0.156	0.171	0.155	0.183	0.171	0.181	0.171

Table C9: Granger-causality tests

The granger causality tests follow the strategy in Dumitrescu and Hurlin (2012), who extend standard granger causality models to panel data by allowing for heterogeneous coefficients in the cross-sectional dimension. We use bootstrapping with 1,000 repetitions to compute p-values and allow for up to 36 lags to be included in the models while leaving the lag order selection to AIC, BIC, and HQIC. To be conservative, we report the lowest p-value resulting from the tests based on the three criteria. ***, **, * indicate significance at the 1%, 5% and 10% levels.
None of the tests rejects the null of a risk measure *not* granger causing one of our bubble measures. The results thus support the findings from our linear probability models. Neither ΔCoVaR nor MES granger causes real estate or stock market bubbles.

	ΔCoVaR		MES	
Underlying statistic:	Z-bar	Z-bar tilde	Z-bar	Z-bar tilde
Real estate bubble	0.51	0.52	0.18	0.18
Stock market bubble	0.44	0.45	0.57	0.58

Table C10: The role of bank and bubble characteristics: alternative clustering

Columns 3 and 4 restate our baseline regressions from Table 5, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered as indicated in the table. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Clustering:	bank & country-time		bank & time		bank & quarter	
Real estate boom	0.09**	0.11***	0.09**	0.11***	0.09*	0.11**
	(0.018)	(0.002)	(0.031)	(0.004)	(0.078)	(0.020)
Real estate bust	0.25**	0.27**	0.25**	0.27**	0.25	0.27*
	(0.027)	(0.012)	(0.036)	(0.018)	(0.104)	(0.066)
Stock boom	0.34***	0.36***	0.34***	0.36***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.25***	0.26***	0.25***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.454)	(0.458)	(0.490)	(0.492)	(0.642)	(0.645)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.16***	0.17***	0.16***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.07***	0.06***	0.07**	0.06**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.018)	(0.023)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-1.49**	-1.59**	-1.49**	-1.59**
	(0.028)	(0.020)	(0.020)	(0.014)	(0.024)	(0.017)
Loan growth · Real estate boom	1.43**	1.58**	1.43**	1.58**	1.43*	1.58*
	(0.041)	(0.024)	(0.044)	(0.026)	(0.090)	(0.058)
Loan growth · Real estate bust	4.47***	4.58***	4.47***	4.58***	4.47***	4.58***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Loan growth · Stock boom	0.86	1.03	0.86	1.03	0.86	1.03
	(0.227)	(0.164)	(0.202)	(0.140)	(0.244)	(0.181)
Loan growth · Stock bust	2.81***	2.94***	2.81***	2.94***	2.81***	2.94***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Leverage	0.00*	0.00	0.00*	0.00	0.00	0.00
	(0.099)	(0.110)	(0.097)	(0.107)	(0.127)	(0.138)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**	0.01*	0.01*
	(0.020)	(0.014)	(0.028)	(0.020)	(0.080)	(0.067)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.130)	(0.216)	(0.123)	(0.206)	(0.200)	(0.295)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01**	-0.01***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.013)	(0.006)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.65***	-0.62***	-0.65***	-0.62***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.21**	0.18*	0.21**	0.18*
	(0.025)	(0.056)	(0.024)	(0.051)	(0.044)	(0.083)
MM · Real estate bust	0.33	0.41*	0.33	0.41*	0.33	0.41*
	(0.110)	(0.059)	(0.122)	(0.063)	(0.159)	(0.088)
MM · Stock boom	0.38***	0.48***	0.38***	0.48***	0.38***	0.48***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
MM · Stock bust	0.31**	0.43***	0.31**	0.43***	0.31*	0.43***
	(0.030)	(0.001)	(0.020)	(0.000)	(0.050)	(0.004)
Real estate boom length	-0.00		-0.00		-0.00	
	(0.183)		(0.224)		(0.293)	
Real estate boom size		-0.00		-0.00		-0.00
		(0.929)		(0.937)		(0.948)
Real estate bust length	-0.01***		-0.01***		-0.01***	
	(0.000)		(0.000)		(0.006)	
Real estate bust size		-0.03***		-0.03***		-0.03**
		(0.001)		(0.009)		(0.050)
Stock boom length	0.01***		0.01***		0.01***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.00***		0.00***		0.00***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.03***		-0.03***		-0.03**	
	(0.001)		(0.001)		(0.013)	
Stock bust size		-0.01*		-0.01		-0.01
		(0.093)		(0.112)		(0.199)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149	165,149	165,149
Adj. R^2	0.831	0.830	0.831	0.830	0.831	0.830
Adj. R^2 within	0.141	0.135	0.141	0.135	0.141	0.135

Table C11: The role of bank and bubble characteristics: global time FEs

Columns 1 and 2 restate our baseline regressions from Table 5, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table C1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	ΔCoVaR			
Fixed effects:	bank		bank and time	
Real estate boom	0.09**	0.11***	0.21***	0.22***
	(0.031)	(0.004)	(0.000)	(0.000)
Real estate bust	0.25**	0.27**	-0.07	-0.08
	(0.036)	(0.018)	(0.409)	(0.361)
Stock boom	0.34***	0.36***	0.27***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.06	0.01
	(0.000)	(0.000)	(0.352)	(0.860)
log(Bank size)	0.26***	0.25***	0.04	0.04
	(0.000)	(0.000)	(0.203)	(0.199)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.03	-0.03
	(0.490)	(0.492)	(0.130)	(0.130)
log(Bank size) · Real estate bust	0.17***	0.16***	0.19***	0.18***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.06***	0.06***
	(0.002)	(0.003)	(0.003)	(0.004)
log(Bank size) · Stock bust	0.11***	0.11***	0.12***	0.12***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-2.17***	-2.19***
	(0.020)	(0.014)	(0.001)	(0.001)
Loan growth · Real estate boom	1.43**	1.58**	2.04***	2.05***
	(0.044)	(0.026)	(0.004)	(0.004)
Loan growth · Real estate bust	4.47***	4.58***	4.02***	4.23***
	(0.003)	(0.002)	(0.005)	(0.003)
Loan growth · Stock boom	0.86	1.03	0.98	1.09*
	(0.202)	(0.140)	(0.103)	(0.074)
Loan growth · Stock bust	2.81***	2.94***	1.74**	1.68**
	(0.001)	(0.001)	(0.018)	(0.024)
Leverage	0.00*	0.00	0.00**	0.00**
	(0.097)	(0.107)	(0.014)	(0.012)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**
	(0.028)	(0.020)	(0.021)	(0.026)
Leverage · Real estate bust	-0.01	-0.01	-0.01*	-0.01
	(0.123)	(0.206)	(0.078)	(0.112)
Leverage · Stock boom	-0.01***	-0.01***	-0.02***	-0.02***
	(0.002)	(0.001)	(0.000)	(0.000)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.42***	-0.43***
	(0.000)	(0.000)	(0.001)	(0.001)
MM · Real estate boom	0.21**	0.18*	0.20**	0.21**
	(0.024)	(0.051)	(0.021)	(0.013)
MM · Real estate bust	0.33	0.41*	0.09	0.12
	(0.122)	(0.063)	(0.617)	(0.490)
MM · Stock boom	0.38***	0.48***	0.54***	0.58***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.40***	0.43***
	(0.020)	(0.000)	(0.000)	(0.000)
Real estate boom length	-0.00		0.00*	
	(0.224)		(0.073)	
Real estate boom size		-0.00		0.00*
		(0.937)		(0.063)
Real estate bust length	-0.01***		-0.01***	
	(0.000)		(0.001)	
Real estate bust size		-0.03***		-0.01**
		(0.009)		(0.026)
Stock boom length	0.01***		0.01***	
	(0.000)		(0.004)	
Stock boom size		0.00***		0.00
		(0.000)		(0.165)
Stock bust length	-0.03***		-0.01	
	(0.001)		(0.271)	
Stock bust size		-0.01		-0.01**
		(0.112)		(0.045)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149
Adj. R^2	0.831	0.830	0.878	0.878
Adj. R^2 within	0.141	0.135	0.063	0.061

Table C12: Correlation between the business cycle indicator and bubble indicators

The business cycle indicator equals 1 during the boom phase of the business cycle and 0 otherwise. If business cycles moved in line with financial cycles we would thus see a positive (negative) correlation between the business cycle indicator and the bubble boom (bust) indicators. Hence, business cycles and financial cycles do not significantly co-move in our sample.

	Real estate boom	Real estate bust	Stock market boom	Stock market bust
Business cycle boom	-0.14	0.16	-0.21	0.27