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Not all Housing Cycles are Created Equal: Macroeconomic Consequences of Housing Booms*

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ABSTRACT: This paper shows that not all housing price cycles are alike. The nature of the housing expansion phase—especially whether a housing price boom characterized by rapid and persistent house price growth is present—plays a key role in shaping the severity of the subsequent contraction, and the net macroeconomic impact over the full cycle. Analyzing 180 housing expansions across 68 countries, we classify 49 percent as housing booms, characterized by rapid and persistent real house price increases. We find that economic downturns are significantly deeper and longer when housing contractions are preceded by a housing boom. The housing contraction is more severe the more intensive the preceding housing boom, and when accompanied by a credit boom. Overall, while housing booms spur stronger economic growth during the expansion phase, their sharp reversals lead to severe housing contractions, resulting in significant net negative effects on the real economy.

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1 Introduction

The 2007-09 Global Financial Crisis (GFC) shattered the popular belief that house prices 'can only go up'. The housing boom-bust cycle during that period in several countries exposed how severe housing corrections can leave long-lasting economic scars and increase financial stability risks (Claessens et al. 2009, Mian et al. 2013, Mian and Sufi 2014, Cerutti, Dagher and Dell'Ariccia 2017). House price corrections are particularly damaging when preceded by very rapid increases in credit, so-called credit booms (Claessens et al. 2009, Jordà et al. 2015, Dell'Ariccia et al. 2016, Cerutti, Dagher and Dell'Ariccia 2017, Albuquerque and Krustev 2018).

The COVID-19 pandemic and the rapid monetary tightening to rein in inflation brought about renewed interest in housing markets. Despite these shocks, house prices have held up relatively well in several countries. However, as global monetary policy tightening intensified, many house price booms came to an end. More recently, countries are progressively entering into housing expansion phases, with the monetary easing cycle that started in most countries potentially reinforcing upward house price pressures. In this context, the key question is whether we can distinguish between 'good' housing expansions—which do not pose macrofinancial stability risks—from 'bad' ones—which have lasting negative effects on the real economy.

This paper argues that not all housing cycles are alike, and that the characteristics of the expansion are key factors for determining both the severity of the subsequent contraction and the net macroeconomic effects over the cycle. We take a novel approach by separating expansions into boom and non-boom phases. We first identify housing cycles, namely expansions and contractions, for a large panel of countries—68 countries, of which 35 Advanced Economies (AEs) and 33 and Emerging Markets and Developing Economies (EMDEs)—from 1970Q1 to 2023Q4. We use the Harding and Pagan (2002) BBQ algorithm that focuses on the identification of turning points. Second, building on the methodology from Cerutti, Dagher and Dell'Ariccia (2017), we define housing booms as periods of rapid house price increases above a country-specific threshold for a prolonged period of time. We identify 180 housing expansions, of which 49 percent refer to housing booms. We find that, on average, housing expansions last longer than contractions, roughly eight and five years, respectively. There is also considerable heterogeneity across countries: housing expansions tend to last longer in AEs, almost nine years, than in EMDEs, with an average of six years. In turn, housing booms tend to be shorter, an average of 12 quarters, with no clear difference between AEs and EMDEs.

After distinguishing between non-boom housing expansions and housing booms, we empirically analyze the housing cycle with three main exercises. First, we use Jordà (2005) Local Projections to trace out the predictable pattern of the real economy during both non-boom and boom housing expansions. This exercise focuses on the expansion phase of the housing cycle. Second, we examine the economy's predictable pattern when a *housing expansion ends*, i.e., how the economy evolves during a housing contraction following either a boom or a non-boom expansion. Third, we attempt to estimate the net effects of housing expansions and contractions over the full sample. Drawing on the credit boom literature (Schularick and Taylor 2012, Jordà et al. 2013, Dell'Ariccia et al. 2016, Mian et al. 2017, Greenwood et al. 2022), we assess the macrofinancial effects from a variable that captures housing innovations over the full housing cycle sample.[1] Although our analysis focuses on the prediction properties and not causal effects, our rich empirical specification with several country-specific characteristics, country fixed effects, and time fixed effects, increases our confidence that the estimated conditional economic trajectory should be closely linked to the housing cycle.

Our main findings are as follows. First, housing boom expansions are not only characterized by higher house price growth but also by higher GDP and private consumption growth. This apparent temporary buoyant effect, however, may bring about subsequent significant negative spillovers to the rest of the economy related to a misallocation of resources toward the housing sector. In fact, evidence for the US and China show that housing booms have negative spillovers effects on nonfinancial firms' investment (Chakraborty et al. 2018, Hau and Ouyang 2024). In particular, banks more active in strong housing markets tend to curtail bank lending and increase the cost of funding for nonfinancial firms, especially for financially constrained firms and for firms located in more bank-dependent regions. These spillover effects are amplified when banks are more capital constrained. As a corollary, Basco et al. (2025) find that the decline in overall productivity growth in Spain between 2003-07 can be partially accounted for by the capital misallocation induced by local housing booms that led to higher bank credit and investment for firms more exposed to real estate.

Second, focusing on housing market contractions, we show that economic downturns are significantly deeper and more prolonged when housing contractions follow a preceding boom

[1] We measure housing innovations with the 12-quarter change in house prices relative to GDP per capita. This horizon is consistent with the literature on credit booms that take long changes in debt to income or GDP to capture debt imbalances (Mian et al. 2017, Giroud and Mueller 2021, Greenwood et al. 2022, Albuquerque 2024, Müller and Verner 2024). The three-year horizon is also fully consistent with the median length of a housing boom in our dataset.

expansion. This echoes the literature highlighting the role of the US housing bust in exacerbating the economic decline during the GFC (Mian et al. 2013, Mian and Sufi 2014, Sarto 2024).

Third, our results point to strong nonlinearities in the relationship between housing contractions and the real economy. Stronger booms, measured with the cumulative house price growth during a boom, make the economic recovery more challenging when the boom ends. Furthermore, the combination of household credit and housing booms further amplifies the downturn (Claessens et al. 2009, Jordà et al. 2015, Cerutti, Dagher and Dell'Ariccia 2017).

Fourth, we find that house price appreciation, with the presence of housing booms, is associated on average with large net negative effects on the real economy. In particular, housing innovations over the full sample predict lower economic activity over the medium term, consistent with existing literature that suggests slower and prolonged recoveries after rapid house price increases (Claessens et al. 2009, Jordà et al. 2015, Cerutti, Dagher and Dell'Ariccia 2017). We also find tentative evidence that the decline in economic activity is intensified when housing innovations occur alongside household credit expansions, highlighting the role of excessive household leverage in amplifying business cycles via consumption cuts (Schularick and Taylor 2012, Jordà et al. 2013, Mian et al. 2017, Albuquerque and Krustev 2018, Albuquerque 2019). Importantly, we find that housing innovations only seem to be associated with lower medium-term economic growth when accompanied by housing booms. To be sure, after housing booms—where house prices surge rapidly and significantly above country-specific norms—economic activity falls sharply, deviating from the typical growth seen in non-boom periods.

Finally, we find evidence that countries with less restrictive housing supply constraints tend to experience less painful economic adjustments during a housing contraction. This suggests that policies that ease land-use regulations, and promote an enabling business environment that stimulates housing construction, may help mitigate the macroeconomic effects of a housing downturn. Moreover, macroprudential policies, namely borrower-based measures that impose limits on loan-to-value (LTV) ratios or debt service to income (DSTI) ratios, may also help reduce the likelihood of a severe economic contraction following the end of a housing boom.

Our main results are robust to: (i) defining housing expansions based on the house price-to-income ratio instead of real house prices; (ii) using alternative measures of housing booms, including the presence of housing bubbles;[2] (iii) excluding the Covid-19 sample or the GFC;

[2] Housing bubbles are often associated with explosive price patterns that cannot be explained by fundamentals (Phillips et al. 2015, Pavlidis et al. 2016, Martínez-García and Grossman 2020, Aastveit, Anundsen, Kivedal and Larsen 2023). Our housing boom definition, capturing rapid and persistent housing price growth, corresponds

and to (iv) allowing for a heterogeneous effect of housing booms on AEs versus EMs.

Our paper contributes to the literature on housing cycles and the macroeconomy in several ways. First, we contribute to the literature on housing cycles, booms and bubbles (e.g., Cerutti, Dagher and Dell'Ariccia (2017), Classens et al. (2012), Claessens et al. (2009), Martínez-García and Grossman (2020)) by offering a novel approach to categorize the housing market into three phases for a large number of countries: non-boom expansion, boom and contraction. We also expand the coverage of countries and time series significantly compared to the previous studies. Specifically, we expand the Cerutti, Dagher and Dell'Ariccia (2017) dataset on house prices and credit with more countries (68 versus 53), additional variables (including private consumption and housing supply measures), and 11 more years of data (from 2012 to 2023). Covering the post-GFC period is particularly important given the significant changes in the housing market, including tighter mortgage regulation, stricter land-use constraints (Herkenhoff et al. 2018, Aastveit, Albuquerque and Anundsen 2023), and structural shifts in demand due to the COVID-19 pandemic.

Second, our paper adds to the debate on the macroeconomic effects of housing booms and busts (Mian et al. 2013, Mian and Sufi 2014, Martínez-García and Grossman 2020, Aastveit, Anundsen, Kivedal and Larsen 2023). Mian et al. (2013), and Mian and Sufi (2014) focus on the US housing bust during the GFC, finding that large declines in household net worth from the collapse in house prices had a large negative effect on consumption and employment. Considering a longer time dimension, the closest paper to ours is perhaps Aastveit, Anundsen, Kivedal and Larsen (2023), who study the economic implications of local house price bubbles and non-bubble housing expansions for US counties over 1980-2019. Apart from differences in the definition of housing booms/bubbles, we complement their paper by analyzing at aggregate levels a global sample, by focusing on the intensity of the boom, and also by exploring the amplification effects from housing booms that coincide with credit booms. The latter finding aligns with the literature studying the macroeconomic implications of bad and good credit booms (Dell'Ariccia et al. 2012, 2016, 2020, Gertler et al. 2020, Gorton and Ordoñez 2020, Richter et al. 2021, Müller and Verner 2024). Our main contribution is to show that housing booms alone can have significant detrimental net macroeconomic effects.

Third, we add to the literature on the predictive power of housing innovations/expansions for economic activity (Claessens et al. 2009, Jordà et al. 2015, Cerutti, Dagher and Dell'Ariccia

not only to a broader definition than housing bubbles, but it is also an easier measure to implement in real time (e.g., not based on unit root tests).

2017, Greenwood et al. 2022). Our contribution is to demonstrate that not all prolonged increases in house prices relative to income may signal lower future economic growth. In particular, we show that only housing expansions characterized by rapid and substantial price increases beyond a historical country-specific threshold, indicative of a housing boom, are associated with considerably reduced economic growth in the medium term.

Our final contribution addresses possible policies to mitigate the effects of housing boom-bust cycles. We find suggestive evidence that countries with less restrictive constraints on housing supply, such as land-use regulation, may better withstand the end of a housing boom. This is consistent with the notion that housing supply constraints matter for the transmission of demand shocks (Gyourko et al. 2008, Saiz 2010, Glaeser et al. 2014, Herkenhoff et al. 2018, Albuquerque et al. 2020, forthcoming, Aastveit and Anundsen 2022, Cooper et al. 2022, Aastveit, Albuquerque and Anundsen 2023). Moreover, our findings suggest that countries with tighter borrower-based measures at the end of the housing expansion may experience more stable business cycles in the aftermath of housing booms. This reinforces the view that the post-GFC implementation of macroprudential measures may have mitigated financial stability risks stemming from the housing market (Claessens 2015, Kuttner and Shim 2016, Cerutti, Claessens and Laeven 2017, Akinci and Olmstead-Rumsey 2018, Richter et al. 2019, Biljanovska et al. 2023).

The paper is structured as follows. Section 2 provides an overview of the data. Section 3 discusses housing market dynamics across countries, including housing market cycles and booms. Section 4 analyzes the macrofinancial impact of housing non-boom expansions, booms and contractions. Section 5 estimates the net effects of housing market expansions, including boom and non-boom expansions. Section 6 investigates the role of borrower-based macroprudential policy tools and supply factors in the macrofinancial impact following a housing boom. Section 7 offers a battery of robustness checks. Section 8 concludes the paper.

2 Data

We build an international dataset with information on house prices, private credit, and several other macroeconomic indicators for a large panel of countries: 68 countries, 35 AEs and 33 EMDEs. House price data are based on widely used Bank for International Settlement's residential property price database,[3] augmented with Global Property Guide and national authorities'

[3]BIS data are based on residential property price series sourced by various public and private compilers, such as national statistical offices, central banks, ministries, associations of real estate agents, mortgage banks and

data. We use BIS residential property price indices when available. For countries where BIS data are not available, we use the aforementioned alternative sources; if the time series of the BIS data is short, we extend the house price indices backwards using the alternative databases, following Cerutti, Dagher and Dell'Ariccia (2017). We define real house prices as nominal house prices deflated by consumer price indices. We also calculate house price-to-income ratios by dividing nominal house prices by nominal GDP per capita. We use quarterly data dating back as far as 1970Q1 and up to 2023Q4.

Data on real credit to the private sector for the same list of countries is based on the BIS database, which we augment with data from the national authorities. We obtain the other macroeconomic and financial variables from various sources, including the IMF WEO database and International Financial Statistics. Table A.1 in Appendix A provides details on data sources and definitions.

3 Identification of housing cycles and housing booms

3.1 Housing cycles

To identify turning points in housing market cycles, we employ the algorithm proposed by Harding and Pagan (2002), which extends the BBQ algorithm developed by Bry and Boschan (1971). The algorithm searches for local maxima and minima in a given period. In particular, for the window size of two quarters, where y_t stands for real house prices, a peak at time t is identified if:

$$\{(y_t - y_{t-2}) > 0, (y_t - y_{t-1}) > 0\} \text{ and } \{(y_{t+2} - y_t) < 0, (y_{t+1} - y_t) < 0\}. \tag{1}$$

Similarly, a trough at time t is identified if:

$$\{(y_t - y_{t-2}) < 0, (y_t - y_{t-1}) < 0\} \text{ and } \{(y_{t+2} - y_t) > 0, (y_{t+1} - y_t) > 0\} \tag{2}$$

In addition to setting the window size of two quarters, we impose additional restrictions by setting the minimum phase length at eight quarters, and the minimum length of a cycle at 20 quarters. This setting is different from the standard setting for identifying business cycles—a

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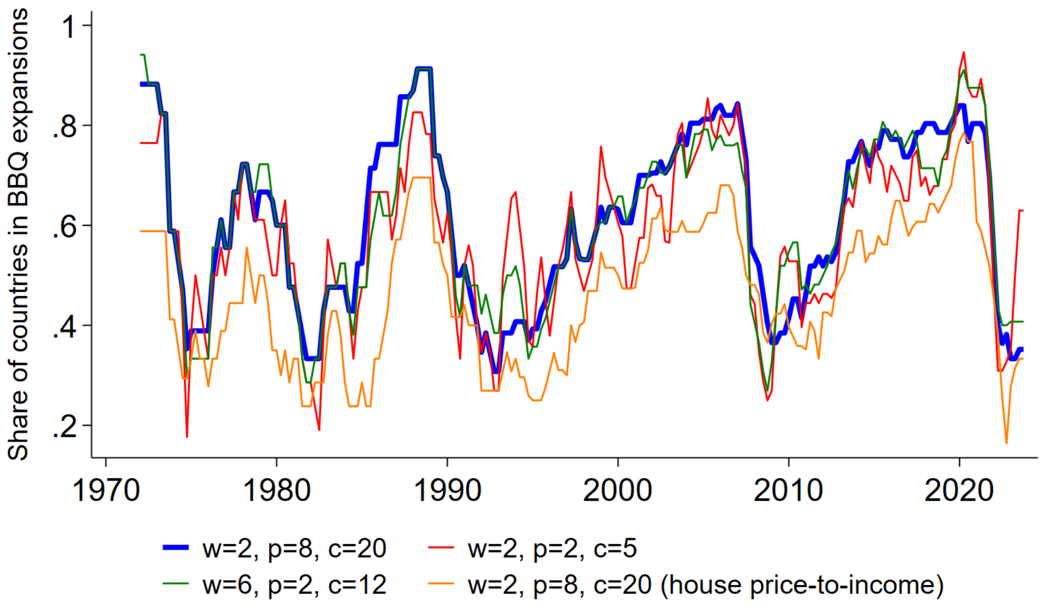
window size of two quarters, a minimum phase length of two quarters, and a minimum cycle length of five quarters—but is suitable to capture the financial cycle, which is typically longer than business cycles. The period between a trough and the next peak is defined as the expansion phase, and the period between a peak and the next trough is the downturn phase.

We compare our preferred setting with alternative combinations of the BBQ parameter settings: (i) the standard setting for the business cycle, i.e., minimum window size of two quarters, minimum phase length of two quarters, and minimum cycle length of five quarters; the setting employed by Rozite et al. (2019) for housing cycle analysis for the US economy, i.e., window size of six quarters, minimum phase length of two quarters, and minimum cycle length of 12 quarters; and (iii) our baseline BBQ algorithm to the house price-to-income ratio.

Figure 1 shows the share of countries in the expansion phase over the full sample with different parameter settings of the BBQ algorithm. In the benchmark setting (solid blue line), the BBQ algorithm clearly identifies a global expansion in house prices in mid- to late-1980s, in the late-1990s, early-2000s, and the recovery post-GFC, which continued until the early stages of the Covid-19 pandemic. By contrast, we identify housing downturns, shown in a smaller share of countries in a housing expansion phase, in the early-1990s, during the GFC, and in the most recent post-pandemic period. These patterns are remarkably similar when using alternative parameter settings, and when using the house price-to-income ratio instead of real house prices.

Figure 1: Housing price cycles



Notes: Share of countries in housing expansions as identified by the BBQ algorithm for real house prices and house price-to-income ratios. The legend shows the parameter settings, where w, p, and c denote respectively the minimum length for window, phase, and cycle.

Table 1 shows the duration of house price cycles identified with our benchmark BBQ specification for both real house prices and house price-to-income ratios. Overall, expansion phases tend to be longer than contraction phases when using real house prices; average sample duration of 31 quarters for expansions, which compares with 21 quarters for an average housing contraction. Housing expansions tend to be considerably longer for AEs (34 quarters) relative to EMDEs (24 quarters). Although expansions and contractions tend to be of a similar length when measuring housing cycles with the house price-to-income ratio, housing expansions still tend to last considerably longer in AEs than in EMDEs.

Table 1: Housing cycle duration

	Expansion			Contraction		
	Total	AEs	EMDEs	Total	AEs	EMDEs
Real house price						
mean	30.8	34.3	24.3	20.5	21.4	19.0
median	26.0	31.0	18.0	19.0	20.0	17.5
std. dev.	22.5	23.6	18.8	12.1	13.0	10.6
House price-to-income						
mean	24.0	27.1	18.4	25.9	26.6	24.5
median	19.0	21.5	14.0	21.0	24.0	19.0
std. dev.	18.4	19.8	13.9	21.2	22.5	18.7

Note: Duration of cycles for real house prices and house price-to-income ratios identified with the BBQ algorithm (minimum window length of two quarters, eight quarters for phases, and 20 quarters for cycles). Only completed expansions (trough to peak) and contractions (peak to trough) are included.

We redo a similar exercise in Table 2, but consider instead the duration of output expansions and contraction by employing the BBQ algorithm to real GDP. We thus adapt the BBQ algorithm to the standard parameter settings for business cycles (i.e., window size of two quarters, minimum cycle length of two quarters, and minimum phase length of five quarters). Compared to housing cycles, the overall business cycle tends to be shorter, mainly due to shorter economic contractions (average of 6 quarters). This is consistent with the financial cycle literature, which points to financial cycles being considerably more long-lived compared to business cycles.

Table 2: Business cycle duration

	Expansion			Contraction		
	Total	AEs	EMDEs	Total	AEs	EMDEs
mean	27.4	35.7	25.6	6.2	5.6	6.3
median	16.0	32.0	16.0	4.0	4.0	4.0
std. dev.	28.7	26.9	28.8	4.4	3.3	4.6

Note: Duration of cycles for real GDP identified with the BBQ algorithm (minimum window length of two quarters, two quarters for phases, and five quarters for cycles. Only completed expansions (trough to peak) and contractions (peak to trough) are included.

We now look at the synchronization of housing cycles with credit and business cycles, in the spirit of Claessens et al. (2009), who use pre-GFC long-term data for 21 OECD countries to investigate the overlap between housing market busts, credit crunches, and equity market busts. For credit cycles, we use total private credit-to-GDP and employ the BBQ algorithm with the same parameter settings as in the benchmark case of housing cycles; for business cycles, we take those based on real GDP, as reported in Table 2. Although Table 3 shows that the synchronization of housing cycles with credit cycles is relatively high (greater than 70 percent), we find that contractionary phases are not well-synchronized, suggesting that housing downturns do not tend to coincide with credit busts. Moreover, we find only a moderate synchronization between housing cycles and business cycles, suggesting that housing cycles do not necessarily co-move with business cycles.

Table 3: Synchronization with credit and business cycles

	Credit	GDP	Credit & GDP
Real house price			
expansion sync.	0.61	0.38	0.38
contraction sync.	0.18	0.09	0.04
total sync.	0.79	0.47	0.41
House price-to-income			
expansion sync.	0.47	0.31	0.31
contraction sync.	0.25	0.09	0.04
total sync.	0.72	0.40	0.35

Note: Synchronization of housing market cycles with credit cycles (credit-to-GDP) and business cycles (real GDP), during expansion and contraction phases identified with the BBQ algorithm. Synchronization is defined as the number of synchronized data points, divided by the number of observations. For credit cycles, the minimum window is set at two quarters, minimum phase at eight quarters, and minimum cycle at 20 quarters. For business cycle, the minimum window and minimum phase are set at two quarters, and minimum cycle at five quarters.

We also look at the synchronization of housing with household credit and housing supply cycles. Household credit cycles have important macrofinancial linkages, and strong predictive power for GDP growth (Mian et al. 2017). In turn, housing supply affects the persistence and intensity of housing price cycles (Glaeser et al. 2008). We use household credit-to-GDP data and housing permits to analyze these two dimensions, employing the BBQ algorithm with the same parameter settings as in the benchmark case of housing cycles. Table 4 shows that the synchronization of housing cycles with household credit cycles is relatively high (around 70 percent), but again the co-movement during downturns is rather weak. The synchronization between housing cycles and housing supply is also not necessarily high, consistent with the notion that the co-movement of these variables depends on the source of the fluctuations (Ben-David et al. 2024). The total synchronization of all three types of cycles is about 40 percent.

Table 4: Synchronization with household credit and housing supply cycles

	HH Credit	Hsg. Supply	HH Credit & Hsg. Supply
Real house price			
expansion sync.	0.60	0.30	0.30
contraction sync.	0.15	0.22	0.10
total sync.	0.75	0.52	0.40
House price-to-income			
expansion sync.	0.46	0.24	0.24
contraction sync.	0.22	0.26	0.12
total sync.	0.68	0.51	0.36

Note: Synchronization of housing market cycles with household credit cycles (household credit-to-GDP) and housing supply (housing permits), during expansion and contraction phases identified with the BBQ algorithm. The minimum window is set at two quarters, minimum phase at eight quarters, and minimum cycle at 20 quarters.

3.2 Housing booms

In this section we distinguish between moderate housing market expansions and expansions that coincide with too rapid house price increases. There is no consensus on how to empirically identify too rapid house price growth episodes. On the one hand, the related literature broadly considers housing booms as large and persistent deviations of house prices from some reference levels (Borio and Lowe 2002, Cerutti, Dagher and Dell'Ariccia 2017); and, on the other hand, the literature focuses on bubbles or explosive price growth dynamics.

The latter definition is based on the methodology popularized by Phillips et al. (2015), and used subsequently to study housing market bubbles by Pavlidis et al. (2016), Martínez-García and Grossman (2020), and Aastveit, Anundsen, Kivedal and Larsen (2023). It essentially involves running recursive right-tailed variations of the augmented Dickey-Fuller (ADF) tests on real house prices to test for explosive house price developments. One of the drawbacks of this approach, however, is the assumption that bubbles exhibit an explosive, exponential price growth pattern. Arguably, not all housing booms may conform to this pattern—bubbles or booms may buildup over time but without an initial explosive pattern. More importantly, although this approach was initially designed to identify explosive bubbles, it also detects crisis or downturns, such as the stock market downturn in 2002-2003, which does not fit our purpose (Phillips and Shi 2019, 2022). In particular, in the context of real house prices, this algorithm frequently detects downturns as being bubbles, including the housing downturn in Japan in the 2000s, and in some European countries in the 2010s. In addition, this approach tends to be highly sensitive to the choice of the estimation window size, while also facing challenges with small time series samples.

Given the above reasons, our baseline method to identify too rapid house price growth episodes follows the housing booms definition by Cerutti, Dagher and Dell'Ariccia (2017).[4] Specifically, we focus on the year-on-year growth of real house prices, to define boom episodes as deviations from a country-specific standard. More specifically, we classify an episode as a housing boom if two conditions related to the intensity and persistence of real house price growth are met. The first (intensity) condition ensures that the real house price growth is above five percent or greater than the average growth plus two standard deviations of the country-specific distribution in a given quarter. The second (persistence) condition ensures that the real house price growth is above five percent or greater than the average growth plus one standard deviation of the country-specific distribution for a period of at least six quarters.[5] Finally, we apply judgment to ensure that one long boom episode is not artificially classified into multiple short episodes or start/end periods are not misidentified due to minor and/or short-lived breaches of thresholds set out in our two conditions.[6]

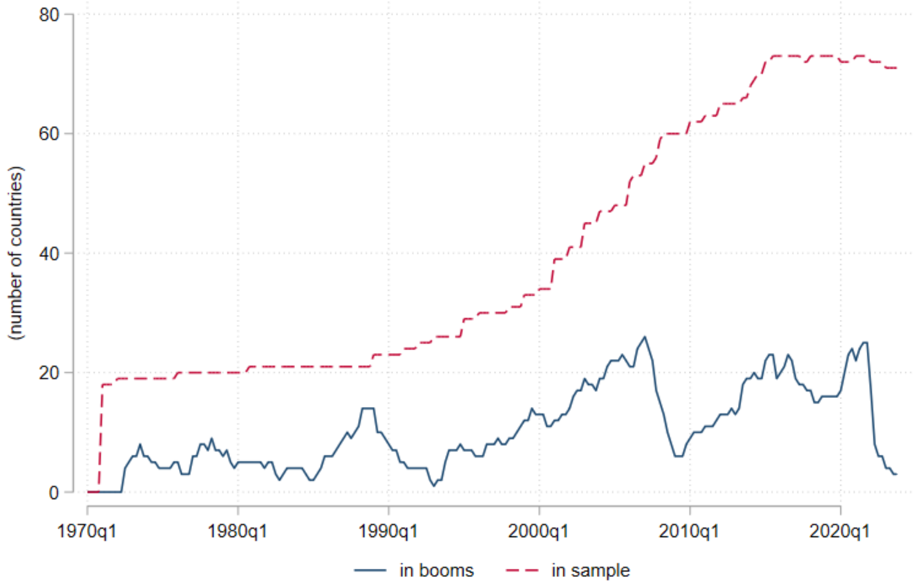
Based on our definition, we identify 152 housing boom episodes across 59 countries during 1972q1-2023q4. Since the starting point of our country sample is 68 countries, this means that 9 countries have never experienced a housing boom according to our classification. Figure 2 shows the number of countries experiencing house price booms (solid blue line), and the total number of countries in our sample over time (dashed red line). Figure 3 depicts the same as a percentage of the countries in the sample. Acknowledging the increase in country coverage over time, we note that the number of countries in a housing booms peaks around the late-1980s, in the run up to the GFC, and during the early stages of the Covid-19 pandemic. The most recent data, however, indicate a sharp fall in the number of countries experiencing booms, at the same time that the global monetary tightening started to take place. Table B.1 in Appendix B provides the full list of house price booms we identify, including the duration, average growth rate, standard deviation, and cumulative growth of each boom. An average boom in our sample lasts about 15 quarters (median of 12 quarters), with real house prices posting about 11 percent growth rate on average.

[4]Section 7 shows that our results remain robust to using a concept of housing bubbles (Phillips et al. 2015). In doing so, given the frequent detection of downturns with this method, we impose an additional restriction that bubbles can only take place during housing expansions as identified with the BBQ algorithm.

[5]Cerutti, Dagher and Dell'Ariccia (2017) requires the second condition to be met for a period of at least eight quarters or two years. We revise this duration requirement to six quarters to account for house price dynamics during the post-pandemic period characterized by a rapid increase in house prices and the ensuing globally synchronized monetary tightening that triggered house price declines.

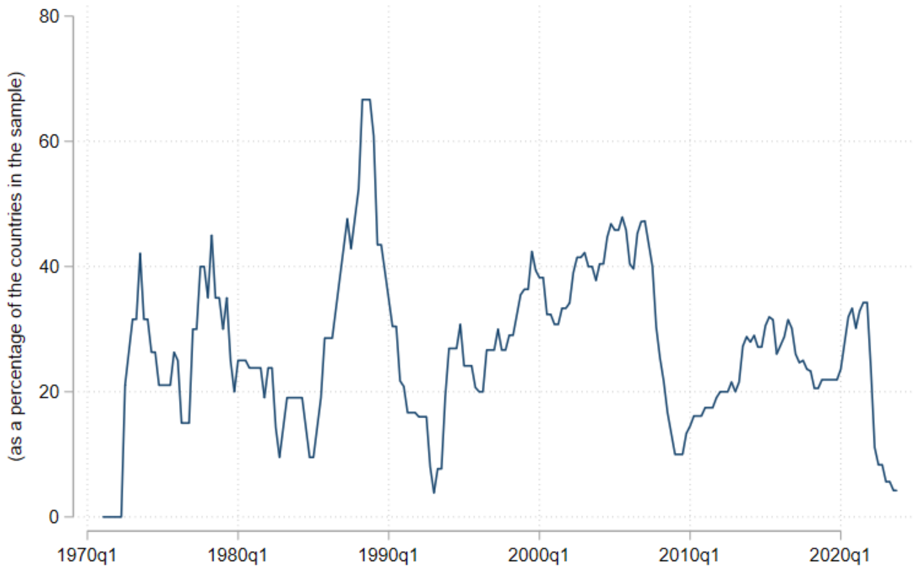
[6]We only classify a breach to be minor if (i) the year-on-year growth of real house prices is positive or (ii) if the year-on-year growth of real house prices is negative and quarter-on-quarter growth is positive. We classify a breach to be short-lived if the breach occurs for a maximum of four consecutive quarters.

Figure 2: House price booms over time: Number of countries



Notes: Solid blue line shows the number of countries experiencing a housing boom over time, while the dashed red line shows the total number of countries in our sample over time.

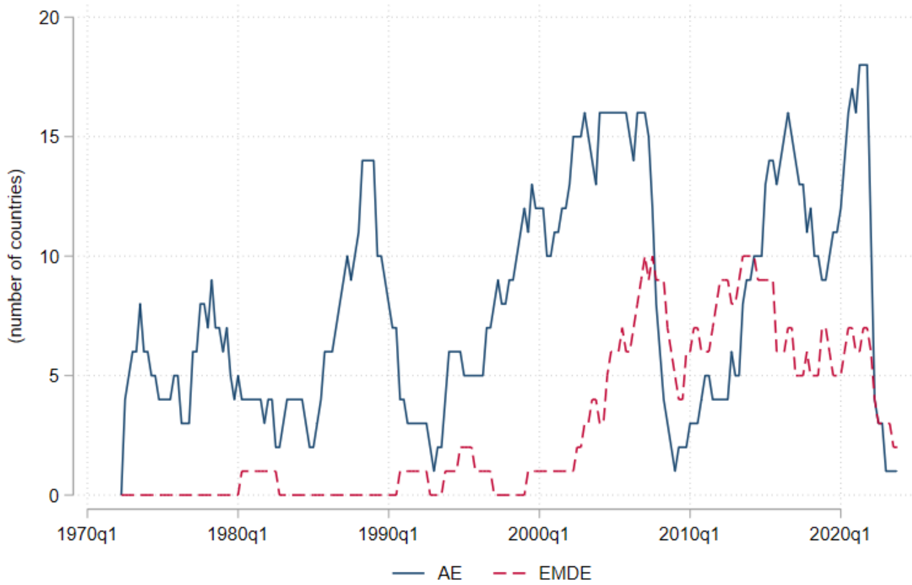
Figure 3: House price booms over time: Share of the sample



Notes: Solid blue line shows the number of countries experiencing a housing boom over time as a percentage of the countries in the sample (varying over time).

Figure 4 indicates that our sample is dominated by episodes of housing price booms in AEs. Specifically, we identify 114 booms across 34 AEs, which compares with 38 booms across 25 EMDEs. Although housing booms are substantially more frequent in AEs, the average AE boom is broadly comparable to an average EM boom in our sample in terms of duration and cumulative growth. Appendix figures C.1 and C.2 shows the the number of AEs and EMDEs (respectively) experiencing house price booms (solid blue line), and the total number of AEs and EMDEs (respectively) in our sample over time (dashed red line).

Figure 4: House price booms over time: AEs and EMDEs



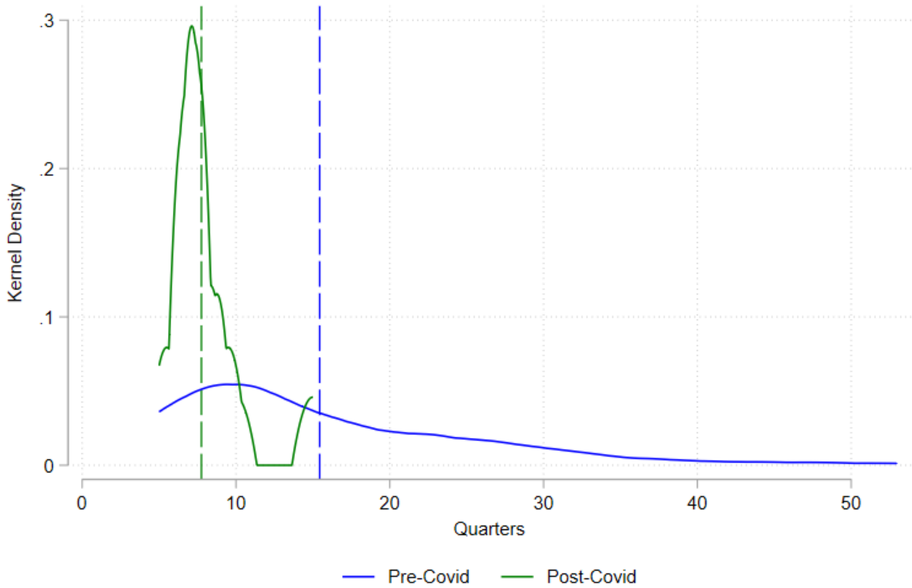
Notes: Solid blue and dashed red lines show the number of advanced economies (AEs) and emerging market and developing economies (EMDEs) experiencing a housing boom over time.

Our sample covers 140 pre-Covid booms across 57 countries, and 12 post-COVID booms across 12 countries. Pre-Covid booms begin before 2020Q1, and end in or after 2020Q1, while post-Covid booms begin in or after 2020Q1. We find that post-Covid booms tend to be shorter relative to the pre-Covid standards, with an average post-Covid boom lasting for eight quarters, roughly half of the duration of a typical boom during the pre-Covid period (Figure 5). However, we do not observe a noticeable distinction in average real house price growth during booms across both periods.

3.3 Housing market dynamics

We now bring together the previous two sections to classify the state of housing market in a particular country into three categories. Specifically, the state of housing market $h(y_{i,t})$ can be categorized into non-boom expansion, boom expansion, and contraction:

Figure 5: Housing boom duration: distribution of booms pre-Covid and post-Covid



Notes: Based on 152 housing boom episodes across 59 countries (140 pre-Covid and 12 post-Covid). Pre-Covid booms (blue) are booms that begin before 2020Q1, and end in or after 2020Q1. Post-Covid booms (green) are booms that begin in or after 2020Q1. Vertical lines correspond to the mean of the pre-Covid (blue) and post-Covid (green) distributions.

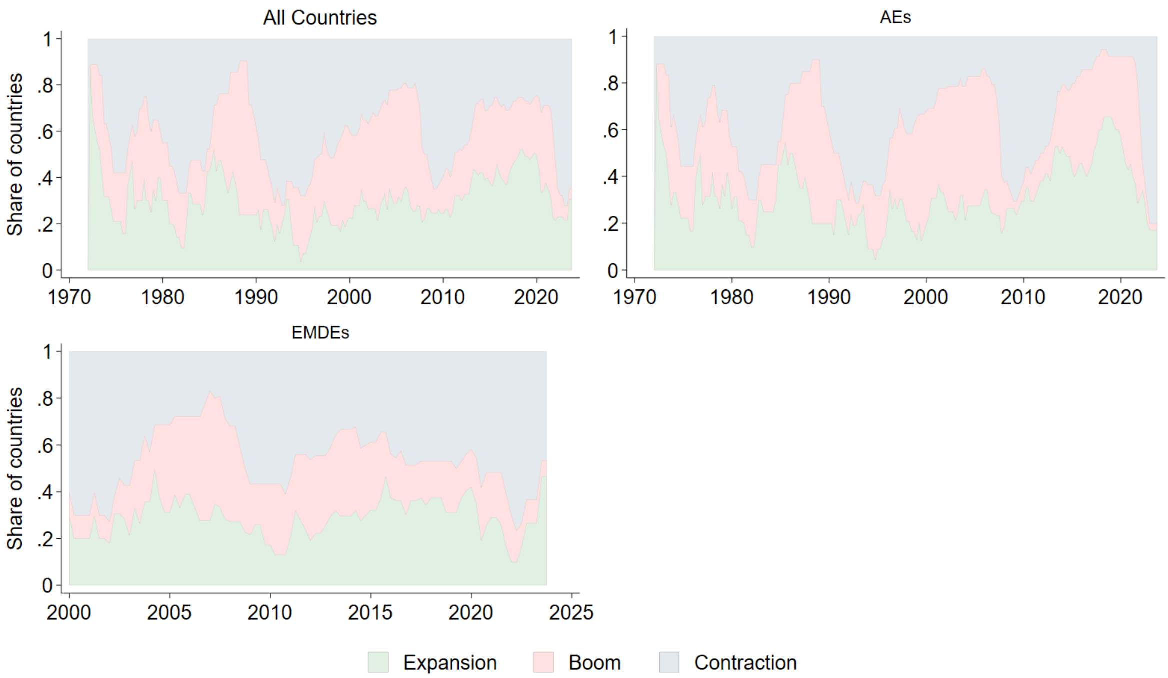
$$h(y_{i,t}) = \begin{cases} \text{Non-boom expansion} & \text{if BBQ expansion} = 1 \text{ and Boom } = 0 \\ \text{Boom expansion} & \text{if BBQ expansion} = 1 \text{ and Boom} = 1 \\ \text{Contraction} & \text{if BBQ expansion} = 0, \end{cases} \tag{3}$$

where *BBQ expansion* and *Boom* take respectively the value of one at the expansion and boom phases for each country in each quarter, as identified in the previous two sub-sections.

Figure 6 shows the share of countries in each phase of the housing market, as identified with the BBQ algorithm and our boom classification. When we focus on the housing cycle by income level, we find that AEs tend to experience higher volatility, with a faster increase in the share of countries experiencing an housing boom, followed by a subsequent steep increase in the share of countries going through a housing contraction. In particular, in the most recent years after the Covid-19 pandemic, we estimate that a larger share of AEs experienced housing booms, but then this gave way to fast contractions. In turn, EMDEs seemed to have experienced housing booms more frequently before the GFC, which contrasts with the recent experience during the pandemic, as a larger share of countries in this group went through non-boom expansion.

We zoom in on the different housing market phases by showing the evolution of real house

Figure 6: Global housing market dynamics



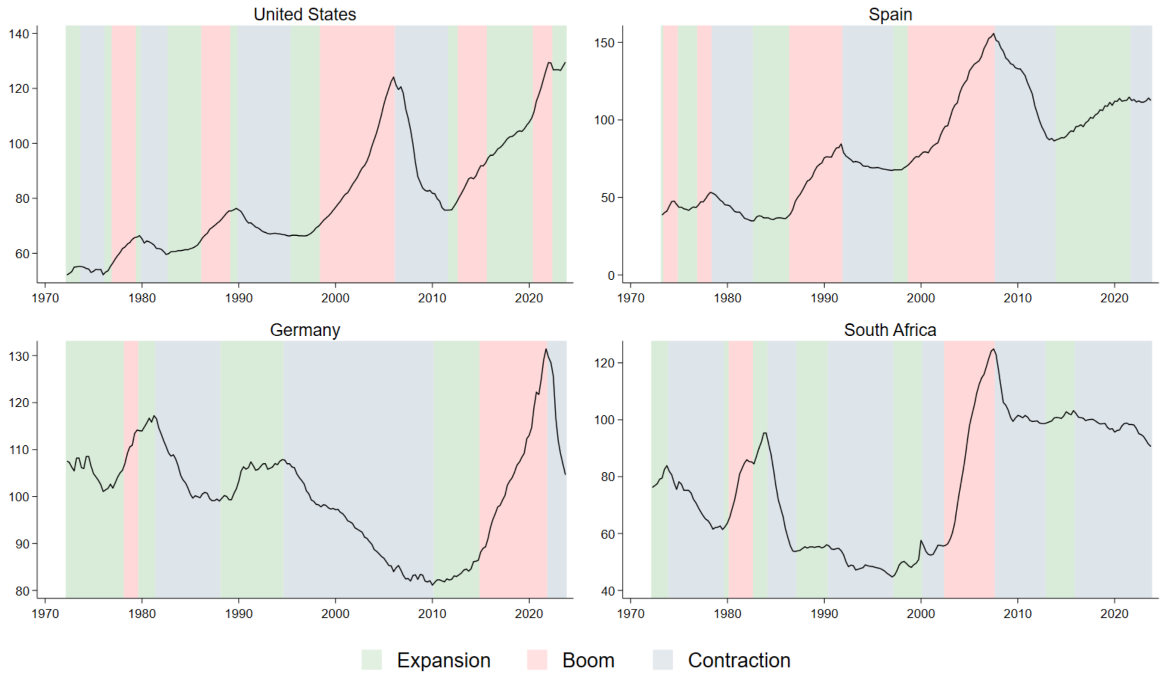
Notes: The panels show the share of countries in the different phases of the housing market, as identified by the BBQ and boom algorithm.

prices for selected countries in Figure 7. For instance, we estimate that the US economy experienced five housing expansions as identified by the BBQ algorithm. During these periods, real house prices exhibited signs of a boom, particularly in the late-1980s, early-2000s, and after the Covid-19 pandemic. These episodes tend to lead to a subsequent large contraction in real house prices. Similarly, Spain experienced relatively large housing booms around the early-1990s and mid-2000s. The Spanish housing market then went through severe adjustments following the booms, notably in the post-GFC period. By contrast, in Germany and South Africa housing cycle patterns are somewhat irregular, yet both countries have also experienced large housing downturns following housing booms.

4 Empirical analysis of Housing Expansions and Contractions

In this section, we first examine the real economy's predictable response during non-boom housing expansions and housing booms—using our previously computed housing boom variable (Section 4.1). In a second exercise, we focus on the economy's predictable pattern when the *housing expansion ends*, that is, the housing contraction phase (Section 4.2). This analysis aims to assess the macrofinancial impact in the aftermath of 'moderate' housing expansions, i.e., where there are no signs of a housing boom, against too rapid housing expansions that often

Figure 7: Real house price indices



Notes: Real house price index, with the level set to 100 in 2015. Shaded green areas show non-boom expansions, shaded red areas show boom expansions, and shaded blue areas show housing contractions.

lead to destabilizing contractions. This analysis thus allows us to compare how the presence of a housing boom influences economic performance during downturns.

4.1 Predictable pattern of the economy during housing expansions

We investigate how the economy typically evolves during housing expansions that exhibit signs of booms against expansions that do not show too rapid and persistent house price increases. We select several dependent variables that capture different dimensions of the macroeconomy: the real sector (GDP, private consumption, and gross fixed capital formation), housing market variables (house prices and building permits), and financial variables (private credit or household credit).[7] We deflate all nominal variables with the respective country-specific CPI. We use Jordà (2005) local projection methods to run separate country panel regressions for each h=0, 1,..., 12 quarters ahead:

$$\Delta_h Y_{i,t+h} = \alpha_i^h + \alpha_t^h + \beta_1^h NoBoom_{i,t-1} + \beta_2^h Boom_{i,t-1} + \Gamma_h' Z_{i,t-1} + e_{i,t}^h, \quad (4)$$

where $\Delta_h Y_{i,t+h}$ is computed as the cumulative percentage change in the logarithm of the depen-

[7]Permits are available for a smaller set of countries (41 countries). This mostly relates to missing data for EMDEs (11 countries covered).

dent variable from time t to $t+h$ for each country i. The coefficients of interest are β_1^h and β_2^h which measure respectively the predictable pattern of the dependent variable during non-boom housing expansions ($NoBoom$) and housing booms ($Boom$) as defined in Section 3. Non-boom housing expansions take the value of one when the housing market is in an expansionary phase, as identified in Section 3.1, but does not experience a housing boom; housing booms take the value of one during periods of strong increases in house prices, and zero otherwise (see Section 3.2).

We control for several lagged country-specific characteristics in $'Z$: lagged dependent variable, log of real GDP per capita to control for income effects, private credit-to-GDP ratio to control for the level of private leverage in the economy, house prices-to-GDP per capita ratio to account for possible initial imbalances in house prices, and the current account as a percentage of GDP to control for external sector developments. We also interact all control variables with the boom and non-boom expansion dummies to capture possible heterogeneous effects in the macroeconomic relationships during these two types of housing expansions.[8]

Finally, we add country fixed effects α_i^h to account for time-invariant country-specific characteristics, and time fixed effects α_t^h to control for all possible unobserved global shocks that may influence the evolution of the domestic economy. As is standard with quarterly data, we use four lags in the specification, and double-cluster standard errors by country and time.

We minimize possible reverse causality issues running from the real economy to housing cycles by lagging the housing expansion dummies by one quarter, and by including a rich set of controls and fixed effects. However, we note that our specification still *cannot* speak to causal effects of housing expansions on the economy due to possible confounders that may drive both developments in the housing market and in the real economy; instead, we interpret the coefficients β_1^h and β_2^h as the prediction of how the economy would evolve at a given horizon during housing expansions (without and with booms in house prices). This is consistent with the aforementioned cited literature that typically studies the (in-sample) prediction properties of credit booms for economic growth.

Our results in Figure 8 and indicate that housing booms tend to lead to stronger economic

[8] Our results are unchanged when adding one additional variable that controls for household credit expansions, measured with the 12-quarter changes in household credit relative to GDP. This variable has been shown to be a strong predictor of weaker consumption and economic growth, and also of a higher likelihood of a financial crisis materializing (Schularick and Taylor 2012, Jordà et al. 2013, 2015, Dell'Ariccia et al. 2016, Mian et al. 2017, Albuquerque and Krustev 2018, Greenwood et al. 2022, Müller and Verner 2024). Our results also remain qualitatively similar when replacing household credit with total private credit, which includes nonfinancial firms.

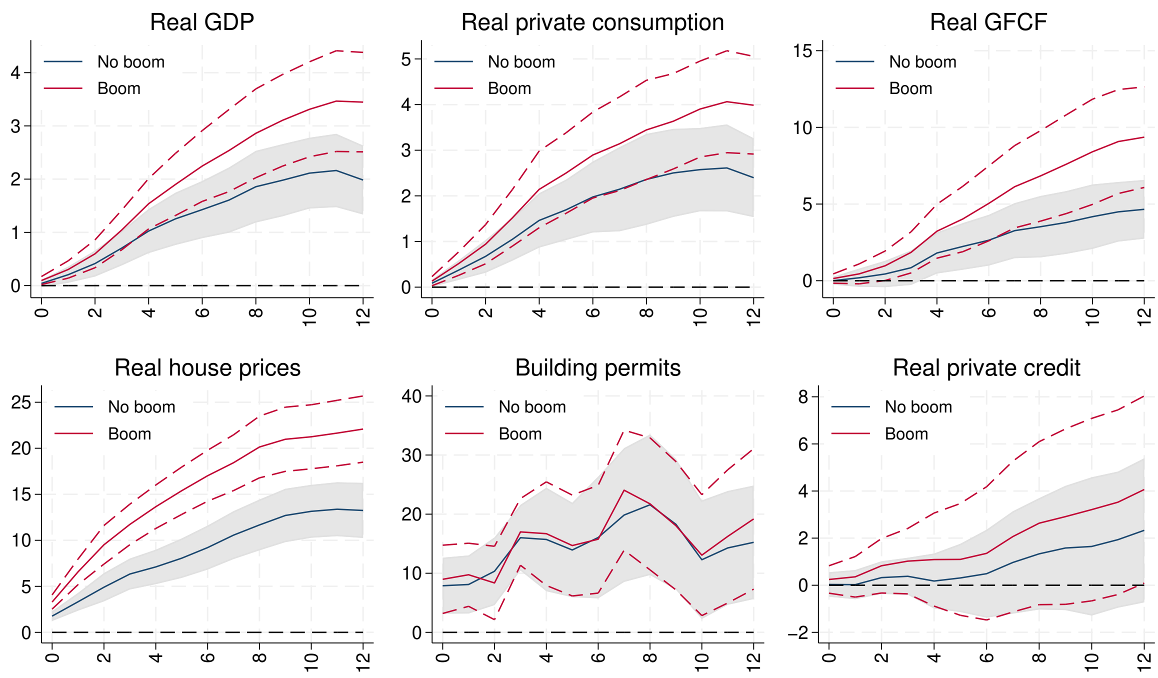
growth in the order of 1-1.5 percentage points over the medium run compared to housing expansions (Figure C.3 in Appendix C shows that this difference is highly statistically significant). While our reduced-form regressions can neither speak to the mechanisms at play nor to general equilibrium effects, we offer evidence that stronger growth seems to be supported by private consumption: housing wealth effects and increases in the collateral (driven by higher house prices) encourage mortgagors to extract equity to finance consumption expenditures and investment (Iacoviello 2005, Bhutta and Keys 2016, Aladangady 2017, Cloyne et al. 2020, Andersen and Leth-Petersen 2021). This is also consistent with the evidence that mortgagors tend to be associated with the largest marginal propensity to consume (Cloyne et al. 2020).

The differential effects we find between housing booms and other housing expansions are not explained by differences in policy support, as monetary policy (proxied with central banks' policy rates or short-term rates), and macroprudential policy (captured by average LTVs values from the iMaPP database) typically evolve at the same pace across both types of housing expansions (Figure C.4 in Appendix C). In addition, fiscal policy (captured by the fiscal balance as a percentage of GDP) tightens more during housing booms: this runs against the argument that fiscal support may help explain stronger economic growth during housing booms.

While by construction real house prices increase by considerably more during boom periods relative to non-boom housing expansions—of around eight percentage points after 12 quarters—housing supply, measured with the number of building permits, remains remarkably similar across the two types of housing expansions. This is suggestive evidence that housing booms only lead to additional increases in house prices, not quantities, relative to non-boom housing expansions.

Moreover, we do not find that the faster increase in house prices during boom periods translates into higher household disposable income, employment growth, or residential investment (Figures C.5 and C.6 in Appendix C.) By contrast, we find that the house price-to-income ratio increases considerably during booms, indicating housing market imbalances. Overall, our interpretation is that higher real GDP growth during housing booms seems to be driven primarily by rapid increases in house prices that fuel private consumption without improvements in the rest of the economy, including in terms of private credit. Our findings align well with research pointing to important costs of housing booms to the real sector, related to a misallocation of resources toward the housing sector. For instance, Chakraborty et al. (2018), and Hau and Ouyang (2024) find, respectively for the US and China, that credit conditions (lending volumes and cost of funding) during housing booms tend to tighten for firms located in strong housing markets. The negative spillovers of housing booms affect disproportionally more financially constrained firms and firms located in more bank-dependent regions. Similarly, Basco et al. (2025) find that housing booms in Spain in the run-up to the GFC led to a significant capital misallocation towards firms more exposed to real estate, with a large negative impact on overall productivity growth. We will see in the next section that housing booms may indeed generate non-negligible costs when the boom ends.

Figure 8: Housing booms versus non-boom housing expansions



Notes: Cumulative impulse responses of selected variables over 12 quarters during non-boom housing expansions (blue line and grey area) and housing booms (red lines). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

4.2 Predictable pattern of the economy during housing contractions

We now focus on the economy's predictable path during housing contractions, that is, following the peak of the housing expansion. In the spirit of the previous section, we separate contractions following non-boom expansions versus housing booms. Our econometric specification is as follows:

$$\Delta_h Y_{i,t+h} = \alpha_i^h + \alpha_t^h + \beta_1^h Peak_{i,t-1}^{NoBoom} + \beta_2^h Peak_{i,t-1}^{Boom} + \Gamma'_h Z_{i,t-1} + e_{i,t}^h, \tag{5}$$

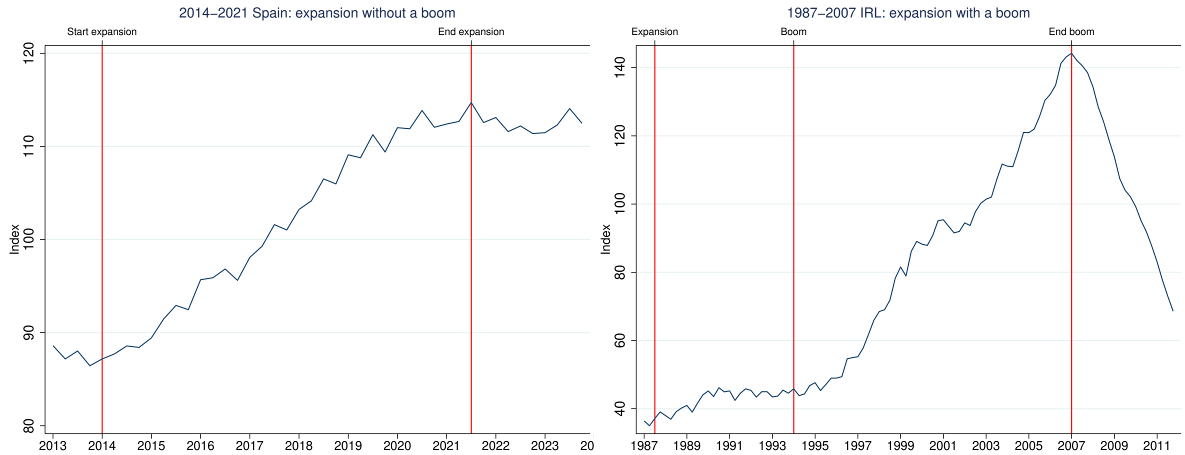
where the coefficients of interest are β_1^h and β_2^h that measure respectively the conditional path of the economy after housing expansions characterized by non-boom and boom behavior reach their respective peak. Specifically, $Peak^{NoBoom}$ is a dummy variable taking the value of one when the non-boom housing expansion ends, and zero otherwise, and $Peak^{Boom}$ is a dummy variable taking the value of one when the peak of the housing expansion coincides with a housing boom, and zero otherwise. The control variables and fixed effects are the same as previously, with the difference that now the control variables are interacted with the peak of booms and non-booms. In essence, this exercise studies the conditional path of the economy during a housing contraction that is preceded by a housing boom or a non-boom housing expansion. Our specification shares some similarities with Aastveit, Anundsen, Kivedal and Larsen (2023), who study the conditional path of US counties following the peak of bubble housing booms and non-bubble housing booms. They define bubbles as strong house price accelerations with the level of house prices following an explosive root process, building on the Phillips et al. (2015) recursive right-tailed ADF test on real house prices.

Figure 9 illustrates graphically our empirical approach. The left panel shows an example of a housing expansion, e.g., Spain from 2014Q1 to 2021Q3, as computed with the BBQ algorithm from Section 3.1. This was a housing expansion that did not show signs of a boom. Our empirical analysis focuses specifically on how economies that experienced this type of expansion typically evolve after the peak (2021Q3 in the example), conditional on several observables and fixed effects. The right panel shows an example of an economy that experienced a housing boom, e.g., Ireland from 1994Q1 to 2007Q1, as defined with our boom methodology from Section 3.2. Our investigation will trace out the typical evolution of these two types of economies following the peak in the housing boom (2007Q1 in this example), again conditional on country-specific characteristics and fixed effects. In total, we have 143 housing expansion peak events, of which 66 are characterized as housing booms.[9]

Figure 10 plots the sequence of coefficients β_1^h (blue line and grey area) and β_2^h (red lines), referring respectively to the predicted path of the real economy following the peak in non-boom housing expansions and housing booms. We find that the contraction in economic activity—GDP, private consumption and investment—during a housing contraction tends to be considerably more severe when it is preceded by a housing boom. Moreover, the decline in the housing market is also stronger during these periods, both for house prices and housing supply

[9] We study 66 and not 152 housing booms, as documented in Section 3.2, reflecting the combination of two factors. First, we condition our analysis on an housing expansion ending, thus excluding from our analysis housing booms that end but the expansion continues. Second, we also exclude housing boom episodes that were still ongoing at the end of the sample (3 episodes in 2023Q4). However, we have carried out additional analysis by including 17 more housing booms that concluded within the four quarters preceding the end of the housing expansion. Our results remain strongly robust to this expanded definition.

Figure 9: Illustrative example of housing expansions: no-boom versus boom expansion

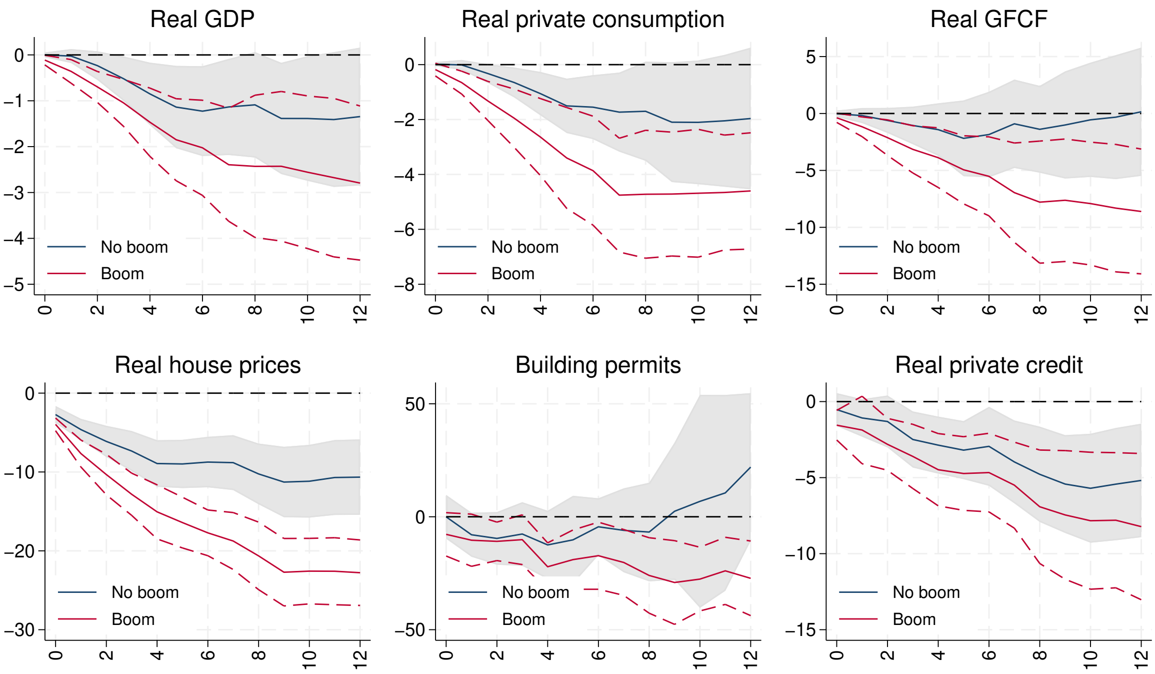


Notes: Left panel shows an example of a country with a housing expansion that does not meet the criteria of a housing boom. Red vertical lines indicate the beginning and end of the housing expansion. Right panel shows a housing expansion that meets the housing boom criteria from Section 3.2 for most of the period. Red vertical lines indicate the beginning and end of the housing expansion and boom.

(building permits), while there is less evidence of a larger decline in private credit. Figure C.7 in Appendix C shows that the difference in the impulse responses to housing boom peaks and non-boom housing peaks is sometimes surrounded by large estimation uncertainty (GDP growth, and private credit). But we do find statistically significant differences at conventional levels for the responses of private consumption, private investment, and house prices over longer horizons. The fact that housing supply declines in the aftermath of housing booms, but not after non-boom housing expansions, aligns well with research finding that declining housing supply elasticities over the last decades make house prices, not quantities, the main driver of housing market cycles, with destabilizing effects on the real economy (Albuquerque et al. 2020, forthcoming, Aastveit and Anundsen 2022, Cooper et al. 2022, Aastveit, Albuquerque and Anundsen 2023).

Our findings are consistent with the view that housing market contractions preceded by rapid increases in house prices tend to leave a long-lasting imprint on the economy, as in Cerutti, Dagher and Dell'Ariccia (2017), who show a negative unconditional association between housing booms and real GDP after three years for a large sample of countries over 1970-2012. Furthermore, Mian et al. (2013), and Mian and Sufi (2014) find that the housing bust during the GFC had a strong impact on consumption and employment in the US economy given the large declines in household net worth; Aastveit, Anundsen, Kivedal and Larsen (2023) find that the contraction in activity is typically larger and longer in US counties that experience housing booms that display a bubbly behavior. Moreover, the literature has also found that

Figure 10: Conditional pattern of selected variables following a housing expansion peak



Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms (red lines) against expansion peaks that do not coincide with housing booms (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

recessions tend to be deeper and longer when preceded by house price boom-busts, especially when combined with credit booms (Claessens et al. 2009, Jordà et al. 2015).[10]

Similarly to the results in the previous section, the differential economic dynamics we find between the end of housing booms and other housing expansions does not seem to be explained by differences in policy paths. Figure C.8 in Appendix C indicates in effect that monetary policy, fiscal policy, and macroprudential policy do not seem to evolve differently over time across both episodes at statistically conventional levels of significance. If anything, monetary policy and fiscal policy seem to be more supportive following the peak of a housing boom.

We examine possible nonlinearities in two ways. First, we investigate whether the decline in economic activity following housing boom-busts are independent of the intensity of the housing boom. This complements our empirical specification in Equation (5) that treated all housing boom peaks the same by assigning the value of one when the boom reaches the peak, and zero otherwise. Specifically, we allow housing boom peaks to differ according to the cumulative house price growth observed during each housing boom: countries with strong booms experience cumulative house price growth that falls in the upper quartile of the house price growth sample

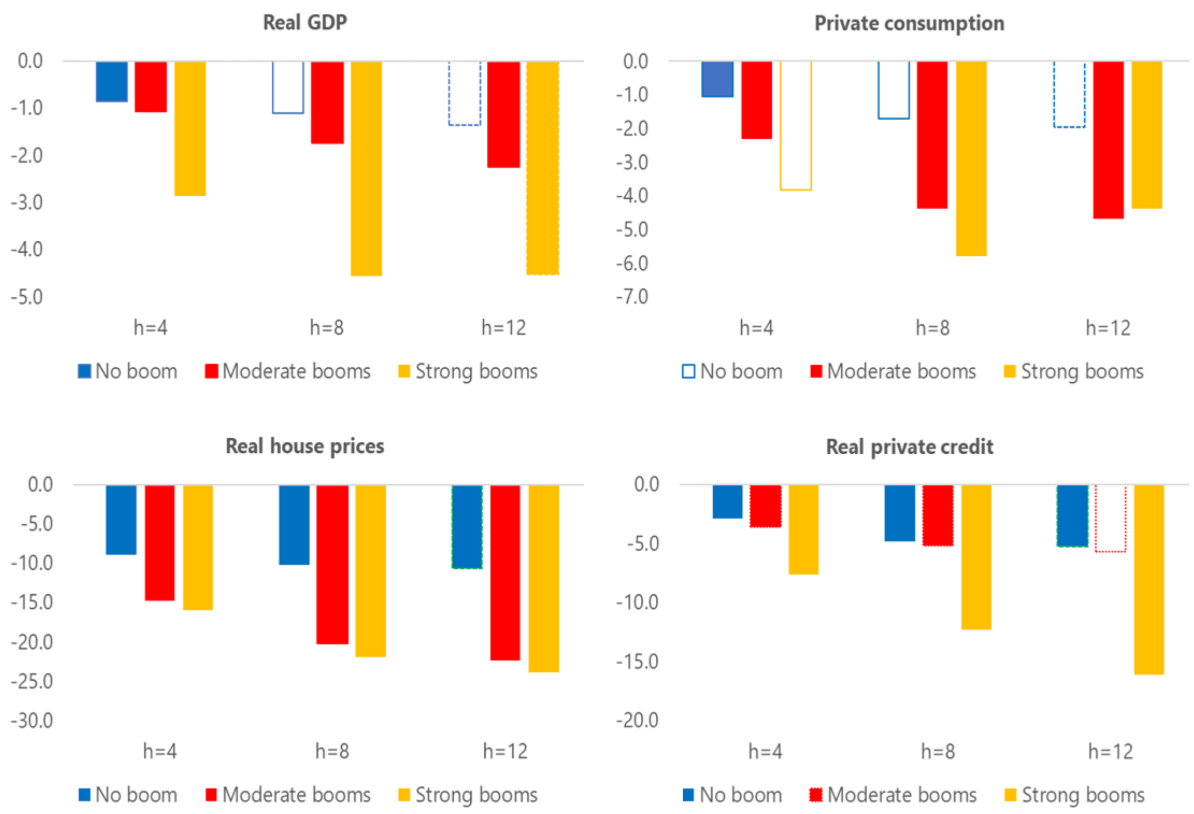
[10]While not covering housing markets, it is well-established in the literature, as shown by Cerra and Saxena (2008), and Blanchard et al. (2015), that the output costs of financial crises are permanent on average.

distribution during all housing booms. We estimate the following regression:

$$\Delta_h Y_{i,t+h} = \alpha_i^h + \alpha_t^h + \beta_1^h Peak_{i,t-1}^{NoBoom} + Peak_{i,t-1}^{Boom} \times (\beta_2^h + \beta_3^h Boom_{i,t-1}^{Strong}) + \Gamma_h' Z_{i,t-1} + e_{i,t}^h, \quad (6)$$

where $Boom^{Strong}$ takes the value of one for countries that experience house price growth that falls in the upper quartile of the cumulative house price growth during booms over the estimation sample, and zero otherwise (which we call 'moderate booms'). We find that a housing contraction preceded by a strong boom is associated with substantially larger falls in economic activity, and private credit over the medium term (Figure 11). Interestingly, house prices seem to fall roughly by similar magnitudes during both moderate and strong booms, although the economic contraction is much more severe in the latter case.

Figure 11: Conditional pattern of selected variables following a housing peak: intensity of the housing boom



Notes: Cumulative impulse responses of selected variables following the peak of: non-boom housing expansions (blue bars), housing expansions that coincide with moderate housing booms (red bars), and housing expansions that coincide with strong housing booms (yellow bars). The x-axis represents the effects over horizons four, eight, and 12 quarters ahead. Full bars refer to statistically significant coefficients at the 90 percent confidence level, while statistically insignificant coefficients are represented by hollow bars.

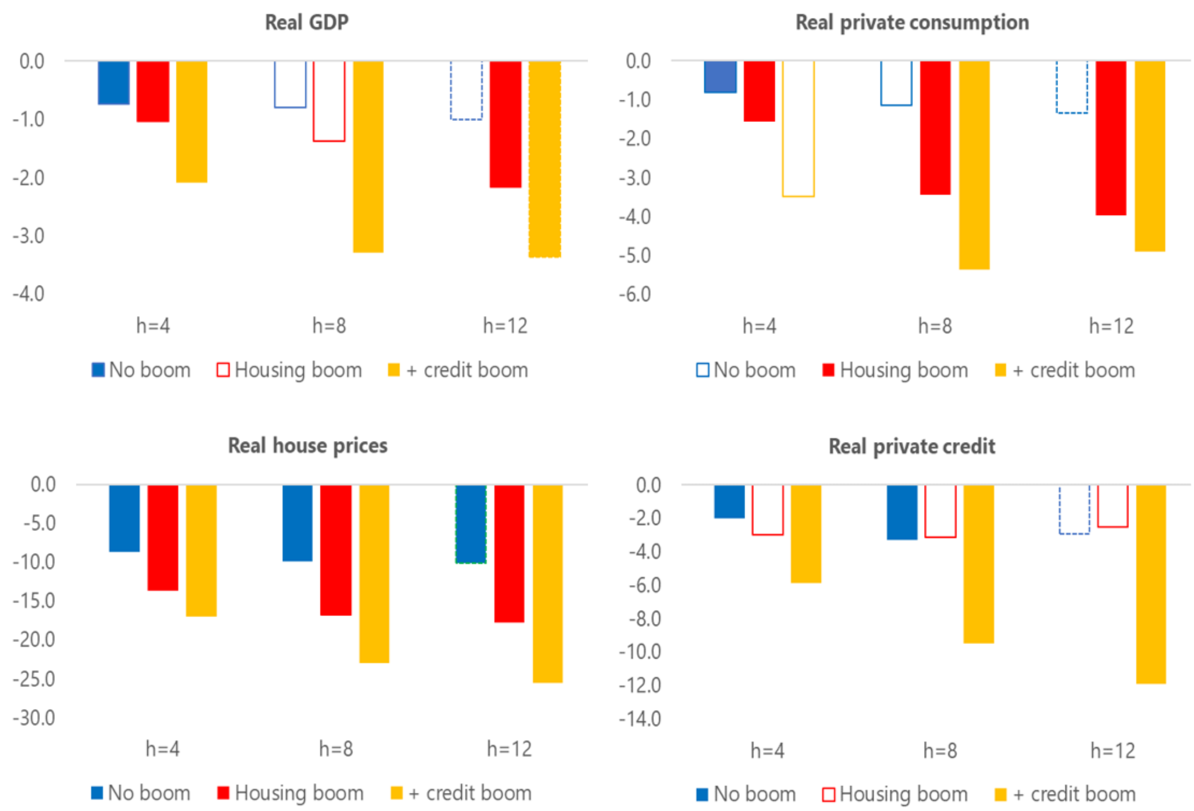
One possible explanation is linked to the stronger contraction in credit, creating incentives in households to deleverage and thus cut back more strongly on consumption. Our result highlights that strong housing booms can cause significant nonlinearities on economic activity, prompting households to deleverage and reduce consumption (Mian et al. 2013). Also, the higher potential reallocation of resources after a stronger housing boom could open the door to hysteresis (e.g., among other channels, a recession and the associated high unemployment may lead some workers to drop out permanently, as described in Blanchard et al. 2015, Cerra et al. 2023).

Second, we investigate the nonlinear behavior when housing boom peaks coincide with booms in household credit (results remain qualitatively similar when using credit booms in the nonfinancial corporate sector). Our analysis is motivated by evidence that recessions tend to be deeper and longer when house price boom-busts go hand-in-hand with private credit booms (Claessens et al. 2009, Jordà et al. 2015, Cerutti, Dagher and Dell'Ariccia 2017). Our new specification is as follows:

$$\Delta_h Y_{i,t+h} = \alpha_i^h + \alpha_t^h + \beta_1^h Peak_{i,t-1}^{NoBoom} + Peak_{i,t-1}^{Boom} \times (\beta_2^h + \beta_3^h HHBoom_{i,t-1}) + \Gamma_h' Z_{i,t-1} + e_{i,t}^h, \tag{7}$$

where $HHBoom$ is a dummy variable taking the value of one during household credit booms. We define household credit booms when the 12-quarter change in household debt to GDP falls in the top quartile of the country-specific distribution, similar in spirit to Müller and Verner (2024). The coefficient β_3 thus indicates the predictable path of the economy during housing contractions that are preceded by household credit booms. We find that economic contractions are significantly more severe during housing contractions that are preceded by household credit booms (Figure 12). This is likely driven by household deleveraging and reduced consumption, underscoring the role of household balance sheets and resource reallocation in driving hysteresis after housing boom-bust cycles.

Figure 12: Conditional pattern of selected variables following a housing peak: adding household credit booms



Notes: Cumulative impulse responses of selected variables following the peak of: non-boom housing expansions (blue bars), housing booms (red bars), and housing booms that coincide with household credit booms (yellow bars). The x-axis represents the effects over horizons four, eight, and 12 quarters ahead. Full bars refer to statistically significant coefficients at the 90% confidence level, while statistically insignificant coefficients are represented by hollow bars.

5 Net effect of housing expansions

We have seen that housing booms can lift economic growth (Section 4.1), but the end of the booms brings about considerable economic costs (Section 4.2). An open question is about the net effects of housing booms versus other housing expansions, i.e., whether the gains in economic growth of housing booms during expansions can more than offset the costs during housing downturns. This question is subject to considerable challenges given the substantial heterogeneity in the length of housing booms, and the large uncertainty around the time period over which one should quantify the costs during economic downturns. In particular, it is likely that housing busts that follow strong housing booms may condition the evolution of future housing expansions.

Against this background, to identify the net costs of housing booms and busts, we assess how the economy behaves following *housing innovations* during housing booms and non-boom housing expansions. More specifically, we follow the spirit of the credit booms literature by computing the 12-quarter change in house prices relative to GDP per capita, henceforth called house prices-to-income ($\Delta_{12}HPI$). The choice of the horizon is consistent with the literature on credit booms, which take long changes in debt to income or GDP to capture debt imbalances (Mian et al. 2017, Giroud and Mueller 2021, Greenwood et al. 2022, Müller and Verner 2024). In addition, it aligns well with the median length of a housing boom in our dataset (12 quarters).[11] Our assumption is that increases in this ratio should give us an approximate estimate of the costs (or benefits) *over the full sample* of house prices rising above income per capita in a particular economy. We standardize this variable to facilitate the interpretation of the coefficients. We start our analysis by assessing the average effect of housing innovations:

$$\Delta_h Y_{i,t+h} = \alpha_i^h + \alpha_t^h + \beta^h \Delta_{12}\text{HPI}_{i,t-1} + \Gamma_h' Z_{i,t-1} + e_{i,t}^h, \tag{8}$$

where the coefficient of interest β^h measures how the economy evolves following a one-standard deviation increase in housing innovations (an increase in HPI of around 34 percentage points relative to 12 quarters ago), after controlling for several country-specific characteristics, country fixed effects, and time fixed effects. We increase the window size of the impulse responses to 28 quarters, in line with the hysteresis literature that uses up to 7 years when using quarterly data for measuring post-recession output gaps (Blanchard et al. 2015).

Figure 13 plots the sequence of the β^h coefficients, showing the predictable evolution of each dependent variable following a one-standard deviation increase in housing innovations. The picture that emerges points to a clear association between prolonged housing expansions and declines in economic activity over the medium term, as illustrated by the fall in real GDP growth of around 0.5 percentage points after roughly six quarters. This decline is driven by the fall in both private investment and private consumption, most likely reflecting deleveraging pressures and housing affordability concerns given the rise in house prices relative to income. Zooming in on investment, we find that the housing market activity tends to cool off following housing expansions, as shown by the decline in the number of building permit authorizations. The economy tends to return to the baseline after roughly five years, although credit and housing supply remain depressed for longer.

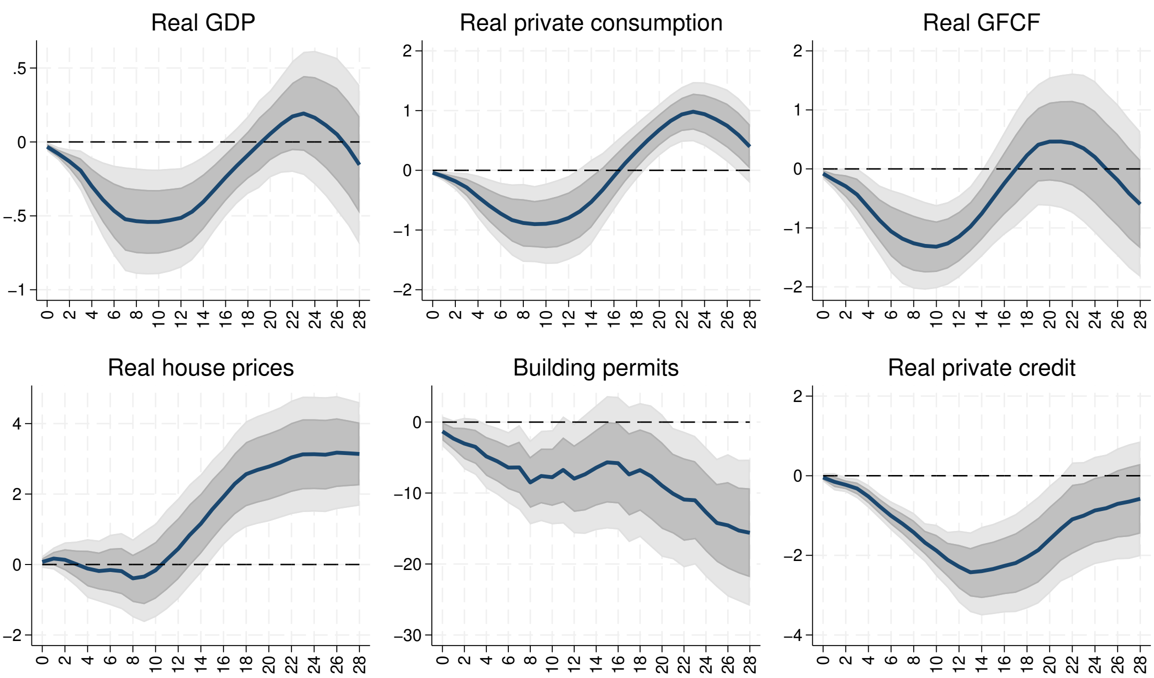
We also find that housing innovations that coincide with recessions—defined as two consecu-

[11] Our results are not sensitive to using instead five-year changes in the HPI.

tive quarterly declines in real GDP growth— tend to be associated with larger falls in economic activity (Figure C.9 in Appendix C). Moreover, Figure C.10 in Appendix C finds some evidence that declines in real GDP, consumption, investment, and house prices tend to be amplified by housing innovations that are accompanied by household credit expansions, echoing the results in Jordà et al. (2015), and Cerutti, Dagher and Dell'Ariccia (2017).[12] We get stronger and more persistent economic effects when using instead credit expansions in the nonfinancial corporate sector (Figure C.11 in Appendix C). This is consistent with recent evidence showing that corporate debt booms, particularly originating in the nontradable sector, predict lower investment, employment and economic growth (Giroud and Mueller 2021, Albuquerque 2024, Müller and Verner 2024).

Overall, our results support the notion that housing innovations over the full sample are, on average, detrimental to the real economy. While our paper cannot speak directly to the channels through which housing innovations may impact the real economy, our findings align with empirical evidence indicating that rapid house price increases are linked to slower economic recoveries (Claessens et al. 2009, Jordà et al. 2015, Cerutti, Dagher and Dell'Ariccia 2017).

Figure 13: Conditional pattern of selected variables following housing innovations



Notes: Cumulative impulse responses of selected variables over 28 quarters following a one-standard deviation increase in housing innovations measured with the 12-quarter change in HPI. Dark (light) grey areas refer to the associated 68% (90%) confidence bands. Standard errors double-clustered by country and time.

[12]The figure shows the coefficient from an expanded Equation (8) with one interaction term between housing innovations and household credit expansions, measured with $\Delta_{12}HHcredit_{i,t-1}$ (we also add this term individually).

The evidence presented so far has referred to the predictive power of housing innovations *on average* for the full sample. To connect to our main argument in the paper that not all housing expansions are the same, we test whether housing innovations may have a differential predictive power for economic activity conditional on a housing expansion with and without signs of a boom. We augment Equation 8 as follows:

$$\begin{aligned}\Delta_h Y_{i,t+h} =& \alpha_i^h + \alpha_t^h + \Delta_{12} HPI_{i,t-1} \times (\beta_0 + \beta_1^h NoBoom_{i,t-1} + \beta_2^h Boom_{i,t-1}) \\ &+ \Gamma_h' Z_{i,t-1} + e_{i,t}^h,\end{aligned} \tag{9}$$

where $\beta_0^h + \beta_1^h$ and $\beta_0^h + \beta_2^h$ measure respectively the predictable pattern of the dependent variable following a one-standard deviation increase in housing innovations during non-boom housing expansions ($NoBoom$) and during housing booms ($Boom$). Our novel results in Figure 14 indicate that housing innovations only seem to be associated with lower overall medium-term economic growth when accompanied by too rapid increases in house prices, i.e., by housing booms (red lines). In addition, the fall in private credit during boom periods is also considerable. Differences between the impulse responses of non-boom housing expansions and housing booms are statistically significant for most variables over more medium to longer horizons (Figure C.12 in Appendix C).[13]

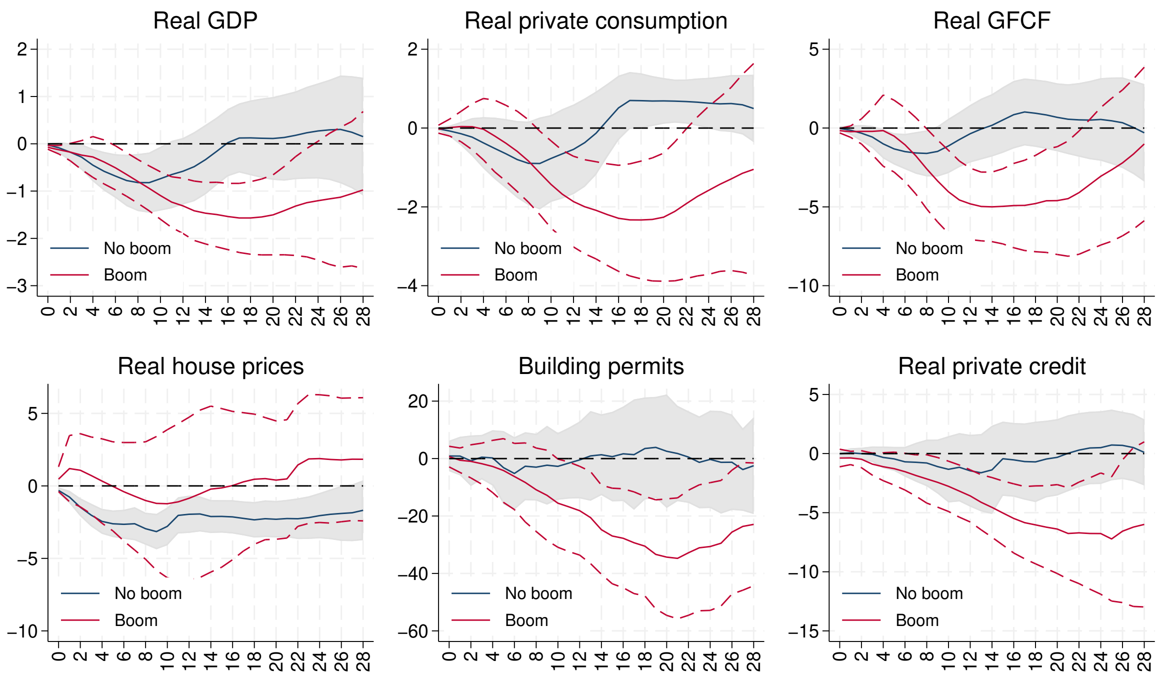
Overall, our findings indicate that housing innovations, measured with the 12-quarter change in HPI, do not inherently predict lower economic growth. To be sure, large increases in house prices do not necessarily indicate housing market imbalances if they align with higher current or expected future income growth. In such cases, the HPI ratio may temporarily rise but will likely revert to the mean over the medium term without major economic disruptions. However, we find that only during housing booms, characterized by sustained and rapid house price increases, does economic activity significantly deviate from the typical growth path seen in non-boom housing expansions.

6 The role of policies and supply during housing contractions

While several factors several factors may be behind the emergence of these booms, we focus in this section on the conditions at the end of housing expansions. For instance, Cerutti, Dagher

[13]Our results remain robust to controlling for both monetary policy and fiscal policy (Figure C.13 in Appendix C). The country sample, however, drops from 68 to 60 countries due to lack of data on policy rates for some countries.

Figure 14: Conditional pattern of selected variables following housing innovations: housing booms versus non-boom housing expansions



Notes: Cumulative impulse responses of selected variables over 28 quarters following a one-standard deviation increase in housing innovations, measured with the 12-quarter change HPI, for non-boom housing expansions (blue line and grey area) and housing booms (red lines). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

and Dell'Ariccia (2017) find that household credit booms and higher LTVs are associated with a higher likelihood of housing booms. This is consistent with evidence that the US housing boom in the run-up to the GFC seems to have been driven by the loosening in credit standards that led to an increase in credit supply, which in turn stimulated household mortgage borrowing (Justiniano et al. 2019, Mian and Sufi 2021, Sarto 2024). We build on this literature but try to answer a seemingly different question: what is the role of macroprudential policy and housing supply in determining how a housing boom ends?

To investigate this question, we resort to two strands of the literature. The first focuses on the role of housing supply constraints, such as tight land-use regulation and geographical constraints, for the transmission of demand shocks (Gyourko et al. 2008, Saiz 2010, Glaeser et al. 2014, Herkenhoff et al. 2018, Albuquerque et al. 2020, forthcoming, Aastveit and Anundsen 2022, Cooper et al. 2022, Aastveit, Albuquerque and Anundsen 2023). In particular, the available evidence suggests that house prices tend to be more sensitive to monetary policy in areas where housing supply constraints are more binding (Albuquerque et al. 2020, forthcoming, Aastveit and Anundsen 2022, Cooper et al. 2022, Aastveit, Albuquerque and Anundsen 2023). Tighter constraints are then linked to a higher likelihood of house price booms (Aastveit, Anundsen, Kivedal and Larsen 2023). In this context, we test whether countries with fewer restrictions on housing supply may recover faster after the housing boom ends. Given data availability issues for our large sample of countries, we cannot use granular measures such as land-use regulation (Gyourko et al. 2008), geographical constraints (Saiz 2010), or supply elasticities (Aastveit, Albuquerque and Anundsen 2023). Similarly to Andaloussi et al. (2024), we use instead population density as a proxy of housing supply restrictions, which has been shown to explain most of the cross-sectional regional variation in US house prices (Saiz 2010).

The second strand of the literature relates to the effectiveness of macroprudential measures in mitigating large fluctuations in housing and credit markets (Claessens 2015, Kuttner and Shim 2016, Cerutti, Claessens and Laeven 2017, Akinci and Olmstead-Rumsey 2018, Richter et al. 2019, Acharya et al. 2022, Biljanovska et al. 2023). The available empirical evidence suggests that borrower-based measures, such as limits on LTVs and DSTIs, seem to be effective in containing house price growth and credit growth, but it may come at a cost of lower economic growth, especially for EMs (Richter et al. 2019).

Following this literature, we use the Alam et al. (forthcoming) integrated Macroprudential Policy (iMaPP) database to test if borrower-based measures may allow countries to smooth the impact from the end of the housing boom. This dataset provides a comprehensive historical account of several macroprudential measures over 1990-2021 for a large set of countries. For each measure, it assigns the value of one for tightening actions, minus one for loosening actions, and zero for no change. We focus on demand measures, i.e., limits on the LTV ratio and DSTI ratio. We follow Akinci and Olmstead-Rumsey (2018) and sum up the binary variables for these two instruments by country and over time to capture the stringency of borrower-based macroprudential policies. Summing up the borrower-based indicators has the drawback that it cannot measure the intensity of the macroprudential actions. But this approach also comes with advantages. Our 'stringency' index on borrower-based measures is more comparable across countries relative to using instead the average LTV levels (also from the iMaPP database). The latter suffers from the caveat that an 'average LTV' may only apply to some households (or none at all), given within-country distributional differences. In addition, our dummy variables capture not only limits on LTVs, but also limits on the DSTI ratio. This is important to account for the fact that some countries use a combination of the two tools to mitigate risks emanating from the mortgage and housing markets. We adapt Equation 5 as follows:

$$\begin{aligned}\Delta_h Y_{i,t+h} =& \alpha_i^h + \alpha_t^h + Peak_{i,t-1}^{NoBoom} \times (\beta_1^h + \beta_2^h Int_{i,t-1}) + \\ & Peak_{i,t-1}^{Boom} \times (\beta_3^h + \beta_4^h Int_{i,t-1}) + \Gamma_h' Z_{i,t-1} + e_{i,t}^h,\end{aligned} \tag{10}$$

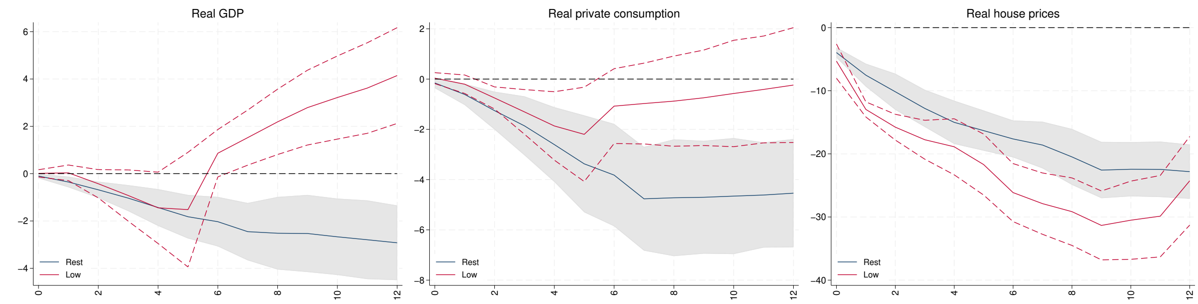
where the term $Int_{i,t-1}$ refers to either countries (i) with low population density, taking the value of one for countries whose population density falls in the first decile of its country-specific distribution in each quarter, or (ii) with tight borrower-based measures, a dummy variable taking the value of one for countries whose borrower-based macroprudential index falls in the upper decile of its country-specific distribution in each quarter.[14] The coefficients of interest are β_3^h and β_4^h. The first measures the impulse responses to the end of the housing boom for countries with population density above the first decile or with a macroprudential index below the upper decile. In turn, $\beta_3^h + \beta_4^h$ indicate the predictable pattern of the economy following the end of housing booms for countries with low population density (first decile) and a tight macroprudential index (upper decile).

We illustrate our results for GDP, consumption, and house prices. Figure 15 indicates that countries with low population density (red lines) tend to experience short-lived economic contractions. At the same time, real house prices seem to fall slightly more than for other countries, but they are not statistically different from each other. Our results support the view that policies that alleviate housing supply constraints, such as loosening land-use regulation, or fostering an enabling business environment that stimulates housing supply, may allow countries to absorb better the shocks stemming from the end of housing booms.

Figure 16 provides some tentative evidence that countries with tighter borrower-based macroprudential measures (red lines) seem to experience smoother economic fluctuations in the aftermath of housing booms. This is consistent with the literature that finds that tighter constraints on household borrowing can dampen housing and credit cycles (Claessens 2015, Kuttner and Shim 2016, Cerutti, Claessens and Laeven 2017, Akinci and Olmstead-Rumsey 2018, Richter et al. 2019, Acharya et al. 2022, Biljanovska et al. 2023). We find similar results when splitting the countries according to the average LTV levels. In particular, countries with LTVs below the bottom decile—tight MaPP—tend to weather better the aftermath of housing booms (Figure C.14 in Appendix C).

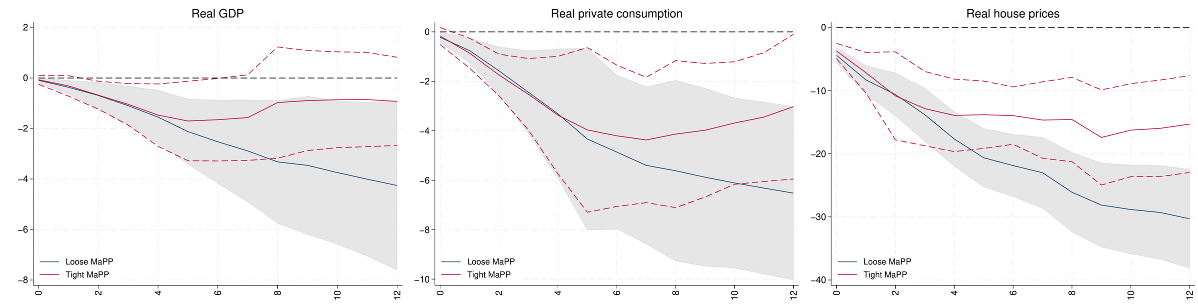
[14] Splitting countries below/above the median did not generate any meaningful statistical difference. This suggests that most of the potential action from housing supply restrictions or macroprudential measures is driven by a few observations falling in the tails of the distribution.

Figure 15: Conditional pattern of selected variables following a housing boom peak: conditional on population density



Notes: Cumulative impulse responses of selected variables over 12 quarters following the peak of housing booms for countries with low population density (red lines) and the rest of the countries (blue line and grey area). Low population density is a dummy variable taking the value of one in each quarter for countries that have population density that falls in the first decile of the country-specific distribution. The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure 16: Conditional pattern of selected variables following a housing boom peak: conditional on borrower-based macroprudential measures



Notes: Cumulative impulse responses of selected variables over 12 quarters following the peak of housing booms for countries with tight macroprudential measures (red lines) against the rest of the sample (blue line and grey area). Tight macroprudential is a dummy variable taking the value of one in each quarter for countries with borrower-based measures (LTV and DSTI) that fall in the upper decile of the country-specific distribution. The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

7 Robustness checks

We subject our main specification in Equation (5) and the resulting Figure 10 to a battery of robustness checks. All robustness checks can be found in Appendix C.

Alternative housing boom definitions

We use three alternative ways to define our housing boom dummy variable: (i) when house prices are ten percent above the country-specific estimated trend, estimated with the Hamilton (2018) filter; (ii) when house prices are one-standard deviation above the country-specific estimated trend, estimated with the Hamilton (2018) filter; and (iii) when the cumulative 12-quarter change in the HPI ratio is one-standard deviation above its country-specific mean, similar in spirit to Müller and Verner (2024). Figure C.15 shows—only the impulse response for housing booms—that our baseline results are remarkably stable to employing alternative housing boom definitions.

Housing bubbles

Our paper has focused on housing booms, which are a distinct concept from housing bubbles, as identified in the related literature (Phillips et al. 2015, Pavlidis et al. 2016, Martínez-García and Grossman 2020, Aastveit, Anundsen, Kivedal and Larsen 2023). Housing bubbles display an explosive pattern, which can be a subset of our housing boom definition, as not all housing booms exhibit an exponential price growth pattern. To clarify, not all housing booms are housing bubbles, but almost all housing bubbles are housing booms. Bearing in mind this important distinction, we test how the real economy typically performs during housing contractions that follow the burst of a housing bubble against housing contractions that were not preceded by housing bubbles.

We follow Phillips et al. (2015), and run recursive right-tailed ADF-unit root tests on real house prices to test for explosive house price developments, and then date-stamp multiple episodes of explosive behavior. Specifically, we calculate backward supremum ADF (BSADF) statistics with window size set at 0.01 $+1.8/\sqrt{T}$ fraction of the sample, where T is number quarters in the sample, and maximum lag of one quarter. We then compare them with the 95 percent critical values based on 499 wild bootstrap. To eliminate short-lived explosive behavior, we impose the restriction that a bubble should last at least for five consecutive quarters. We also impose that bubbles can only take place during housing expansions, as defined with the BBQ algorithm. This is important, as the Phillips et al. (2015) test comes with the issue that it also tends to detect explosive behavior during contractions/downturns. We then run Equation (5) by replacing booms with bubbles and non-booms with non-bubbles. Figure C.17 shows that our main results remain robust to using a concept of housing bubbles, although the estimation uncertainty is larger.

Housing expansions based on the HPI ratio

We re-run Section 3 by defining housing expansions based on the HPI ratio instead of the level of real house prices. Figure C.16 shows that our baseline results are qualitatively similar. Although this alternative method comes with larger estimation uncertainty, we still obtain significant differences in the responses of most variables to the peak of non-boom housing expansions and housing expansions that coincide with housing booms.

Pre- and post-GFC, and excluding the Covid-19 sample

We do not find that that the dynamics of the economy following housing expansion peaks that coincide with housing booms differ if we were to exclude the Covid sample (Figure C.18), or if we were to allow a differential response between the pre-GFC and the post-GFC (the pre-GFC sample goes up to 2007Q4, and the post-GFC sample starts in 2010Q1)—Figure C.19 shows only the impulse response for housing booms.

AEs vs EMs

The predictable pattern of the real economy following the end of housing expansions that coincide with housing booms also does not seem to generally differ between AEs and EMDEs (Figure C.20). The exception is private credit and consumption which fall by more in EMDEs.

Year-on-year growth rates

Our baseline results are also qualitatively unchanged when using instead year-on-year growth rates in the dependent variables, to address potential concerns with seasonality (Figure C.21).

8 Conclusion

Recent decades have shown us that housing expansion-contraction cycles have often been severe, with several countries experiencing housing corrections following housing boom expansions that triggered lasting economic scars and heightened financial stability risks. Based on the analysis of 68 countries—35 AEs and 33 EMDEs—from 1970Q1 to 2023Q4, we identify 180 housing cycles, with about one-half of them classified as having experienced housing boom expansions due to their rapid and persistent real house price increases. While there is considerable heterogeneity across countries, housing expansions tend to be longer than contractions. Housing booms tend to be shorter, an average of three to four years, but produce long-lasting effects on the real economy.

Our findings indicate that economic downturns are significantly deeper and more prolonged when housing contractions follow an expansion with the presence of a housing boom. This is in line with the notion that the US housing contraction played an important role in exacerbating the economic decline during the GFC (Mian et al. 2013, Mian and Sufi 2014, Sarto 2024). We also find that the stronger the boom, the more challenging the economic recovery becomes when the boom ends. Furthermore, we find that the combination of credit and housing booms further amplifies the downturn, consistent with Claessens et al. (2009), Jordà et al. (2015), and Cerutti, Dagher and Dell'Ariccia (2017).

Although our analysis shows that housing booms are associated with higher house prices, GDP growth, and private consumption during the expansion phase, the net effect of a housing boom across the housing cycle is negative on average. In fact, housing innovations only seem to be associated with lower medium-term economic growth when accompanied by housing booms: during housing booms, economic activity falls sharply, deviating from the typical growth seen in non-boom periods.

In this context, the role of, and the room for, policy actions are key. Our findings suggest that countries with less restrictive housing supply constraints tend to experience smoother business cycles during a housing contraction. This indicates that policies that target housing supply may help mitigate the macroeconomic effects of a housing downturn. In addition, macroprudential policies also appear to help reduce the risk of severe downturns following the end of housing booms. Nonetheless, further research is needed to better understand the transmission channels and the optimal timing for implementing the appropriate policies.

Appendix A: Data

Table A.1: Data description

Variable	Description	Sources
Real private credit	Nominal credit to the private sector in local currency deflated by CPI	Monetary and Financial Statistics (MFS)/BIS
Real household credit	Nominal household credit in local currency deflated by CPI	MFS/BIS/National authorities
Real mortgage credit	Nominal mortgage credit in local currency deflated by CPI	National authorities
Private credit-to-GDP	Nominal private credit in local currency divided by nominal GDP	MFS/BIS/IMF/National authorities
Consumer Price Index	Headline consumer price index	International Financial Statistics (IFS)
Real private consumption	Real private consumption expenditure in local currency	IMF/National authorities
Real GDP	Real GDP in local currency	IMF/National authorities
Real GFCF	Real gross fixed capital formation in local currency	IMF/National authorities
Real residential investment	Residential investment in local currency	IMF/National authorities
Nominal GDP	Nominal GDP in local currency	IMF/National authorities
Nominal GDP per capita	Nominal GDP divided by population	IMF/National authorities
Population	Population in millions	IMF
Current account-to-GDP	Current account balance as a percent of GDP	IMF/National authorities
Employment	Number of employed people	IMF
Nominal house price	Index of nominal house prices	BIS/Global Property Guide (GPG)/National authorities
Real house price	Index of nominal house prices deflated by CPI	BIS/GPG/National authorities/IFS
House price-to-income	Nominal house price divided by nominal GDP per capita	BIS/GPG/National authorities
Building permits	Number of residential building permits	National authorities
Policy rate	Central banks' policy rate	IFS/BIS/Central banks' websites
Fiscal balance	General government fiscal balance as % of GDP	IMF/National authorities
Average LTVs	Average loan-to-value ratio	IMF iMaPP database
Macroprudential policy	Dummy variables for policy tightenings and loosenings	IMF iMaPP database

Appendix B: Tables

Table B.1: Housing boom episodes

Country	Start	End	Duration	Avg.	SD	Cum.
Australia	1972q3	1974q1	7	9.7	3.4	20.1
Australia	1988q1	1989q1	5	17.0	9.7	25.2
Australia	1997q4	2004q2	27	8.7	5.2	65.7
Australia	2006q4	2008q1	6	7.5	2.0	9.1
Australia	2013q3	2017q3	17	6.3	1.8	26.0
Australia	2020q1	2022q1	9	9.9	6.4	20.2
Austria	2020q3	2022q1	7	8.2	1.5	10.6
Belgium	1975q4	1979q2	15	8.2	2.4	32.2
Belgium	1986q3	1990q3	17	7.2	2.6	29.0
Belgium	1998q1	1999q3	7	5.9	1.5	10.8
Belgium	2002q3	2007q3	21	7.1	1.7	40.4
Brazil	2006q2	2012q3	26	13.9	4.8	126.4
Bulgaria	2016q1	2017q4	8	7.2	1.5	12.3
Canada	1973q1	1976q1	13	9.3	9.0	29.1
Canada	1985q4	1989q1	14	12.5	4.0	44.8
Canada	2002q1	2008q1	25	8.0	2.1	55.0
Canada	2015q2	2018q1	12	11.5	3.8	31.8
Canada	2020q2	2022q1	8	9.3	4.1	17.7
Chile	2009q4	2021q4	49	6.7	2.7	105.2
China, Mainland	2016q3	2019q1	11	4.8	1.7	10.4
Colombia	1993q4	1995q3	8	7.6	1.7	11.9
Colombia	2004q4	2015q2	43	6.3	2.5	85.1
Croatia	2004q3	2007q3	13	11.4	2.3	35.2
Croatia	2017q4	2023q2	23	5.5	2.3	33.3
Cyprus	2004q3	2008q3	17	14.4	6.3	55.1
Czech Republic	2001q3	2003q3	9	19.1	3.6	41.8
Czech Republic	2006q3	2008q4	10	16.5	10.1	42.1
Czech Republic	2016q2	2021q4	23	8.2	3.9	56.5
Denmark	1983q2	1986q1	12	12.9	5.8	28.6
Denmark	1993q4	1999q1	22	7.9	3.2	43.4
Denmark	2004q1	2006q3	11	16.8	7.2	52.5
Denmark	2015q1	2016q3	7	5.7	1.1	7.9
Estonia	2013q3	2016q4	14	9.0	4.6	28.6
Estonia	2019q3	2022q1	11	7.7	2.7	23.1
Finland	1982q1	1984q2	10	9.2	2.5	18.0
Finland	1987q2	1989q1	8	20.8	10.7	50.7
Finland	1996q3	2000q2	16	10.2	3.9	39.7
Finland	2002q2	2006q2	17	6.4	1.4	26.1
France	1987q4	1990q3	12	7.2	1.4	22.3
France	1999q3	2007q2	32	8.7	2.8	86.0
Germany	1978q2	1979q3	6	4.9	0.7	6.6

Continuation of Table B.1

Country	Start	End	Duration	Avg.	SD	Cum.
Germany	2015q1	2021q4	28	5.7	1.8	47.0
Greece	1999q3	2003q1	15	8.6	2.0	32.4
Greece	2005q2	2007q1	8	8.6	1.6	15.3
Greece	2019q2	2022q1	12	6.1	1.5	14.4
Greece	2022q3	2023q4	6	7.7	4.0	10.8
Hong Kong SAR	1985q3	1989q4	18	13.3	5.9	58.2
Hong Kong SAR	1991q2	1992q4	7	29.1	14.8	34.8
Hong Kong SAR	1993q2	1994q4	7	8.4	9.2	10.1
Hong Kong SAR	1996q3	1997q3	5	26.5	14.2	29.9
Hong Kong SAR	2004q1	2005q4	8	22.2	7.8	20.5
Hong Kong SAR	2007q2	2008q3	6	14.9	6.3	16.4
Hong Kong SAR	2009q2	2013q4	19	13.3	9.2	75.5
Hong Kong SAR	2017q1	2018q3	7	14.1	2.3	20.7
Hungary	1999q2	2003q4	19	13.7	5.1	77.0
Hungary	2014q4	2022q2	31	10.5	4.2	106.1
Iceland	2003q1	2007q4	20	11.0	8.3	59.6
Iceland	2014q1	2018q1	17	9.7	5.0	44.8
Iceland	2021q2	2022q4	7	10.9	1.9	15.0
India	2011q3	2015q3	17	10.5	4.4	43.1
Ireland	1974q4	1976q1	6	7.7	2.3	5.1
Ireland	1977q3	1980q1	11	11.9	7.5	25.3
Ireland	1988q2	1990q3	10	7.6	2.9	25.0
Ireland	1994q1	2007q1	53	9.3	5.9	209.9
Ireland	2013q4	2018q4	21	10.9	4.3	64.5
Israel	2008q4	2016q4	33	7.6	3.9	78.5
Israel	2021q2	2022q4	7	10.3	2.9	16.0
Italy	1973q3	1974q3	5	25.2	9.8	26.5
Italy	1980q1	1981q3	7	12.4	7.7	25.6
Italy	1988q2	1992q3	18	9.7	1.5	49.0
Japan	1972q3	1973q3	5	18.3	4.7	22.4
Japan	1979q2	1982q2	13	5.5	0.5	17.2
Japan	1987q1	1991q1	17	6.9	2.6	29.1
Korea, Republic of	1977q3	1978q3	5	30.9	6.0	29.7
Korea, Republic of	1983q1	1986q2	14	9.4	4.6	27.2
Korea, Republic of	1988q2	1991q1	12	8.2	1.9	19.5
Korea, Republic of	2001q4	2003q2	7	10.4	4.0	14.6
Korea, Republic of	2020q4	2021q4	5	9.9	2.3	11.2
Latvia	2013q2	2014q3	6	8.4	1.5	11.9
Latvia	2018q1	2021q4	28	5.9	2.8	52.0
Lithuania	2001q1	2007q3	27	24.1	12.7	259.0
Lithuania	2019q1	2021q4	12	7.1	3.2	21.3
Luxembourg	2014q4	2021q4	29	7.5	3.8	64.9
Malaysia	1990q4	1992q3	8	14.2	7.5	22.3
Malaysia	1994q4	1996q4	9	11.4	3.4	20.9

Continuation of Table B.1

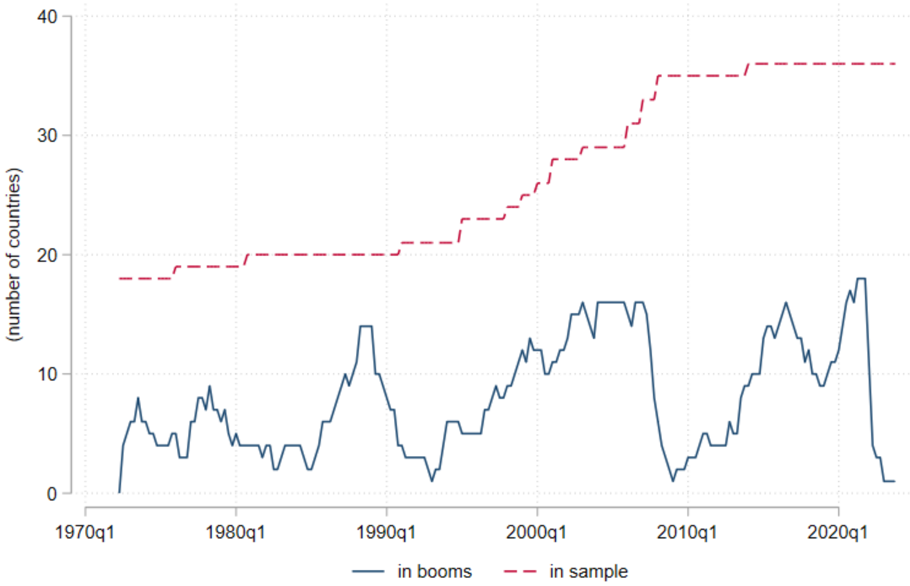
Country	Start	End	Duration	Avg.	SD	Cum.
Malaysia	2009q4	2016q4	29	6.8	2.6	57.7
Namibia	2004q3	2007q1	11	13.9	5.8	26.3
Namibia	2010q2	2015q4	23	7.0	2.4	44.2
Netherlands	1972q4	1978q2	23	13.5	9.4	105.0
Netherlands	1992q1	2001q3	39	8.2	3.9	110.0
Netherlands	2016q3	2022q2	24	7.3	2.5	49.4
New Zealand	1972q3	1974q3	9	18.6	8.5	44.7
New Zealand	1981q3	1984q3	13	8.3	5.6	21.5
New Zealand	1994q1	1997q2	14	7.7	3.1	22.9
New Zealand	2002q2	2007q2	21	11.7	5.0	77.3
New Zealand	2012q4	2017q1	18	9.4	3.6	45.7
New Zealand	2020q2	2021q4	7	16.4	7.3	29.2
North Macedonia	2007q4	2008q4	5	9.9	6.2	15.3
Norway	1977q1	1978q4	8	6.7	4.7	4.5
Norway	1980q4	1982q2	7	13.0	3.5	20.3
Norway	1985q4	1987q2	7	18.4	6.6	29.9
Norway	1993q4	2002q2	35	8.2	3.9	92.0
Norway	2004q1	2007q2	14	10.0	3.1	30.6
Norway	2011q1	2012q4	13	6.3	0.6	17.7
Pakistan	2013q3	2015q3	9	19.0	6.6	37.3
Peru	2007q3	2014q2	28	14.4	6.3	151.0
Philippines	2006q4	2008q2	7	8.7	2.7	12.0
Philippines	2012q1	2016q4	20	7.9	2.3	39.4
Poland	2018q4	2020q4	9	6.6	0.7	13.0
Portugal	1999q1	2000q2	6	6.1	1.0	6.2
Portugal	2016q1	2022q1	25	8.3	1.6	62.7
Romania	2015q3	2017q2	8	6.3	2.2	14.6
Russian Federation	2003q3	2008q3	21	20.0	14.5	141.4
Russian Federation	2020q3	2022q1	7	8.6	4.7	20.1
Serbia	2003q1	2005q3	11	10.8	11.8	12.6
Serbia	2008q3	2010q3	9	9.3	5.7	13.3
Serbia	2018q4	2022q1	14	7.0	1.3	24.2
Singapore	2006q3	2008q2	8	16.6	7.1	30.6
Singapore	2010q1	2011q2	6	17.2	10.7	9.5
Slovak Republic	2015q1	2020q4	24	6.0	2.1	38.4
Slovenia	2016q4	2022q1	22	6.7	2.2	42.4
South Africa	1980q2	1982q3	10	13.4	7.0	29.3
South Africa	2002q3	2007q3	26	16.8	10.8	137.0
Spain	1973q3	1974q4	6	13.3	5.7	13.1
Spain	1977q1	1978q2	6	11.0	2.9	14.9
Spain	1986q3	1991q4	22	15.9	8.7	115.3
Spain	1998q4	2007q3	36	9.3	3.6	118.4
Sri Lanka	2017q3	2019q2	8	12.2	4.0	10.8
Sweden	1975q1	1977q4	12	5.7	2.4	13.8

Continuation of Table B.1

Country	Start	End	Duration	Avg.	SD	Cum.
Sweden	1986q4	1990q1	14	9.8	2.7	35.1
Sweden	1997q2	2007q4	43	8.0	2.8	116.8
Sweden	2013q3	2017q3	17	8.8	3.1	40.0
Switzerland	1978q4	1981q2	11	4.3	1.9	9.1
Switzerland	2010q4	2013q1	10	6.6	0.8	15.9
Thailand	2013q2	2015q3	10	6.3	0.6	13.3
Tunisia	2007q1	2009q1	9	6.8	2.8	12.1
Turkey	2020q2	2023q4	15	28.5	16.8	118.0
U.A.E.	2006q3	2008q2	8	17.2	6.5	25.6
U.A.E.	2011q4	2014q3	12	17.9	8.2	62.9
U.A.E.	2021q3	2023q4	10	7.1	5.6	18.9
Ukraine	2005q3	2008q2	12	40.0	14.5	120.0
United Kingdom	1972q3	1973q3	5	31.9	6.1	19.6
United Kingdom	1978q2	1980q3	10	11.8	5.2	27.5
United Kingdom	1985q2	1989q3	27	13.8	7.5	98.7
United Kingdom	1997q1	2005q1	33	10.7	4.4	119.6
United Kingdom	2006q3	2007q3	5	7.2	1.2	7.1
United Kingdom	2014q2	2016q3	10	6.6	0.9	15.2
United States	1977q1	1979q2	10	7.7	1.7	16.2
United States	1986q2	1989q1	12	5.6	0.9	15.0
United States	1998q3	2006q1	31	7.6	2.6	75.2
United States	2012q4	2015q3	12	6.1	1.9	15.7
United States	2020q3	2022q2	8	9.0	1.7	16.0

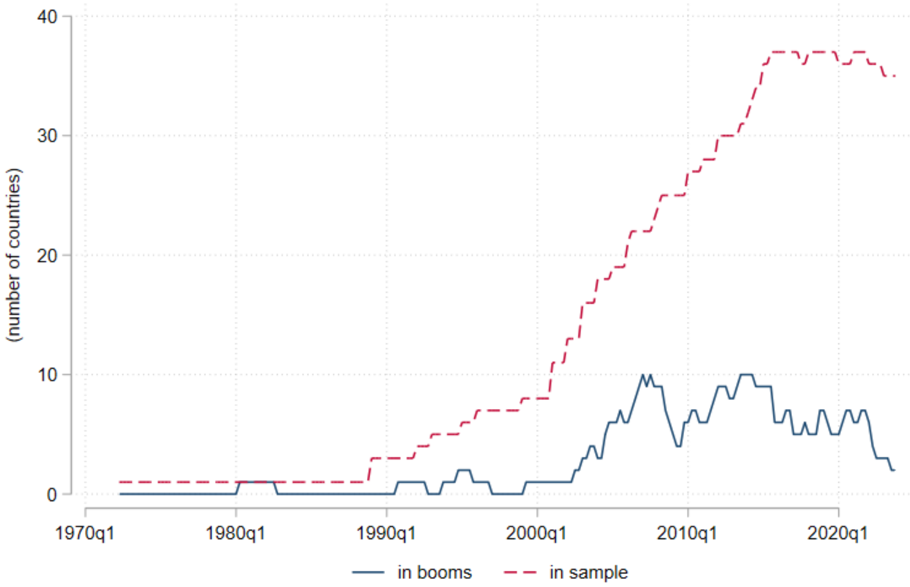
Appendix C: Figures

Figure C.1: House price booms over time: AEs



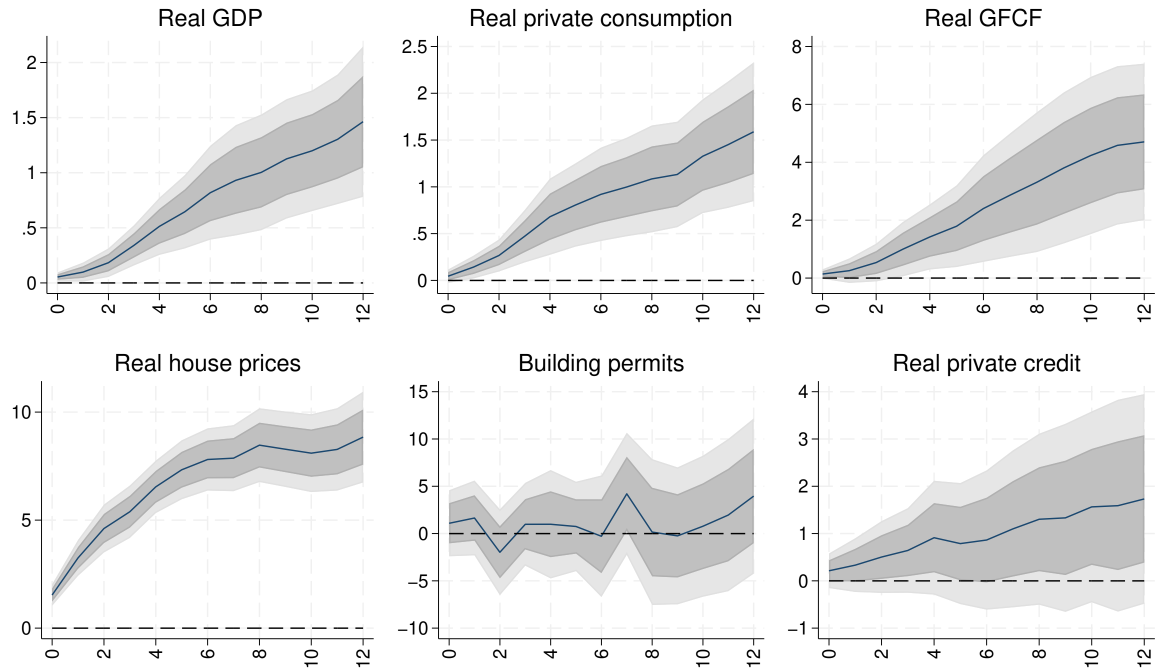
Notes: Solid blue line shows the number of AEs experiencing a housing boom over time, while the dashed red line shows the total number of AEs in our sample over time.

Figure C.2: House price booms over time: EMDEs



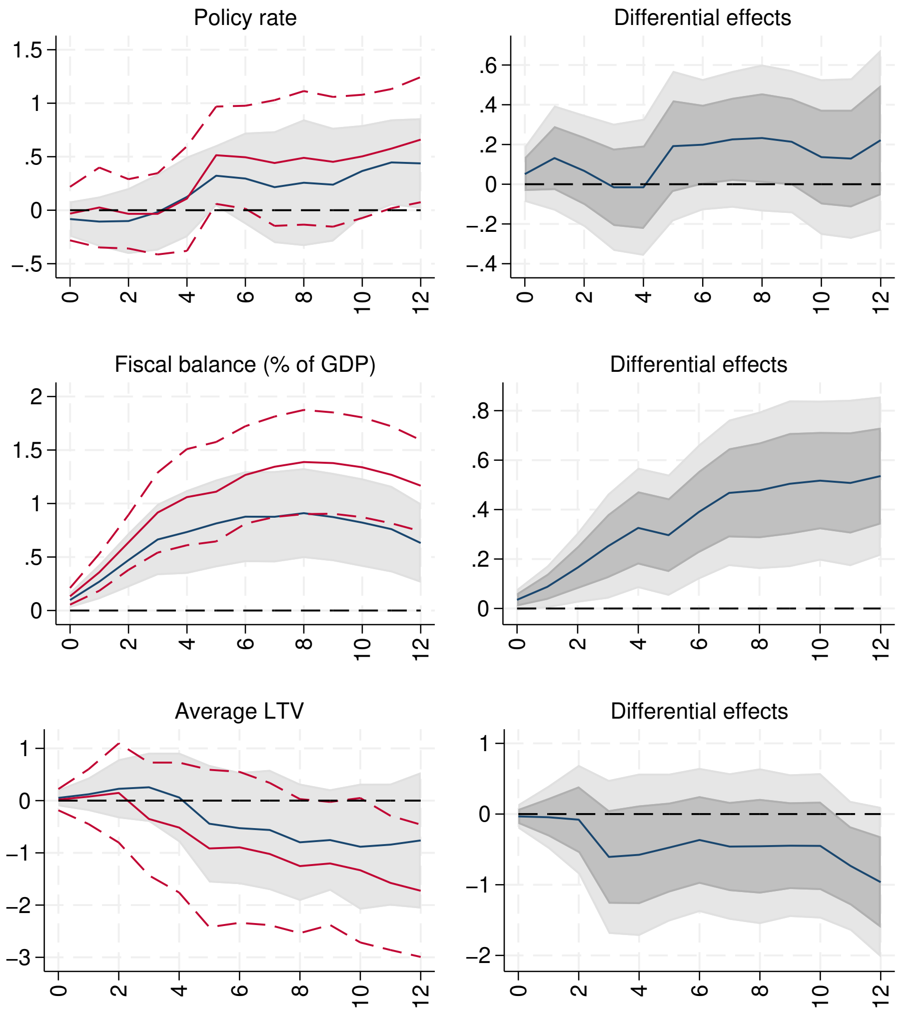
Notes: Solid blue line shows the number of EMDEs experiencing a housing boom over time, while the dashed red line shows the total number of EMDEs in our sample over time.

Figure C.3: Difference in the predictable pattern between housing booms and non-boom housing expansions



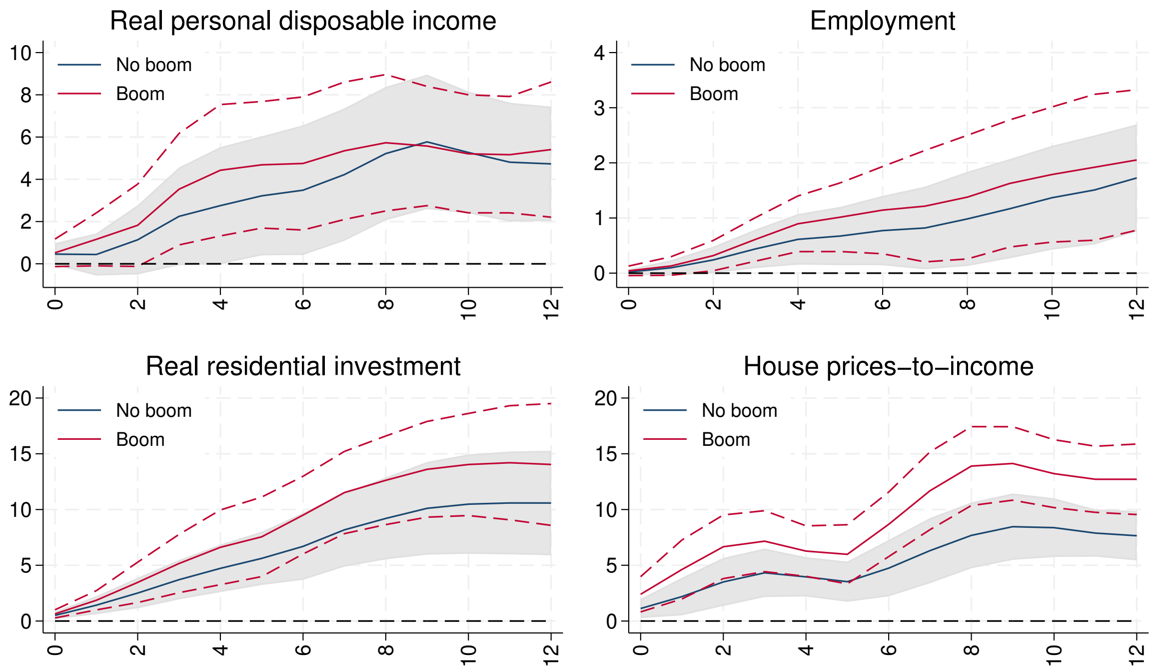
Notes: Dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy during housing booms and non-boom housing expansions. Standard errors double-clustered by country and time.

Figure C.4: Housing booms versus non-boom housing expansions: role of policies



Notes: Left panels: cumulative impulse responses of selected variables over 12 quarters during non-boom housing expansions (blue line and grey area) and housing booms (red lines). Right panels: dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy during housing booms and non-boom housing expansions for each selected variable. Standard errors double-clustered by country and time.

Figure C.5: Housing booms versus non-boom housing expansions: additional variables

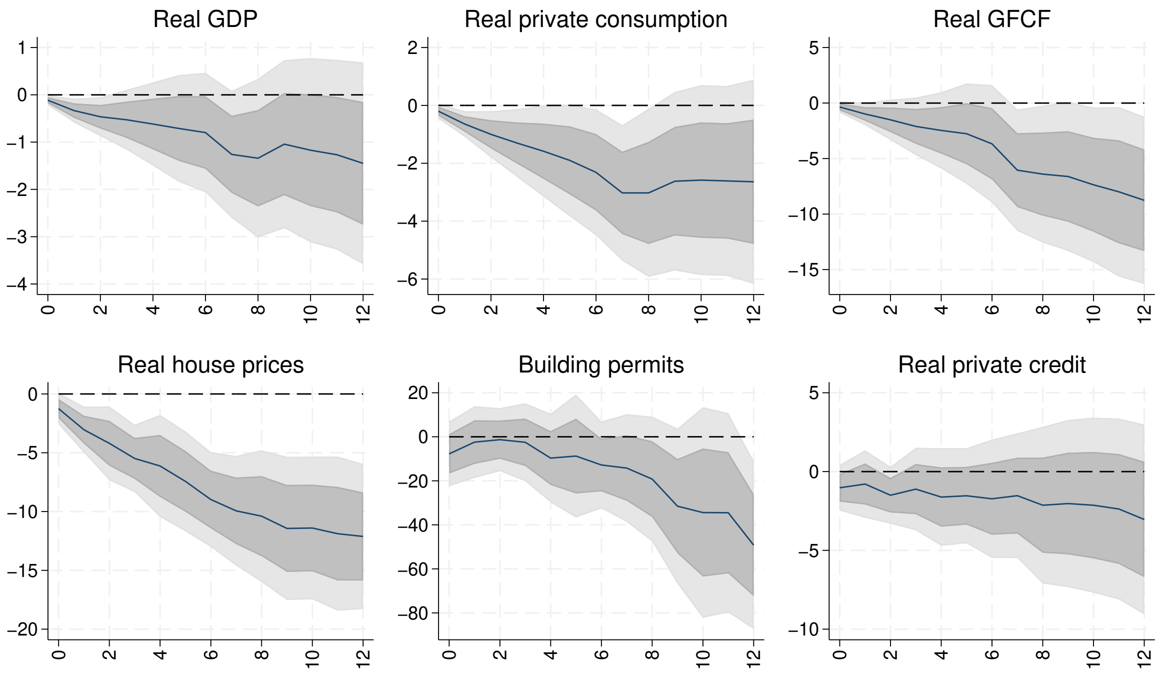


Notes: Cumulative impulse responses of selected variables over 12 quarters during non-boom housing expansions (blue line and grey area) and housing booms (red lines). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.6: Difference in the predictable pattern between housing booms and non-boom housing expansions: additional variables

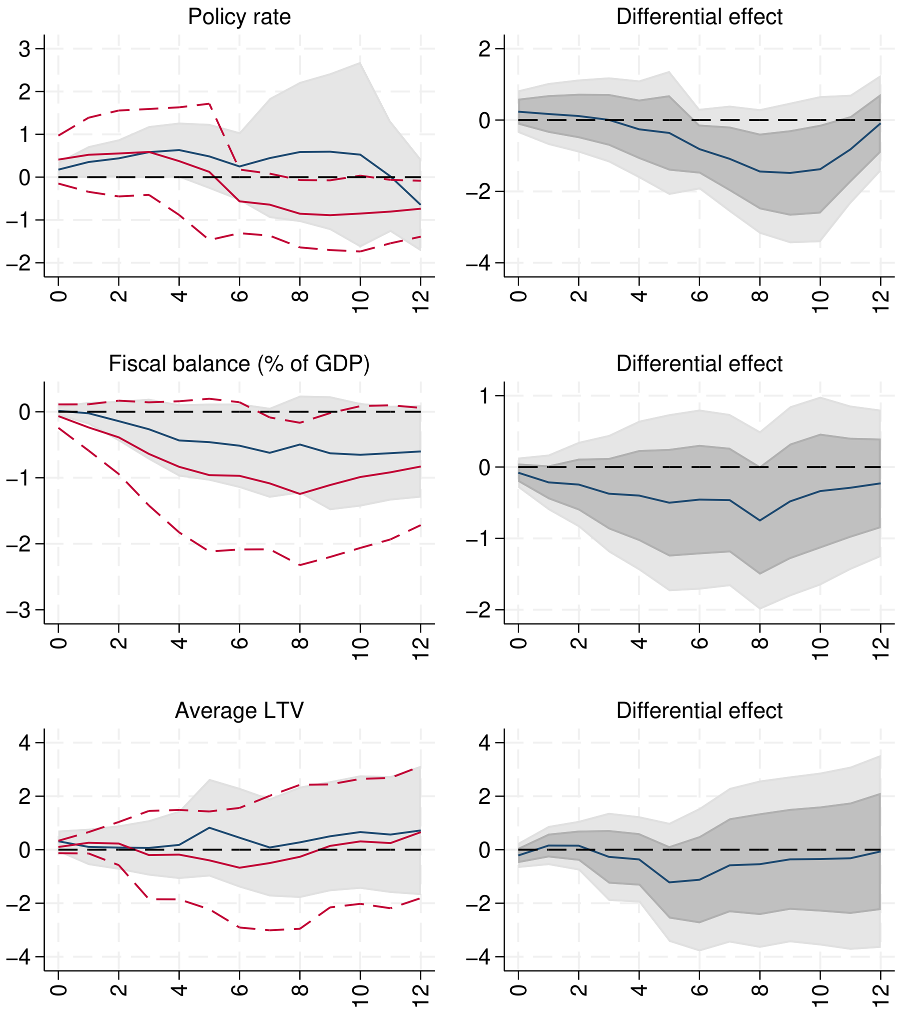
Notes: Dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy during housing booms and non-boom housing expansions. Standard errors double-clustered by country and time.

Figure C.7: Difference in the conditional pattern of selected variables following a housing expansion peak



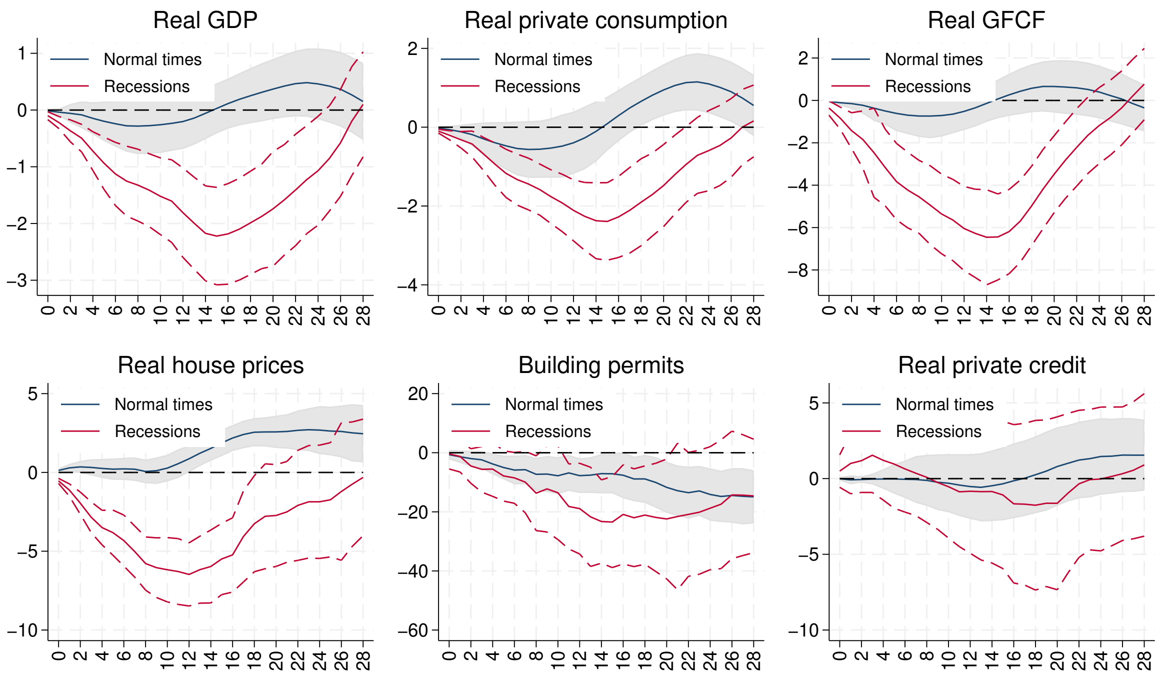
Notes: Dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy following housing expansion peaks, comparing those coinciding with housing booms to those that do not.

Figure C.8: Conditional pattern following a housing expansion peak: the role of policies



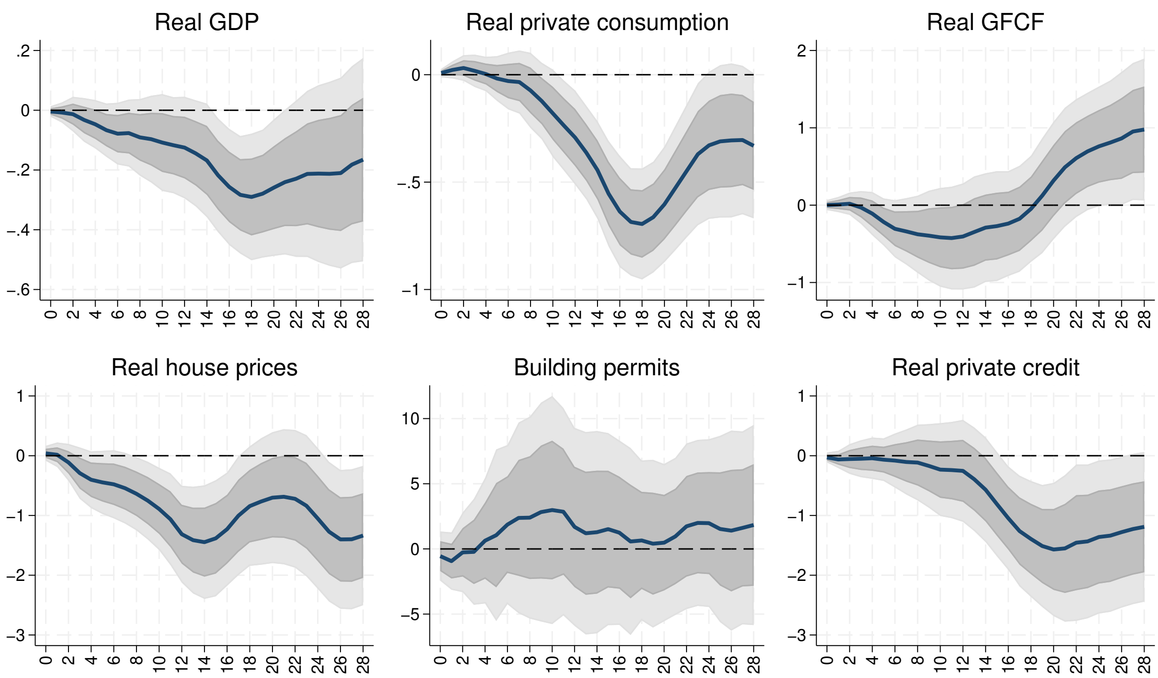
Notes: Left panels: cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms (red lines) against expansion peaks that do not coincide with housing booms (blue line and grey area). Right panels: dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy following housing expansion peaks, comparing those coinciding with housing booms to those that do not.

Figure C.9: Conditional pattern of selected variables following housing innovations: recessions versus normal times



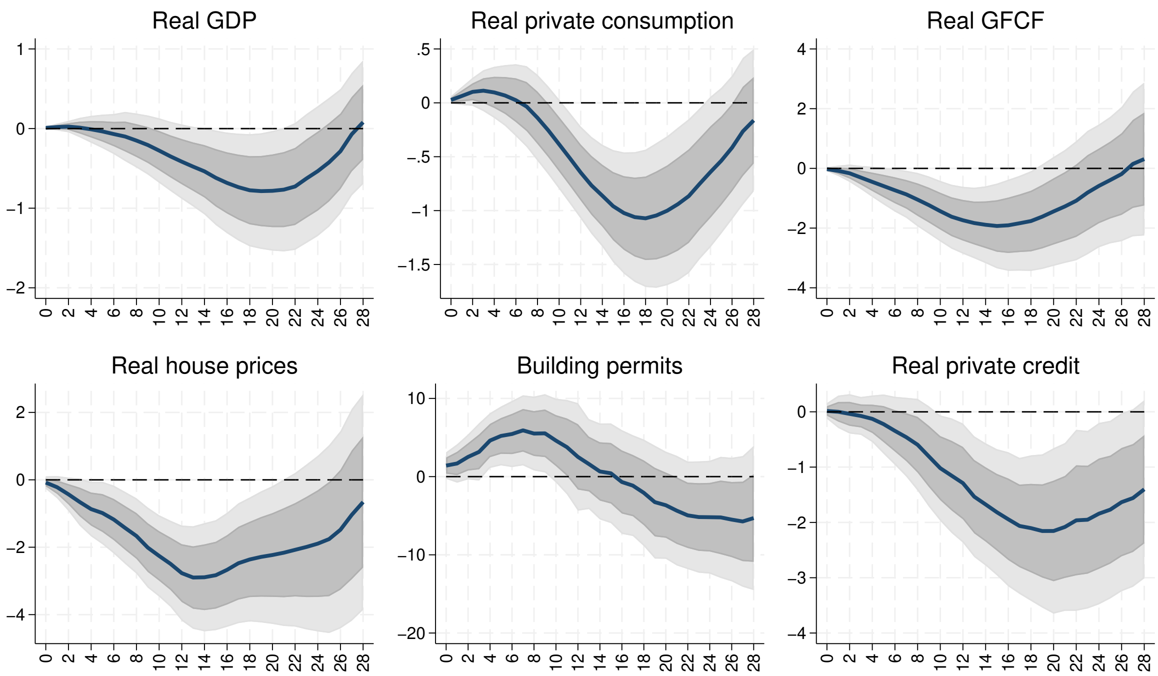
Notes: Cumulative impulse responses of selected variables over 28 quarters following a one-standard deviation increase in HPI for normal periods (blue line and grey area) and recessions (red lines). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.10: Marginal effects on selected variables from housing innovations that coincide with household credit expansions



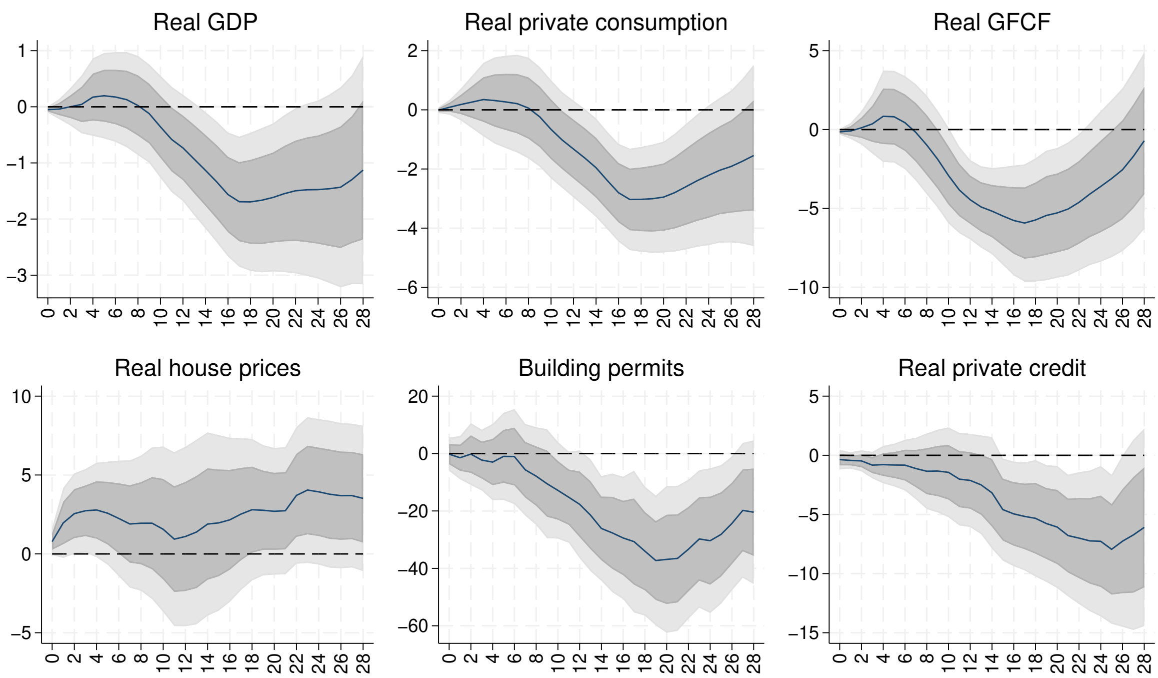
Notes: Cumulative marginal effects over 28 quarters from the interaction of a one-standard deviation increase in both housing innovations and household credit expansions. Dark (light) grey areas refer to the associated 68% (90%) confidence bands. Standard errors double-clustered by country and time.

Figure C.11: Marginal effects on selected variables from housing innovations that coincide with nonfinancial credit expansions



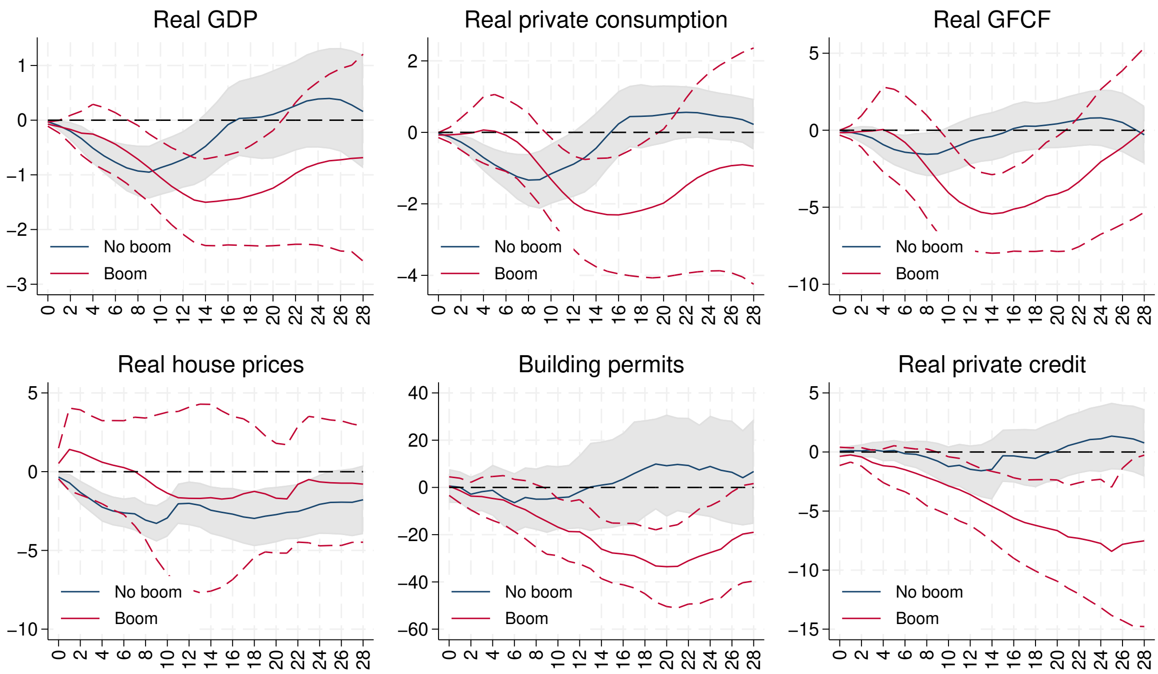
Notes: Cumulative marginal effects over 28 quarters from the interaction of a one-standard deviation increase in both housing innovations and nonfinancial corporate credit expansions. Dark (light) grey areas refer to the associated 68% (90%) confidence bands. Standard errors double-clustered by country and time.

Figure C.12: Difference between housing booms and non-boom housing expansions



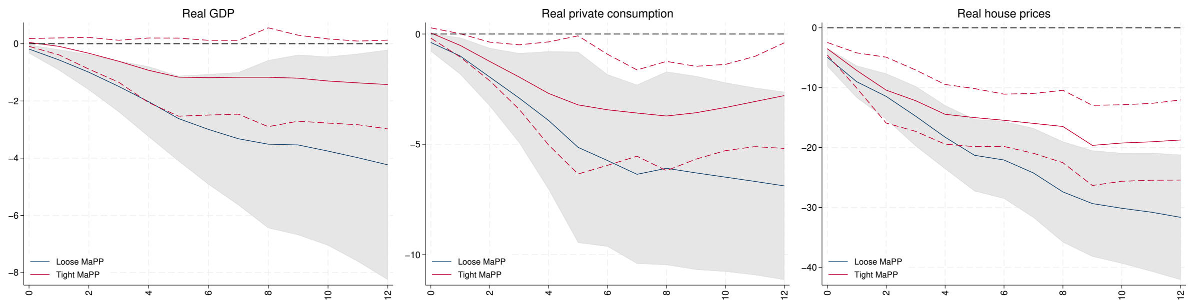
Notes: Dark (light) grey areas refer to the 68% (90%) confidence bands in the difference between the conditional path of the economy following housing booms and non-boom housing expansions.

Figure C.13: Conditional pattern of selected variables following housing innovations: controlling for fiscal and monetary policy



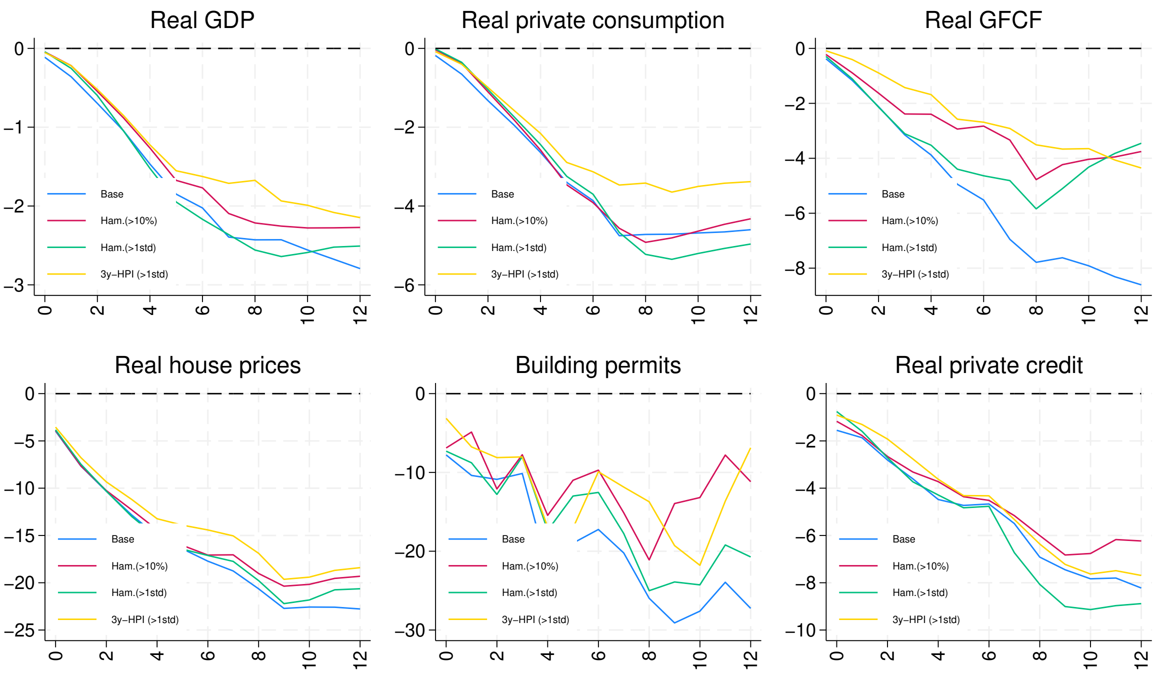
Notes: Cumulative impulse responses of selected variables over 28 quarters following a one-standard deviation increase in housing innovations, measured with the 12-quarter change HPI, for non-boom housing expansions (blue line and grey area) and housing booms (red lines). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.14: Conditional pattern of selected variables following a housing boom peak: conditional on average LTVs



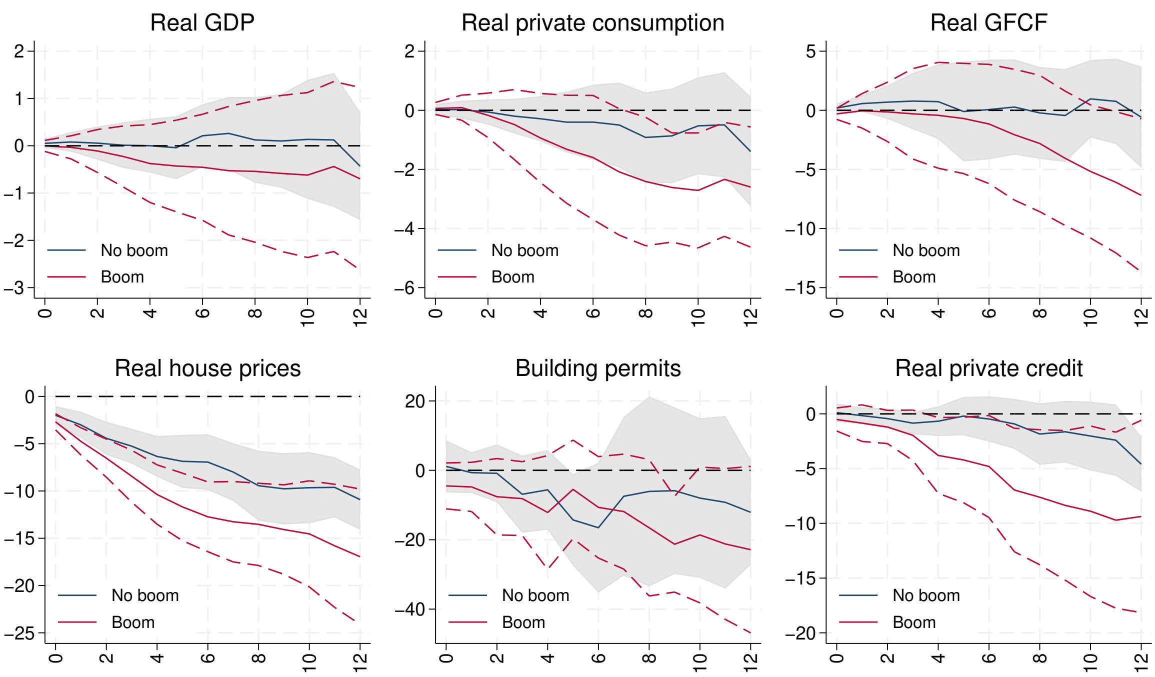
Notes: Cumulative impulse responses of selected variables over 12 quarters following the peak of housing booms for countries with tight LTVs (red lines) against the rest of the sample (blue line and grey area). Tight LTVs is a dummy variable taking the value of one in each quarter for countries with an average LTV that falls in the bottom decile of the country-specific distribution. The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.15: Conditional pattern of selected variables following a housing expansion boom: alternative housing boom definitions



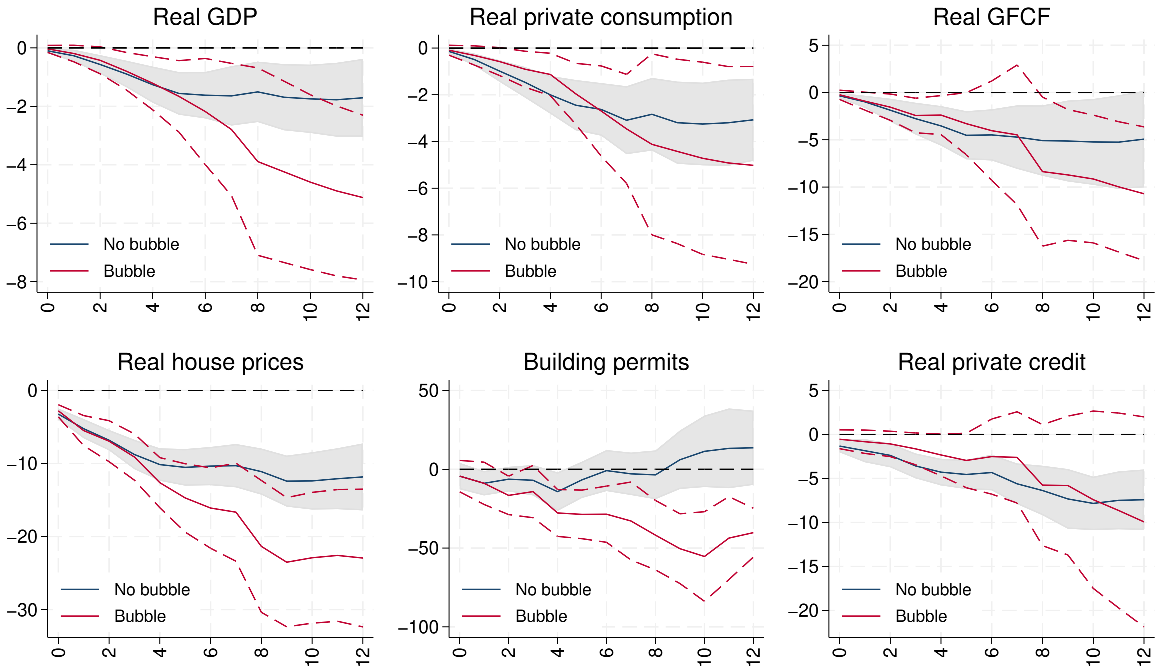
Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms for alternative housing boom definitions.

Figure C.16: Conditional pattern of selected variables following a housing expansion peak: expansion defined based on HPI



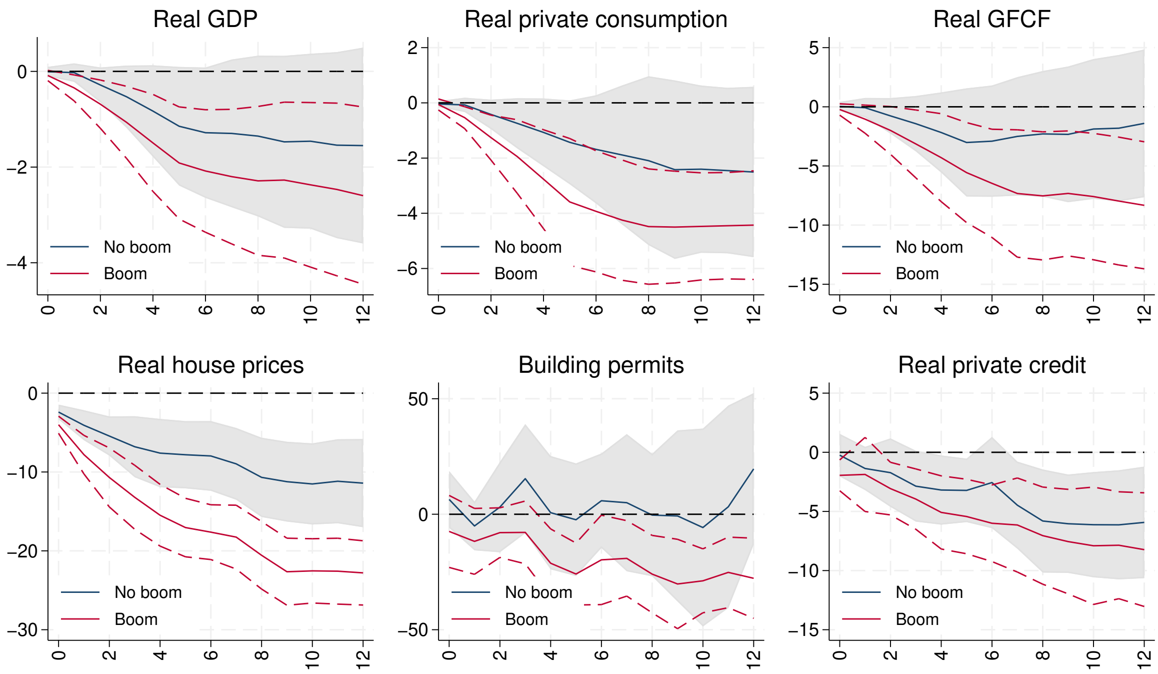
Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms (red lines) against expansion peaks that do not coincide with housing booms (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.17: Conditional pattern of selected variables following a housing expansion peak: bubbles vs non-bubbles



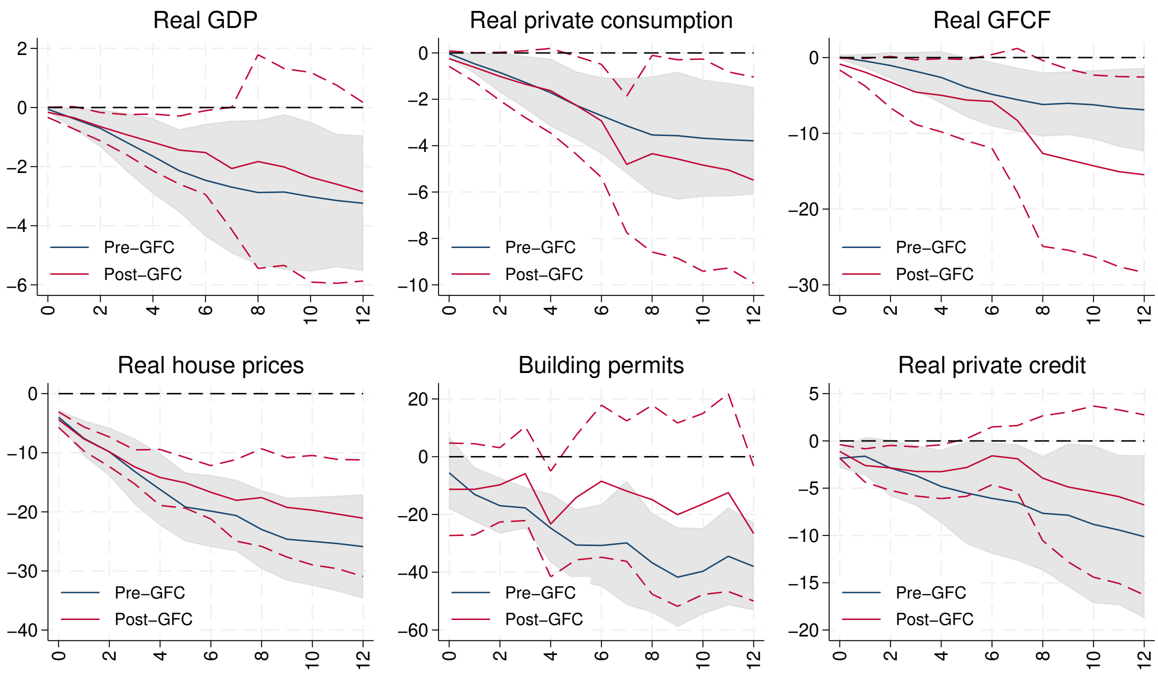
Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing bubbles (red lines) against expansion peaks that do not coincide with housing bubbles (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time. Housing bubbles are identified with the Phillips et al. (2015) method.

Figure C.18: Conditional pattern of selected variables following a housing expansion peak: excluding Covid sample



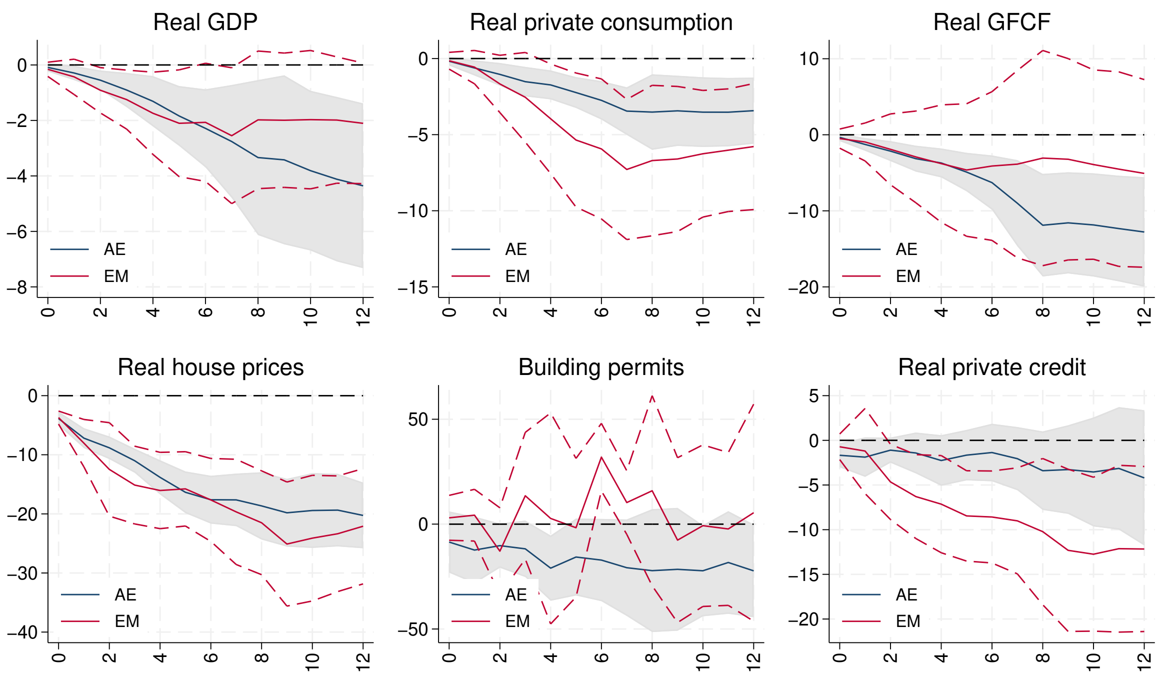
Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms (red lines) against expansion peaks that do not coincide with housing booms (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.19: Conditional pattern of selected variables following a housing expansion boom: pre-GFC vs post-GFC



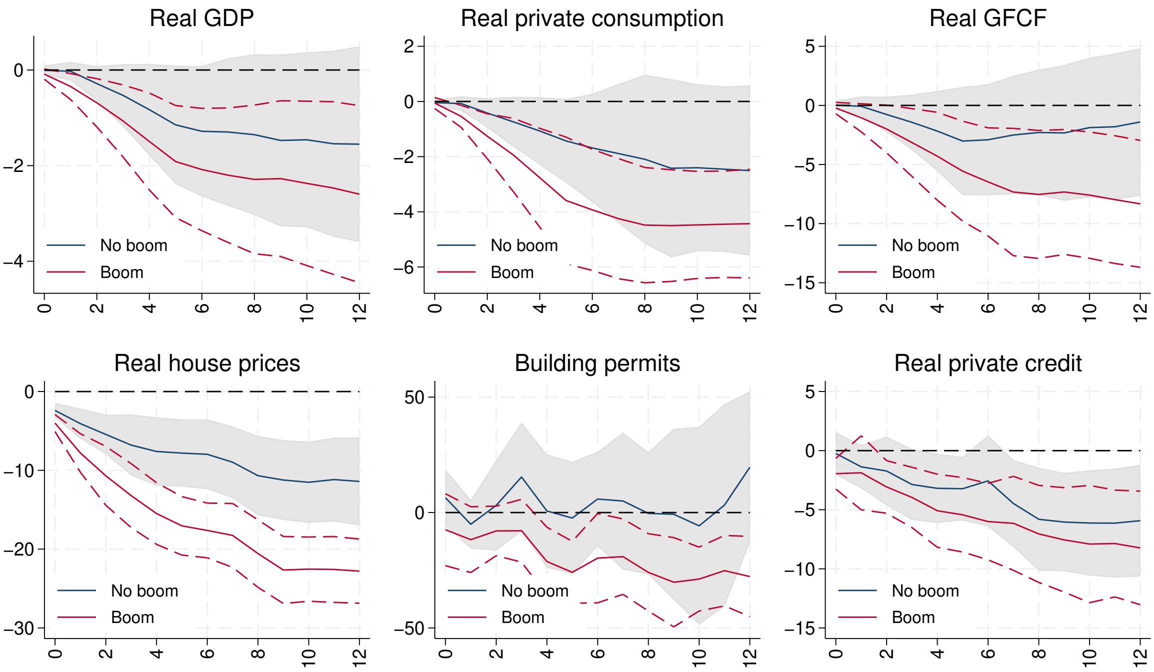
Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms after the GFC (red lines) and before the GFC (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.20: Conditional pattern of selected variables following a housing expansion boom: AEs vs EMs



Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms for EMs (red lines) and AEs (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

Figure C.21: Conditional pattern of selected variables following a housing expansion peak: year-on-year growth rates



Notes: Cumulative impulse responses of selected variables over 12 quarters following housing expansion peaks that coincide with housing booms (red lines) against expansion peaks that do not coincide with housing booms (blue line and grey area). The grey area and dashed red lines refer to the respective 90% confidence bands. Standard errors double-clustered by country and time.

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