Disentangling the drivers of exuberant house prices*

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Abstract

This paper explores the fundamental drivers of U.S. housing price exuberance using a Time-Varying Parameter VAR model with Stochastic Volatility, combined with the recursive right-tailed unit root testing framework of Phillips et al. (2015a,b). The goal is to identify the structural shocks behind periods of exuberance—characterized by rapid increases in house prices beyond their fundamental values—and provide deeper insights into their dynamics. While exuberance is often attributed to non-fundamental factors, our analysis shows that it can also emerge from fundamental shocks, particularly those related to credit supply and demand. The results demonstrate statistically significant differences in the first-moment dynamics of house prices to credit-related shocks during exuberant versus non-exuberant periods, highlighting their critical role in driving housing market fluctuations. Additionally, our approach reveals previously undetected periods of exuberance when house prices are conditioned on structural shocks, which remain hidden when analyzing the broader housing price dynamcis alone.

Keywords: House prices, Time-varying VAR, Explosive time series, Generalized sup ADF test.

JEL Classification: C22, E30, E32

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1 Introduction

Since 2012, real house prices in the United States have experienced a steady upward trajectory, with a marked acceleration since the early 2020s. This trend has raised significant concerns among policymakers, as housing prices influence inflation through their impact on the rental market and represent a substantial portion of household wealth, making real estate a critical financial asset. Understanding the factors driving these price increases is essential, particularly during periods of exuberance—characterized by mildly explosive dynamics, as outlined by Phillips and Magdalinos (2007) and Magdalinos (2012). A deep understanding of these drivers and close monitoring can equip policymakers with the necessary tools to prevent or mitigate the formation of housing bubbles through sound policy measures.

The main goal of this research is to develop a new tool that can help monitor house prices in terms of the sources of exuberance. In the literature, housing exuberance can be defined as a period when house prices increase rapidly and significantly beyond their fundamental value. In fact, the notion of exhuberance results from unknown structural breaks from a stationary or random walk process which can be tested in the time series data. However, techniques for detecting episodes of exuberance or explosive dynamics are limited to identifying its beginning and end points,−as seen in Phillips et al. (2015a,b), LeRoy and Porter (1981), Shiller et al. (1981), West (1987), among others−lacking the ability required to dissect and understand the drivers of these exuberance periods (or but fall short in explaining its causes). To illustrate, periods of exuberance can be compared to the experience of having a high body temperature, or fever—a condition where the body's temperature rises above the normal range, signaling an underlying health issue like an infection or inflammation. Hence, in this paper, we aim to complement the literature by identifying the economic drivers that cause periods of exuberance in the housing market.

We propose a methodology that combines standard VAR techniques with the recursive right-tailed unit root testing and date-stamping procedure, proposed by Phillips et al. (2015a,b), to overcome this limitation. This approach allows us to examine the impact of structural shocks—such as uncertainty, credit demand, credit supply, and housing service expectations—on house prices, identified with zero-sign restrictions. Our approach, takes into account possible changes in the macroeconomic environment. This allows to obtain reliable estimates as major changes have occurred in recent years. For example, (i) time series displaying boom-and-bust dynamics, such as real house prices, feature nonlinear dynamics (because they burst), and (ii) the 2008 economic-financial crisis and the recent pandemic may have induced gradual structural changes in the economy. Moreover, there is evidence that the volatility of shocks may have changed over time (Cogley and Sargent (2005); Fernández-Villaverde and Rubio-Ramírez (2010)). The Phillips et al. (2015a,b) test is adopted in our procedure for its power to identify one or more periodically-collapsing episodes of mildly explosive behavior in-sample (as shown in Homm and Breitung (2012), Martínez-García and Grossman (2020), Phillips and Shi (2020)). The approach works as follows, after conditioning the path of house prices to each of these shocks, we apply the exuberance test, enabling us identify which structural shocks are inducing periods of exuberance.

Incorporating insights from the macro-housing literature, our research builds on the pioneering work of Pavlidis et al. (2016) and Martínez-García and Grossman (2020), who employed a dynamic panel probit and logit frameworks to empirically investigate whether macro and financial fundamentals can predict housing market exuberance. They find that financial variables, such as interest rates or credit growth, as well as the traditional housing fundamentals, such as growth in real personal disposable income, are among the best predictors. Extending these novel results, our methodology allows us to pinpoint the specific periods during which fundamental shocks exhibit exuberant behavior. Our research also builds on the broad literature that analyses the main drivers of house price fluctuations to appropietaly identify them in our framework. Foundational work of Davis and Heathcote (2007) and Liu et al. (2013) emphasize the importance of housing demand shocks, as key drivers of land price fluctuations and hence house price fluctuations. Additionally, Adelino et al. (2016) and Favilukis et al. (2017) underscore the significant roles of income and credit in driving house prices, illustrating how financial deregulation can amplify housing price dynamics. Justiniano et al. (2019) identify credit supply shocks as significant contributors to housing booms, a finding that Dong et al. (2022) further develop by linking credit supply to housing demand through a framework of heterogeneous beliefs. From the role of expectations, Shiller (2007) highlights its critical role in shaping housing markets, where psychological factors and feedback loops can lead to price bubbles. This view is further developed by Kaplan et al. (2020), who demonstrate how shifts in household expectations can drive housing booms and busts. Similarly, Nathanson and Zwick (2018) show how builders' expectations, particularly regarding land availability, influence housing prices, aligning with the broader analysis of how expectations shape market dynamics.

Our main results extend these findings by pinpointing specific periods when these structural shocks exhibit exuberant behavior, underscoring a novel understanding of housing market dynamics. The results of our empirical analysis reveal that periods of exuberance in the housing market are not solely driven by non-fundamental factors but can also be attributed to fundamental shocks such as credit demand and supply. Furthermore, our findings indicate that uncertainty and household expectations also generate significant periods of exuberance, underscoring the complexity of the housing market- as recently Kaplan et al. (2020) suggested. However, with respect to Kaplan et al. (2020), we do not find that household expectations are the sole driver of the U.S. housing boom-bust, but a mix of credit (supply and demand) factors, as Justiniano et al. (2019) and Adelino et al. (2016) pointed out. Moreover, our new approach uncovers new periods of exuberance prompted by these varied structural shocks, which were previously undetected when analyzing the principal series of house prices alone. Furthermore, the most recent surge in housing exuberance is traced back to a confluence of shocks related to credit supply, credit demand, uncertainty, and expectations. However, in the current period, the exuberant episode is being driven by supply credit, uncertainty, and household expectations shocks. Notably, house prices conditioned on household expectations have exhibited positive exuberant behavior since 2004, suggesting a prolonged influence of expectations on market dynamics. This comprehensive view of the drivers of exuberance is very useful for policymakers. It offers nuanced insights into the underlying mechanisms of the housing market and provides a foundation for formulating specific macroeconomic policies, since under this framework the drivers of house price exuberance are uncovered.

Finally, we assess whether the identified periods of exuberance are driven by structural changes in the model's dynamics. Specifically, we investigate whether the impulse response functions (IRFs) of house prices to each structural shock exhibit significant differences between exuberant and non-exuberant periods. Our results show that the responses to credit supply and credit demand shocks exhibit statistically significant differences between these periods. During exuberant periods, the impulse responses to these credit-related shocks are consistently larger in magnitude from impact up to 10 quarters ahead, suggesting a structural change in house price behavior during these periods. This indicates that credit-related factors play a critical role in driving housing market exuberance. In contrast, uncertainty, household expectations, and residual shocks do not show significant differences between exuberant and non-exuberant periods, suggesting that these shocks may influence the market more gradually or indirectly (through changes in second moments).

The remainder of the paper is structured as follows. Section 2 illustrates the empirical approach and describes the data. Section 3 reports and discusses the results. Section 4 provides conclusions.

2 The empirical approach

In this section, we describe the econometric approach used as well as the data.

2.1 Testing for exuberant periods

In this paper, we adopt the real-time bubble detection method proposed by Phillips et al. (2015a,b), henceforth PSY. This approach employs a generalized sup Augmented Dickey-Fuller (GSADF) procedure, a method for recursive right-tailed unit root testing, aimed at identifying and marking periods of mildly explosive behavior. Moreover, as Phillips and Shi (2019) show, this approach not only detects bubbles but can also detect steep market declines. This procedure involves the recursive execution of the ADF test, contrasting the hypothesis of a unit root with that of a mildly explosive root (the right tail of the distribution), applied across a series of subsamples.

We standardize the entire dataset for the GSADF analysis to the interval $[0, 1]$ by normalizing with the total count of observations, T. The start and finish of each subsample are represented by r_1 and r_2, respectively, ensuring $0 \leq r_1 < r_2 \leq 1$. The term $rw = r_2 - r_1$ specifies the window size of the regression estimation. The minimum span r_0 is necessary to encompass the initial and final points of the subsample, thus setting bounds $r_1 \in [0, r_2 - r_0]$ and $r_2 \in [r_0, 1]$. Following the approach by Phillips et al. (2015a,b), the GSADF test involves a recursive estimation of the ADF regression for each subsample as follows:

$$\Delta y_t^{r_1,r_2} = a_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{j=1}^{k} \psi_j^{r_1,r_2} \Delta y_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d., (0, \sigma^2_{r_1,r_2}), \tag{1}$$

where y_t represents the time series analyzed for explosive traits, with Δy_t indicating the first differences of the series across $j = 1, \ldots, k$, and ε_t is an i.i.d. error term. The parameters $a_{r_1,r_2}, \beta_{r_1,r_2}$, and $\psi_j^{r_1,r_2}$ correspond to the regression's intercept, autoregressive coefficient, and the coefficients for the lagged differences, respectively, for any given subsample from r_1 to r_2.

The recursive estimation of (1) generates a sequence of ADF statistics, $ADF_{r_1}^{r_2}$ defined as $\frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})}$. The GSADF statistic of Phillips et al. (2015a,b) is computed as the supremum value within the sequence of $ADF_{r_1}^{r_2}$ statistics, formally represented as:

$$\text{GSADF}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ \sup_{r_2 \in [r_0, 1]} \text{ADF}_{r_1}^{r_2} \right\}. \tag{2}$$

If the GSADF(r_0) statistic exceeds its critical value on the right tail of its distribution, this leads to the rejection of the null hypothesis, which posits a unit root presence. Instead, it supports the alternative hypothesis indicating a mild explosive behavior.

Let's define $EX_{i,t}$ as a binary indicator for a time series i, which is assigned a value of 1 during periods of detected exuberance and 0 in its absence.

$$EX_{i,t} = \begin{cases} 0 & \text{if } BSADF_{i,t}(r_0) < scv_{at}, \\ 1 & \text{if } BSADF_{i,t}(r_0) > scv_{at}. \end{cases} \tag{3}$$

Where $BSADF_{i,t}(r_0)$ denotes the Backward Sup ADF statistic for sequence i, computed as $BSADF_{i,t}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{i,r_1}^{r_2}$ for each designated endpoint sample r_2, where $t = \lfloor r_2 T \rfloor$ translates to the corresponding endpoint observation. The comparison of $BSADF_{i,t}(r_0)$ against the critical value scv_{at}, which corresponds to the $100(1-\alpha)\%$ critical value for the Sup ADF statistic for observation $t = \lfloor r_2 T \rfloor$, a sample comprising T observations, and a specified significance level α, forms the basis for determining the presence of an explosive behavior in the sequence.

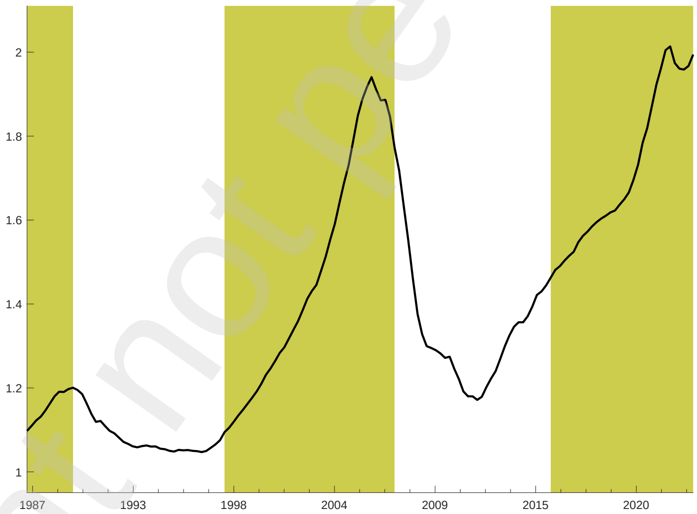


Figure 1: Exuberant Periods of U.S. House Prices

Note: The solid line is the U.S. Real Residential Property Prices for United States index 1981:Q1=1 and the green areas are the periods where the PSY statistic exceeds its 95% bootstrapped critical value.

The beginning of an exuberant period, as described by the preceding equation, occurs when the BSADF statistic first exceeds its critical threshold. Conversely, the end of this period is identified when the BSADF statistic falls back below this critical value. Following the recommendation of Phillips et al. (2015a,b) and Pavlidis et al. (2016), we require that a meaningful episode of exuberance must last for at least a fraction $\frac{\ln(T)}{T}$ of consecutive periods for a series of sample size T.[1] Therefore, we adjust the dummy variable $EXU_{i,t}$ accordingly to ensure a minimum duration for

[1] In our case, the number of consecutive periods is five.

each episode of exuberance counted in the chronology and exclude very short occurrences.

The minimum window size r_0 needs to be large enough to allow initial estimation but not too large to miss an early bubble episode. As recommended in PSY, the minimum window size r_0 is set equal to $0.01 + 1.8/\sqrt{T}$. Finally, following Phillips and Shi (2020), we implement the PSY testing procedure that incorporates a new bootstrap method that simultaneously addresses heteroskedasticity and multiplicity (the probability of making false positive identifications increases with the number of hypotheses tested) in detecting bubbles.[2]

Figure 1 plots the chronology of exuberant behavior in real house prices for the U.S. We can identify three distinct periods of strong exuberance at the national level: the first episode is between 1986Q4 and 1989Q4; the second is from 1998Q1 to 2007Q2, which is the longest exuberant period of our sample, including the expansionary phase of the bubble and the crisis period. The third one is from 2015Q4 to 2023Q3.

This test has proven instrumental in detecting periods of exuberance, which are typically attributed in the literature to non-fundamental factors. However, it is equally important to examine whether various drivers could underlie such behaviors. One might question whether these exuberant periods are driven not only by non-fundamental factors but also by shocks related to expectations, uncertainty, or even fundamental economic changes. In the following section, we introduce a framework designed to address these questions.

2.2 Data: Sources, and Transformation

Sources. Data are collected from the United States, featuring a quarterly frequency covering the period from the 1978Q1 to 2023Q3. Data compilation involved two primary sources: (i) The Federal Reserve Economic Data (FRED), which provided metrics on real disposable personal income, the average 30-year fixed-rate mortgage, real residential property prices, and total mortgages held by households and nonprofit organizations; and (ii) the University of Michigan's Survey of Consumer Expectations, which included households' outlook on the buying conditions for houses and large household goods. These expectations are qualitatively reported as aggregated diffusion time series, designed to monitor anticipated cyclical movements. Specifically, households were surveyed regarding their perception of the current time as either good or bad for: (i) purchasing a house, and (ii) acquiring major household items.

Transformations. The series not already available in the seasonally adjusted form are seasonally adjusted using JDemetra+ 2.2 -this software uses the following algorithm X-13ARIMA-SEATS.[3] Data are transformed in growth rates, except for the 30-year fixed-rate mortgage. The two survey variables are averaged out to summarize their information into a single variable.

[2] In the bootstrapping procedure, we implement an empirical size control spanning four years. This empirical size refers to controlling the probability of committing Type I errors. The larger the empirical size, the lower the probability of committing Type I errors. Phillips and Shi (2020) recommend utilizing a two-year empirical size for this purpose.

[3] For robustness, data is also seasonally adjusted using the TRAMO-SEATS algorithm provided by JDemetra+ 2.2.

2.3 Model

We use a time-varying VAR model with stochastic volatility (TVP-VAR-SV) along the modelling lines of Benati and Mumtaz (2007) and Galí and Gambetti (2009). Let y_t be a vector containing the following variables: real disposable income, the 30 year fixed rate mortgage, credit, housing services expectations and real house prices. Let us assume that y_t follows

$$y_t = A_{0,t} + A_{1,t}y_{t-1} + ... + A_{p,t}y_{t-p} + \epsilon_t = X_t'\theta_t + \epsilon_t \tag{4}$$

where ϵ_t is a Gaussian white noise vector of innovations with time-varying covariance matrix Σ_t, $A_{0,t}$, is a vector of time-varying intercepts and $A_{i,t}$, are matrices of time-varying coefficients, $i = 1, ..., p$. Let $A_t = [A_{0,t}, A_{1,t}, ..., A_{p,t}]$, and $\theta_t = vec(A_t')$ being the stacking column operator. The VAR coefficients are assumed to evolve as random walk

$$\theta_t = \theta_{t-1} + \nu_t, \tag{5}$$

where ν_t is a Gaussian white noise vector with covariance Ω, and independent of ϵ_t at all leads and lags. The innovation variance is decomposed as $\Sigma_t = F_tD_tF_t'$, where F_t is a lower triangular matrix with ones on the main diagonal and D_t a diagonal matrix. Let σ_t be a column vector that contains the diagonal elements of $D_t^{1/2}$ and let λ_t be a vector containing all the elements of F_t^{-1} below the diagonal, stacked by rows. Their law of motion are as follows

$$log\ \sigma_t = log\ \sigma_{t-1} + \varepsilon_t, \tag{6}$$

$$\lambda_t = \lambda_{t-1} + \psi_t, \tag{7}$$

where ε_t and ψ_t are Gaussian white noise vectors with zero mean and variance Ξ and Ψ, respectively. We assume that Ψ has a block diagonal structure, i.e., all the covariances between coefficients belonging to different equations are zero, and that Ξ is diagonal;

$$\Psi = \begin{bmatrix} S_1 & 0_{1\times 2} & \cdots & 0_{1\times 5} \\ 0_{2\times 1} & S_2 & \ddots & 0_{2\times 5} \\ \vdots & \ddots & S_i & 0_{i\times 5} \\ 0_{5\times 1} & \cdots & 0_{5\times i} & S_5 \end{bmatrix}, \ \Xi = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \ddots & \vdots \\ \vdots & \ddots & \sigma_i & \vdots \\ 0 & \cdots & 0 & \sigma_5 \end{bmatrix}.$$

Finally, we assume that ν_t, ε_t and ψ_t are all mutually independent.

We assume that the vector of reduced-form VAR innovations ϵ_t is a linear transformation of the vector of underlying "structural" shocks $\boldsymbol{u}_t \equiv \left[u_t^{cd}, u_t^{cs}, u_t^{un}, u_t^{hh}, u_t^{r}\right]'$, satisfying $E\left\{\boldsymbol{u}_t\boldsymbol{u}_t'\right\} = \mathbf{I}$ for all t, where $u_t^{cd}, u_t^{cs}, u_t^{un}, u_t^{hh}, u_t^{r}$ represents a credit demand shock, credit supply shock, uncertainty shock, households expectation shock, and a residual shock, respectively. Thus, we assume $\epsilon_t = \mathbf{C}_t\boldsymbol{u}_t$ for all t for some nonsingular matrix $\mathbf{C}_t$ satisfying $\mathbf{C}_t\mathbf{C}_t' = \Sigma_t$. Identification of structural shocks is achieved with sign and zero restrictions using the algorithm proposed by Arias et al. (2018) (see Section 2.6).

2.4 Priors Specification

Following Galí and Gambetti (2009), Benati and Mumtaz (2007), and Primiceri (2005), we assume that the covariance matrices Ω, Ξ, and Ψ and the initial states, θ_0, λ_0 ,and $\log\sigma_0$, are independent.

The prior distributions for the initial states are normally distributed, and the prior distributions for Ω^{-1} and Ψ_i^{-1} are Wishart; the diagonal elements of Ξ^{-1} are Gamma. More precisely,

$$\begin{aligned}
\theta_0 &\sim N\left(\hat{\theta}, \hat{\mathcal{V}}_\theta\right) \\
\log \sigma_0 &\sim N\left(\log \hat{\sigma}, 10 \times \mathcal{I}_n\right) \\
\lambda_{i0} &\sim N\left(\hat{\lambda}_i, \hat{\mathcal{V}}_{\lambda_i}\right) \\
\Omega^{-1} &\sim W\left(\underline{\Omega}^{-1}, \underline{\rho}_1\right) \\
\Psi_i^{-1} &\sim W\left(\underline{\Psi}_i^{-1}, \underline{\rho}_{2i}\right) \\
\Xi_{i,i}^{-1} &\sim G\left(\frac{0.01^2}{2}, \frac{1}{2}\right)
\end{aligned}$$

where $W(\mathbf{S}_W, d_W)$ denotes a Wishart distribution with scale matrix $\mathbf{S}_W$ and degrees of freedom d_W; $G(\mathbf{S}_G, d_G)$ denotes a Gamma distribution with scale matrix $\mathbf{S}_G$ and degrees of freedom d_G, and $\mathbf{I}_n$ is a $n \times n$ identity matrix where n is the number of variables in the VAR.

Prior means and variances of the Normal distributions are calibrated using a time invariant VAR with 2 lags, employing the first 20 observations (1978Q3-1983Q3). Given the short sample, we use a standard Minnesota prior, with the hyperparameter for the overall tightness equal to the commonly used value of 0.2 (Giannone et al. (2015)), with the prior for the "own-lag" parameter centered at 1. Prior for the variance are weakly informative, inverse Wishart distribution, centered at the their standard deviation values. We set $\hat{\theta}$ and $\hat{\mathcal{V}}_\theta$ equal to their posterior mode.

Let $\hat{\Sigma}$ be the covariance matrix of the residuals, $\hat{\epsilon}_t$, from the initial time-invariant VAR. We apply the same decomposition discussed in the text $\hat{\Sigma} = \hat{F}\hat{D}\hat{F}'$ and set $\log \hat{\sigma}_0$ equal to the vector containing the elements of the diagonal matrix $\hat{D}$, $\hat{\lambda}_i$ are the i-th row elements of the lower triangular matrix $\hat{F}^{-1}$, and $\hat{\mathcal{V}}_{\lambda_i}$ are the absolute value of the i-th row elements of the lower triangular matrix $\hat{F}^{-1}$ times 4.

We parametrize the scale matrices as follows $\underline{\Omega} = \underline{\rho}_1 \left(0.0035 \times \hat{\mathcal{V}}_\theta\right)$, $\underline{\Psi}_i = \underline{\rho}_{i,2} \left(0.001 \times |\hat{\lambda}_i|\right)$. The degrees of freedom for the priors on the covariance matrices: Ω^{-1}, $\underline{\rho}_1$ is set equal to the number of rows $\underline{\Omega}^{-1}$ plus the number of observations in the initial sample divided by two (i.e., 10). This "tightness" is desirable to avoid getting stuck rejecting every (or almost every) candidate draw, to find that the VAR coefficients are not explosive. Ψ_i^{-1}, $\underline{\rho}_{i,2}$ are set equal to the number of rows $\underline{\Psi}_i^{-1}$ plus one.

2.5 Estimation

To simulate the posterior distribution of the hyperparameters and the states conditional on the data, we use a Markov-Chain Monte Carlo (MCMC) algorithm, the Gibbs sampler, which works in an iterative way. Each iteration is done in four steps:

step 1: $p(\theta^T | y^T, \lambda^T, \sigma^T, \Omega, \Psi, \Xi)$,

step 2: $p(\lambda^T | y^T, \theta^T, \sigma^T, \Omega, \Psi, \Xi)$,

step 3: $p(\sigma^T | y^T, \theta^T, \lambda^T, \Omega, \Psi, \Xi)$, step 4: $p(\Omega|y^T,\theta^T,\lambda^T,\sigma^T,\Psi,\Xi)$, $p(\Psi|y^T,\theta^T,\lambda^T,\sigma^T,\Omega,\Xi)$, $p(\Xi|y^T,\theta^T,\lambda^T,\sigma^T,\Omega,\Psi)$,

and involves drawing a subspace of coefficients conditional on a specific realization of the remaining coefficients and then utilizing this realization in the conditional densities of the remaining coefficients. Under specified regularity conditions and following a burn-in period, iterations through these four steps yield draws from the joint density. See appendix B of Galí and Gambetti (2009) for details of the Gibbs sampler algorithm. In the estimation, we use 171 observations starting from 1981Q1. We perform 150,000 repetitions. We discard the first 140,000 draws and keep one for every 20 of the remaining 10,000 draws to break the autocorrelations of the draws. Appendix B plots the draws' inefficiency factors, which assess the satisfactory converge of the MCMC algorithm.

2.6 Identification

House price fluctuations can result from credit expansion caused due to looser credit conditions (e.g., a fall in the mortgage rate) or by an increase in borrowers' demand for credit (e.g., an increase in the current or future income). Likewise, an expectations shock affecting the perceived consumption of housing services in the future may cause house price increases without the need of influencing the mortgage market. An easy way to bypass this problem is to impose restrictions that orthogonalize the shocks to ensure that these are not correlated.

In the model, we employ a mixed strategy for the identification framework across the short and medium run. For the short run, identification is achieved through sign restrictions applied over a fifth-quarter horizon, leaving the dynamics on impact unrestricted. In contrast, for the medium run, zero restrictions are used at a horizon of 16 quarters (four-year horizon). Identification is summarized in Table 1, which are mutually exclusive and jointly exhaustive, are sufficient to set apart our structural shocks of interest. Within this framework, we distinguish five types of shocks: a credit supply shock, a credit demand shock, a financial uncertainty shock, a housing services belief shock, and a residual shock. The residual shock, which is not formally interpreted, serves as a buffer, accounting for the impacts of omitted variables and other shocks that do not conceptually align with the first four categories identified.

	Credit Supply	Credit Demand	Financial Uncertainty		HH Belief		Residual
			short-run	medium-run	short-run	medium-run	
Real Disposable Income	NR	+	-	0	NR	0	NR
Credit	+	+	-	NR	NR	0	-
30Y Mortgage Rate	-	+	+	NR	NR	NR	NR
Expectations Housing Services	NR	NR	NR	NR	+	NR	NR
Real House Prices	+	+	NR	NR	+	NR	+

Table 1: Identification restrictions

Note: Sign restrictions are imposed on the cumulative impulse response over five quarters, leaving the dynamics on impact unrestricted for all variables. Zero restrictions are imposed at a horizon of 16 quarters.

Our restrictions are supported by extensive theoretical and empirical literature under the following assumptions:

Credit supply shock. A positive credit supply shock is characterized by the negative comovement between credit and the mortgage rate, leading to increasing credit availability and decreasing mortgage rates; as in Christiano et al. (2010), Curdia and Woodford (2010), Gerali et al. (2010) and Gertler and Karadi (2011). Moreover, house prices are expected to increase, as in Favara and Imbs (2015). Finally, we leave the response on real disposable income unrestricted given that it is not evident that credit supply shocks (on average) have a significant effect on output, see Helbling et al. (2011). An example of a positive credit supply shock is a change to looser credit conditions.

Credit demand shock. This is defined as a shock that affects almost all the variables in the short-run in the same direction - except expectations which we do not restrict. While a credit supply shock moves the mortgage rate spread and credit in opposite directions, credit demand shock affects these variables in the same direction. A potential shifter for credit demand is an increase in the expected future income.

Housing services expectations shock. A positive household belief shock can be interpreted as a increase in the future housing preference of households (i.e., the willingness to invest in housing), along with an increase in real house prices. Moreover, we assume that this shock does not affect the dynamics of fundamental variables such as real disposable income, and credit in the medium-run. This concept is employed by Fève and Guay (2019) to identified sentiment shocks and by Pinilla-Torremocha (2022) to identify expectation shocks.

Finantial Uncertainty shock. A negative uncertainty shock implies a increase in the mortgage rate (i.e., an increase in financing conditions). Mortgage rates rise with increasing uncertainty, either because the true credit quality becomes more ambiguous (Duffie and Lando (2001)) or investors become concerned about the liquidity in financial markets (Dick-Nielsen et al. (2012)). Following well-known results from Bernanke (1983); Dixit and Pindyck (1994) and Bloom (2009), we impose a decrease in the real disposable income and credit. When uncertainty is high, investors, firms and financial institutions increase precautions, generating a negative impact in macroeconomic variables such as unemployment, real gdp and therefore, the real disposable income of the households. Furthermore, to distinguish the financial uncertainty shock from the credit supply shock, we assume that the financial uncertainty shock cannot explain the medium-term dynamics of macroeconomic variables such as real disposable income. This restriction is in line with the recent results of Jurado et al. (2015). Nevertheless, unlike the expectation shock, it can explain the medium-term dynamics of financial variables such as credit.

Residual shock. The residual shock, which we do not formally interpret, moves credit and house prices in opposite directions to differentiate from a credit supply and demand shocks.

2.7 Historical Decomposition in a TVP-VAR-SV

We can write equation (4) in its companion form as follows:

$$\mathrm{Z}_t = \mathrm{H}\mu_t + \mathrm{A}_t Z_{t-1} + \mathrm{H}C_t u_t \tag{8}$$

where

$$\mathrm{Z}_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, \quad \mathrm{A}_t = \begin{bmatrix} \mathrm{A}_{1t} & \mathrm{A}_{2t} & \cdots & \mathrm{A}_{pt} \\ \mathrm{I}_N & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & \mathrm{I}_N & 0 \end{bmatrix}, \quad \mathrm{H} = \begin{bmatrix} \mathrm{I}_N \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

u_t is a vector of structural shocks which are assumed to be each normally and independently distributed with unit variance. The matrix C_t maps the reduce form VAR residuals, ϵ_t, to the structural shocks, u_t.

Recursive substitution of Equation (8) yields:

$$\begin{aligned}
\mathrm{Z_t} &= \mathrm{H}\mu_t + \mathrm{A_t}\mathrm{Z_{t-1}} + \mathrm{H}C_t u_t \\
&= \mathrm{H}\mu_t + \mathrm{A_t}\left\{\mathrm{H}\mu_{t-1} + \mathrm{A_{t-1}}\mathrm{Z_{t-2}} + \mathrm{H}C_t u_{t-1}\right\} + \mathrm{H}C_t u_t \\
&= \mathrm{H}C_t u_t + \mathrm{A_t}\mathrm{HC}_{t-1}u_{t-1} + \mathrm{A_t}\left\{\mathrm{A_{t-1}}\mathrm{Z_{t-2}}\right\} + \mathrm{H}\mu_t + \mathrm{A_t}\mathrm{H}\mu_{t-1} \\
&= \mathrm{H}C_t u_t + \mathrm{A_t}\mathrm{HC}_{t-1}u_{t-1} + \left\{\prod_{\mathrm{i=0}}^{1}\mathrm{A_{t-i}}\right\}\mathrm{Z_{t-2}} + \mathrm{H}\mu_t + \mathrm{A_t}\mathrm{H}\mu_{t-1} \\
&= \underbrace{\mathrm{H}C_t u_t + \sum_{\mathrm{j=1}}^{\mathrm{t-(p+1)}}\left\{\prod_{\mathrm{i=0}}^{\mathrm{j-1}}\mathrm{A_{t-i}}\right\}\mathrm{HC_{t-j}}u_{t-j}}_{\text{Contribution from Shocks}} + \\
&\quad \underbrace{\underbrace{\left\{\prod_{k=0}^{t-(p+1)}\mathrm{A_{t-k}}\right\}\mathrm{Z_p}}_{\text{Initial Conditions}} + \underbrace{\mathrm{H}\mu_t + \sum_{\mathrm{j=1}}^{\mathrm{t-(p+1)}}\left\{\prod_{\mathrm{i=0}}^{\mathrm{j-1}}\mathrm{A_{t-i}}\right\}\mathrm{H}\mu_{t-j}}_{\text{Steady State Component}}}_{\text{Baseline Projection}}.
\end{aligned} \tag{9}$$

Z_t is a linear function of the history of structural shocks, and an exogenous component, known as baseline projection. This baseline projection is the sum of two components: (i) the initial conditions, due to the fact that the VAR takes initial observations as given, and (ii) the steady state component, which is generated due to the inclusion of a constant in the VAR. Under this approach, we can obtain the historical dynamics of house prices conditioned on each of the identified structural shocks. The series tested for explosiveness are reconstructions, in levels, of the historical decomposition of house prices driven by each structural shock. Since the historical decompositions retrieved from the VAR are expressed in growth rates, we reconstruct the level series by normalizing the initial period of each series to 1. This reconstruction enables us to apply the PSY test to identify periods of mildly explosive dynamics for house prices conditional on each structural shock.

3 Results

In this section, we analyze what drivers of house price can create exuberance periods. To this end, we estimate the TVP-VAR-SV over the baseline sample (1981Q1-2023Q3). Given the choice of modeling changes in the macroeconomic environment, we report posterior estimates of these parameters, as well as structural impulse response functions and variance decomposition analysis.

3.1 What drivers could trigger the exuberant periods in U.S. house prices?

Figure 2 displays the PSY test results for the historical decomposition of house prices conditional on each structural shock: credit supply, credit demand, uncertainty, HH expectations, and the residual. This figure highlights new exuberance periods driven by these structural shocks, which are not detected when analyzing the principal series of house prices alone, as we can see in Figure 1. This finding is plausible, as there is a compensatory effect among structural shocks across different periods, meaning not all shocks are positive or negative simultaneously. Another notable feature in the series is the overlapping periods of exuberance during the 2000s boom-bust housing cycle and following the COVID-19 period, which are also evident in the principal series.

A novel finding is that periods of exuberance are detected when house prices are only driven by fundamental structural shocks, such as credit demand or supply. This result contrasts with the prevalent interpretation of such tests when applied to asset price variables, where the detection of exuberance is often attributed to non-fundamental factors. In contrast, our analysis reveals exuberance periods driven by fundamental shocks. Moreover, this result is in line with those of Pavlidis et al. (2016) and Martínez-García and Grossman (2020), who suggest that identified exuberance periods in the principal series can be explained by fundamental variables within a probit/logit framework. As expected, shocks related to uncertainty and expectations also display exuberant behavior. Additionally, our findings regarding residual shocks align with those obtained by Shi (2017). The residual shock, intended to capture omitted variables or serve as a buffer, leads to more sporadic exuberance periods with shorter duration, consistent with Shi's (2017) results using an alternative method.

Furthermore, our approach enables us to determine that the most recent surge in housing exuberance was mainly driven by a combination of four shocks: credit supply, credit demand, uncertainty, and expectation shocks. To date, the current exuberant episode is being driven by supply credit, uncertainty, and household expectations shocks. Interestingly, house prices conditioned on household expectations have shown positive exuberant behavior since 2004. These results confirm that exuberance can be influenced by a variety of shocks, not solely non-fundamental factors. This insight not only informs policymakers about underlying market dynamics but also serves as a powerful tool to develop macroeconomic policies aimed at controlling these exuberant periods. Such policies could help achieve more stable dynamics in house prices.

3.2 Why time-variation in parameters and volatility?

Figure 3 shows the evolution of residual time-varying variances. Significant time variation in these variances is evident in most cases, characterized by notable spikes. For instance, spikes are observed in house prices corresponding with the boom-bust cycle of the 2000s, and in disposable income during the great financial crisis and the Covid-19 pandemic. Additionally, there is a marked decrease in the volatility of mortgage rates throughout the 1980s and 1990s. Overall, the evidence supports the use of stochastic volatility specifications.

To establish whether time-variation in the parameters is a feature of the data, we follow Cogley

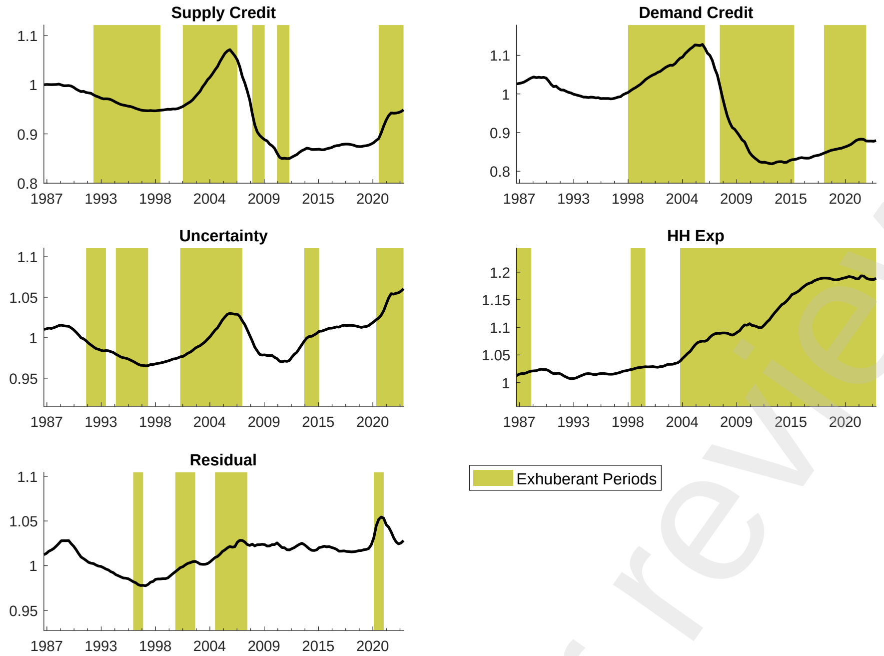


Figure 2: Historical decomposition of U.S. house prices conditional on each structural shock

Note: The shaded areas are the periods where the PSY statistic exceeds its 95% bootstrap critical value. Each variable is normalized to one, for a starting period 1981:Q1.

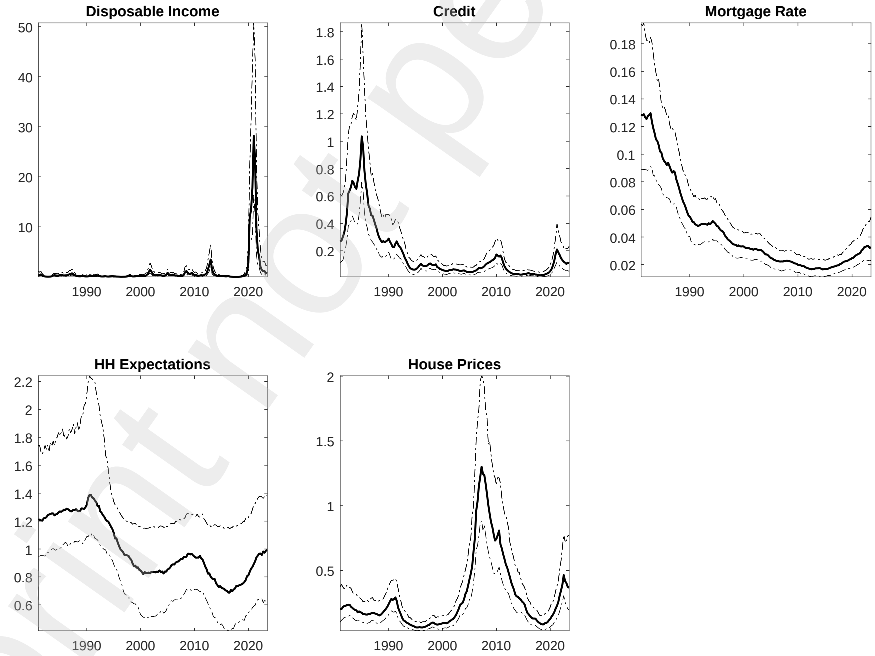


Figure 3: Stochastic volatility

Note: The full lines are the posterior medians of the residual time-varying variances. Dashed lines are the 16th and 84th percentiles of the residual time-varying variances.

and Sargent (2005). The trace of the prior variance-covariance matrix, Ω_0, is smaller than even the 16% percentile of the posterior; thus, the sample points towards greater time variation in the parameters than that of the prior selected.[4] Furthermore, to strengthen the evidence of time variation in parameters, we conduct an analysis similar to that proposed by Cogley et al. (2010). This exercise involves scatter plots of the draws of parameters capturing the impulse responses of house prices to the structural shocks at different horizons (on impact, and at five and fifteen quarters ahead), as shown in Figures 8, 9, 10, 11, and 12 in Appendix A. Each horizon compares the draws at two points in time: 1984Q1 vs 2019Q1, 1994Q1 vs 2022Q2 and 2007Q2 vs 2020Q2, respectively. For example, if the impact impulse response function of house prices to a structural shock had remained relatively stable over time, the parameter combinations from early in the sample (e.g., 1984Q1) and later (e.g., 2019Q1) would cluster near the 45-degree line. However, this is not observed for any shock at any horizon. The figures demonstrate fifteen instances where combinations of parameters deviate significantly from the 45-degree line, reinforcing our conclusion that key parameters have likely evolved over time.

Our analysis reveals detectable time variation in the cumulative impulse responses of house prices to structural shocks over various time horizons, as depicted in Figure 4. Impulse response functions are re scaled to have the same-sized shock at each point in time; this normalization allows to focus on how the system's dynamics (first moments) evolve over time, independent of the changing size or variability of the shocks (second moments). This figure illustrates the responses on impact and at five, fifteen, and thirty quarters ahead. Sign restrictions are imposed five quarters ahead, requiring that responses at this horizon be significant, although the significance of the short-term impact remains undetermined.

We find that the short-term impact of household expectation shocks on real house prices has intensified since the 2000s, becoming more significant over time. This observation aligns with Dong et al. (2022), who emphasize the role of imperfect information and expectations in driving housing and credit cycles. When examining different horizons, particularly thirty quarters ahead, it appears that prior to the 2000s, shocks not significant on impact had significant and lasting effects. Post-2000s, however, shocks were significant on impact but not at thirty quarters ahead. This shift suggests a change in how shocks propagate through the housing market over time, consistent with the structural changes highlighted by Kaplan et al. (2020) in their model of the housing boom and bust.

The impact of supply credit shocks has generally remained negligible, except during the boom-bust cycle of the 2000s. This finding corroborates the work of Justiniano et al. (2019), who identify credit supply expansion as a key driver of the housing boom during that period. Conversely, the impact of demand credit shocks has been significant over the whole sample, except in recent years, supporting the notion that credit demand has been a persistent factor influencing house prices. This is in line with Adelino et al. (2016), who discuss the significant role of middle-class borrowers and credit demand factors in the mortgage crisis. From 1980 to 2000, supply and demand credit shocks affected house prices by an average of between 1.5 and 5 percentage points five quarters ahead. The effect of both shocks increased ten to twenty times during the 2000s boom-bust cycle at the same horizon. This amplification is consistent with the models of Liu et al. (2013) and Garriga

[4]See Table 2 in Appendix A.

et al. (2019), who highlight the substantial macroeconomic implications of land-price dynamics during periods of boom and bust.

Finally, it appears that supply shocks have had persistent effects from the 2000s onward, unlike the impacts of credit demand shocks that were significant primarily around the 2000s. This persistence may reflect structural changes in the housing market and credit conditions, as suggested by Dong et al. (2022), emphasizing the lasting effects of supply-side factors in housing and credit cycles. These findings highlight the evolving nature of these relationships and underscore the importance of considering both demand and supply-side factors, as well as expectations, in analyzing housing market dynamics.

We also ask the model to quantify the relative importance of the structural shocks under consideration. We compute the share of the variance of U.S. house prices attributable to each shock in the system. Figure 5, which presents the variance decomposition of U.S. house prices at different frequencies (median for the whole sample period), reveals how different types of shocks -on average- contribute to fluctuations in house prices across varying time horizons. This decomposition highlights that, over the entire sample, household expectation shocks, credit demand and credit supply shocks are the most dominant drivers at lower frequencies and long-term fluctuations, while uncertainty shocks and other factors play a more limited role. In particular, 50% of the average fluctuations over the sample are explain by credit demand and supply shocks.

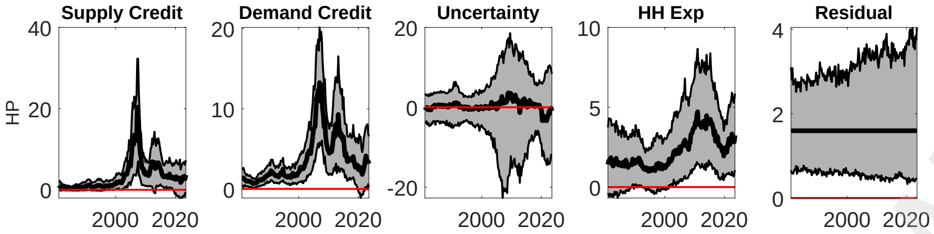
In contrast, Figure 6, which shows the variance decomposition of U.S. house prices at each point in time, provides a more dynamic view, reflecting how the contributions of different shocks have evolved over time. Notably, during the 2000s boom-bust cycle, the impact of credit supply and demand shocks surged significantly across all frequencies, explaining close to 40% and 50% of the total variation, respectively. These results well align with the observed amplification of these factors during this period, as discussed by Liu et al. (2013), Justiniano et al. (2019) and Dong et al. (2022). Post-2000s, the decomposition shows a gradual decline in the influence of credit demand shocks, while the importance of supply-side and expectation-driven shocks has persisted.

3.3 Is the feature of time variation behind the exuberant periods?

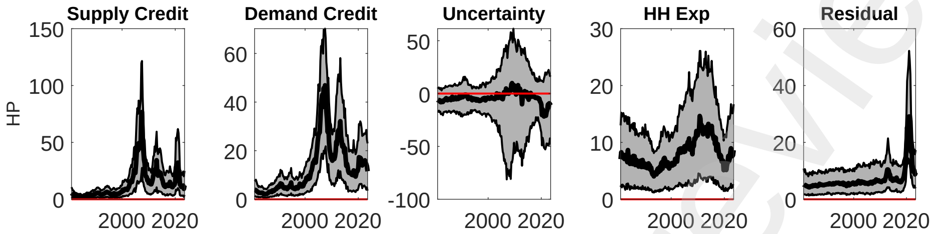
In the next stage of our analysis, we aim to determine whether the identified periods of exuberance are driven by structural changes in the model's dynamics. Specifically, we investigate whether the impulse response functions (IRFs) of house prices to each structural shock exhibit significant differences during exuberant versus non-exuberant periods.

Figure 7 presents the average cumulated IRFs of house prices for exuberant periods (in blue) and non-exuberant periods (in red), categorized by five structural shocks: credit supply, credit demand, uncertainty, household (HH) expectations, and residual shocks. The figure highlights notable distinctions in the responses to credit supply and credit demand shocks. During periods of exuberance, the magnitude of the IRFs is consistently larger from impact up to 10 quarters ahead, indicating a structurally different behavior in these periods.[5] This suggests that there is a

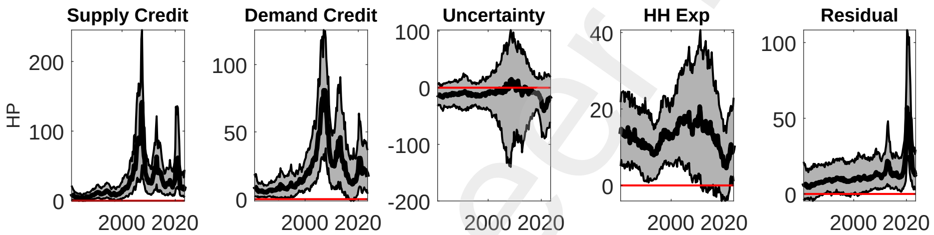
[5]See Figure 13 in Appendix A.



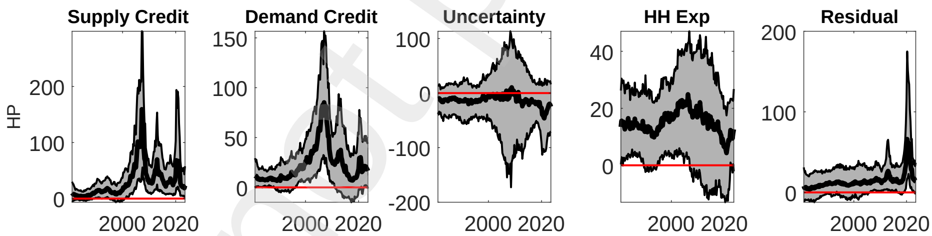
(a) Evolution of house price impulse responses to the different structural shocks on impact



(b) Evolution of house price impulse responses to the different structural shocks five quarters ahead



(c) Evolution of house price impulse responses to the different structural shocks fifteen quarters ahead



(d) Evolution of house price impulse responses to the different structural shocks thirty quarters ahead

Figure 4: Evolution of house price impulse responses to the different structural shocks at different horizons

Note: The figure shows posterior distributions of cumulated impulse response functions of house prices on impact and at five, fifteen, and thirty quarters ahead (over time). Median (solid line) and 68% probability density intervals (shaded area) based on 500 draws.

discernible structural change in the response of house prices to credit-related shocks, which appears to play a critical role in driving periods of housing market exuberance. Specifically, the stronger impulse responses to credit supply and credit demand shocks during exuberant periods indicate that these credit-related factors may be fundamental drivers of such episodes.

In contrast, the impulse responses associated with uncertainty, household expectations, and residual shocks do not display statistically significant differences between exuberant and non-exuberant

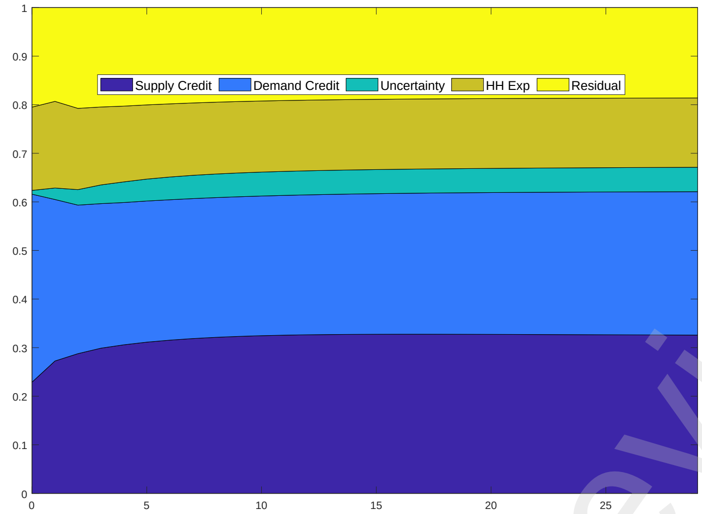


Figure 5: Variance decomposition of U.S. house prices at different frequencies (median whole sample period)

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance contributions of each variable (in cumulative terms) at horizons j = 0, 1, . . . , 29 using baseline restrictions.

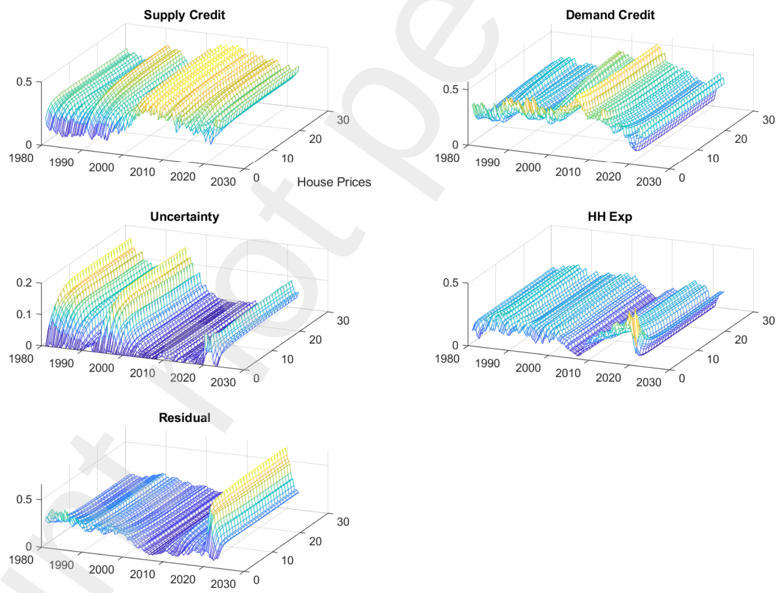


Figure 6: Variance decomposition of U.S. house prices at different frequencies (at each point in time)

Note: Each subplot represents fractions of variance explained by each identified shock for U.S house prices. The lines represent the point-wise median contributions of an identified shock to the forecast error variance contributions (in cumulative terms) at each point in time, and horizons j = 0, 1, . . . , 29 using baseline restrictions.

periods. This could indicate that these shocks do not contribute directly or immediately to the formation of exuberant periods in housing prices, implying that their influence on the market may manifest more gradually or through indirect channels (such as second moments).

One potential explanation for the observed differences in responses between credit-related shocks (demand and supply) and other shocks, such as uncertainty and household expectations, lies in the possibility of a slower adjustment process in the model's autoregressive parameters. Specifically, the parameters associated with uncertainty and expectations might adjust more gradually, which could stem from the underlying structure of the model itself. This could be due to the autoregressive coefficients follow a unit root process with constant and relatively low variance, this would imply that changes in the model's parameters occur very slowly over time.

As a result, changes in coefficients related to uncertainty and household expectations may take longer to significantly influence the model's coefficients, leading to a delayed response in the impulse responses. This contrasts with the quicker adjustments seen in the case of credit supply and demand shocks, which appear to have a more immediate and pronounced impact on housing price dynamics during periods of exuberance. This differential behavior suggests that while credit-related shocks rapidly transmit through the model, other types of shocks may have a more gradual and less immediate effect on house price behavior due to the slower adaptation of the model's parameters to new economic information.

In future research, it may be beneficial to consider alternative modeling frameworks, such as the endogenous models proposed by Leiva-Leon and Uzeda (2023). In these models, the autoregressive coefficients in a time-varying parameter VAR (TVP-VAR) framework are allowed to adjust dynamically in response to structural shocks, which have a higher variance than those of the autoregressive coefficients. This approach, by allowing the coefficients to shift more rapidly in response to economic disturbances, could capture quicker transitions in market behavior that are not as readily observable in traditional TVP-VAR models. However, it is important to note that while such models offer the potential for more dynamic coefficient adjustment, they are still in developmental stages, particularly with respect to incorporating second moment variations alongside structural interpretations. This limits their immediate applicability for capturing the full range of economic dynamics discussed here.

Overall, these finding highlight the importance of monitoring credit conditions and their evolving impact on the housing market, as they seem to trigger and sustain periods of rapid price growth beyond fundamental values.

4 Conclusion

This study has provided a detailed analysis of U.S. housing price exuberance, focusing on the identification of key structural shocks through a Bayesian Structural VAR model with time-varying parameters and stochastic volatility, combined with the recursive unit root testing framework developed by Phillips et al. (2015a,b). Under this methodological approach, we have effectively captured the dynamics behind periods of housing exuberance, highlighting the critical role of credit supply

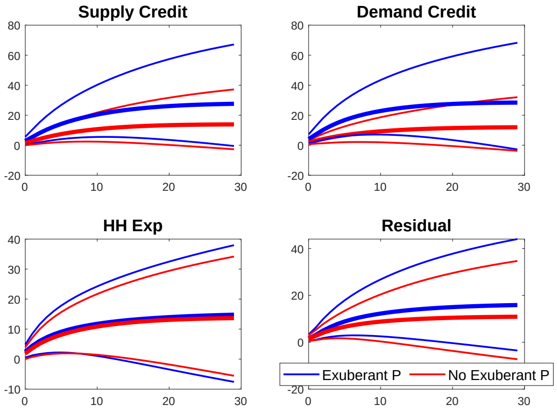


Figure 7: Average impulse response functions of exuberant and non-exuberant periods

Note: The figure shows average posterior distributions of cumulated impulse response functions of house prices of exuberant (blue) and non-exuberant (red) periods. Median (solid line) and 68% probability density intervals based on 500 draws.

and demand shocks in driving such episodes. This framework not only identifies when exuberant periods begin and end but also provides insight into the underlying structural factors that trigger these housing market surges. Our results challenge the view that housing exuberance is solely driven by speculative, non-fundamental factors.

The identification of structural shocks reveals that credit-related factors, specifically credit supply and demand, play a pivotal role in housing market exuberance. Our analysis shows that during exuberant periods, house prices respond significantly more to these credit shocks than in non-exuberant periods, suggesting a structural shift in the relationship (first-moments) between credit and housing prices under exuberant conditions. This highlights the importance of monitoring these credit dynamics as they appear to be fundamental drivers of price bubbles, underscoring the need for targeted policy interventions to mitigate potential housing market risks.

Moreover, while uncertainty and household expectations also generate periods of exuberance, the lack of statistically significant impulse responses between exuberant and non-exuberant periods suggests a different mechanism at play. These findings indicate that the exuberance triggered by uncertainty and expectations may be driven by changes in second moments, rather than shifts in the first-moment dynamics of the model. This distinction underscores the complexity of housing market dynamics, where different shocks can influence the market through distinct channels. Monitoring these second-moment changes could provide additional insight into the risk of future housing exuberance.

In conclusion, this study enhances the understanding of housing price exuberance by identifying the structural shocks at play. Our findings provide a valuable framework for policymakers to better understand the mechanisms driving housing bubbles, thereby offering the potential for more effective macroeconomic policies aimed at promoting stability in the housing market. As structural changes in response to credit shocks are key drivers of exuberance, targeted interventions in credit markets could help mitigate future risks, while further exploration into second-moment dynamics could offer deeper insights into the role of uncertainty and expectations.

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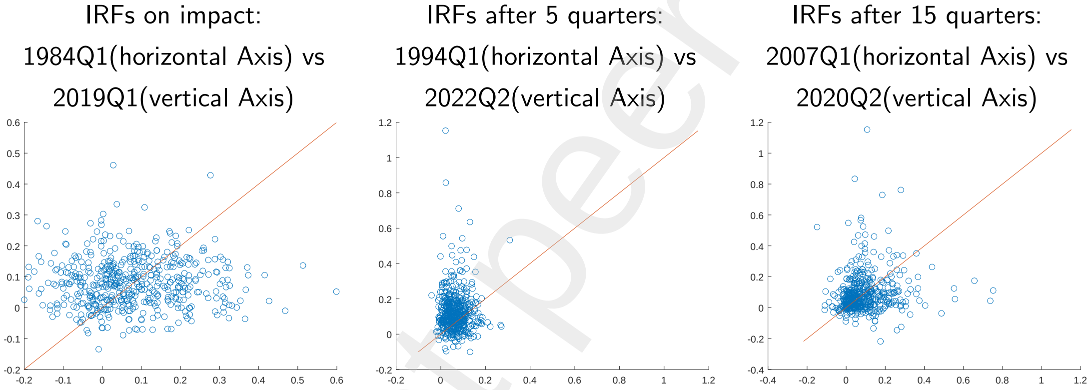
A Supplementary Tables and Figures

16% perc.	50% perc.	84% perc.	trace(Ω_0)
0.0136	0.0192	0.0283	0.0042

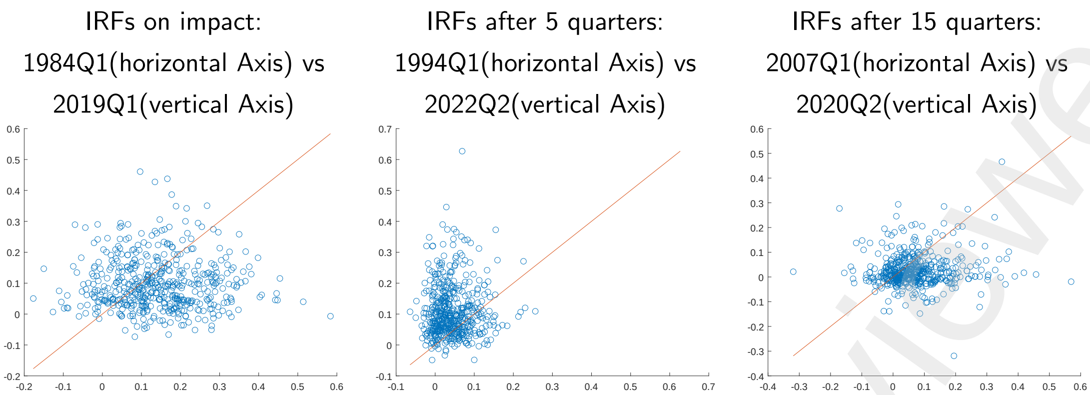
Table 2: Trace test

Note: The three columns in the figures represent the 16%, 50%, and 84% percentiles of the posterior distribution for the trace of the variance-covariance matrix associated with the error term in the VAR parameter dynamics. The trace of the prior variance-covariance matrix is displayed in the fourth column. Echoing the analysis by Cogley and Sargent (2005), the observation that the trace of the prior variance-covariance matrix falls below the 16% percentile suggests evidence of time-varying behavior in the VAR parameters. This indicates that the sample exhibits a greater degree of time variation in the parameters compared to the prior assumptions.



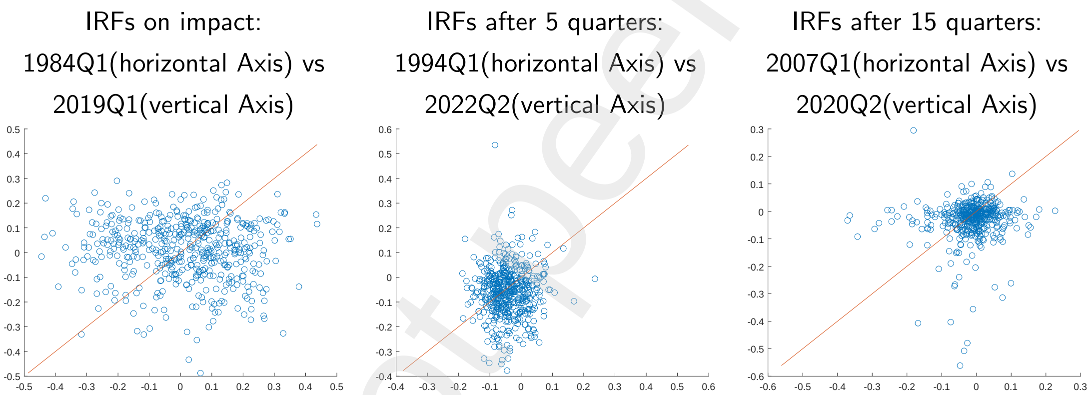
Notes: Joint distribution for posterior impulse responses of house prices after impact, five and fifteen quarters to a credit supply shock, comparing the periods 1984Q1 (horizontal axis) versus 2019Q1 (vertical axis), 19994Q1 (horizontal axis) versus 2022Q2 (vertical axis), 2007Q1 (horizontal axis) versus 2020Q2 (vertical axis).

Figure 8: Impulse Response functions of House Prices to a Credit Supply Shock



Notes: Joint distribution for posterior impulse responses of house prices after impact, five and fifteen quarters to a credit demand shock, comparing the periods 1984Q1 (horizontal axis) versus 2019Q1 (vertical axis), 19994Q1 (horizontal axis) versus 2022Q2 (vertical axis), 2007Q1 (horizontal axis) versus 2020Q2 (vertical axis).

Figure 9: Impulse Response functions of House Prices to a Credit Demand Shock



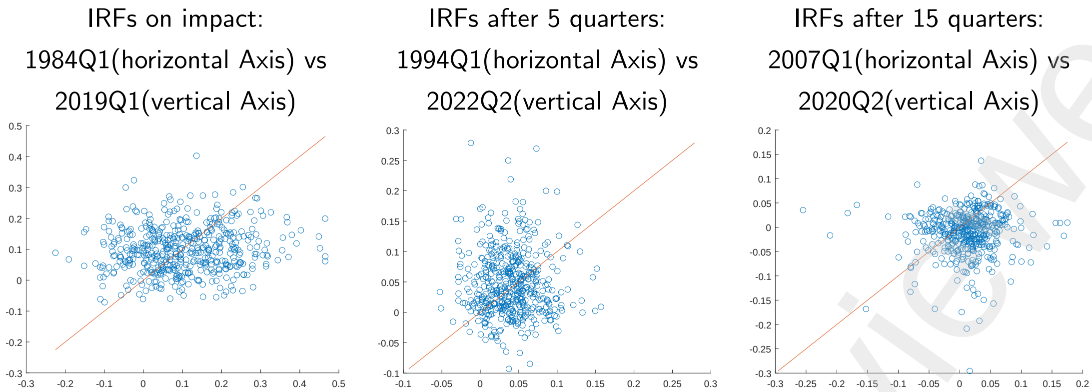
Notes: Joint distribution for posterior impulse responses of house prices after impact, five and fifteen quarters to an uncertainty shock, comparing the periods 1984Q1 (horizontal axis) versus 2019Q1 (vertical axis), 19994Q1 (horizontal axis) versus 2022Q2 (vertical axis), 2007Q1 (horizontal axis) versus 2020Q2 (vertical axis).

Figure 10: Impulse Response functions of House Prices to an Uncertainty Shock

B Convergence of the Markov chain Monte Carlo algorithm

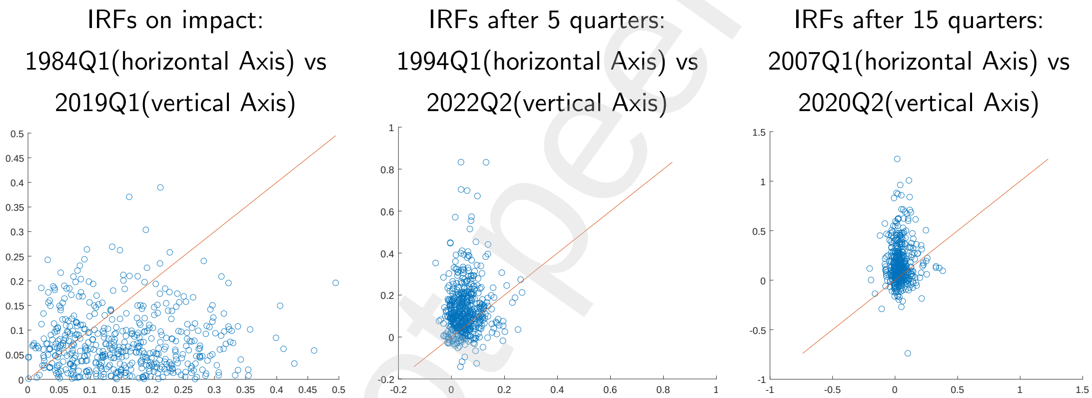
This section of the appendix assesses convergence of the Markov chain Monte Carlo algorithm in the baseline application to the Euro area data. Following Primiceri (2005), we assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws. In order to judge how well the chain mixes, common practice is to look at the draws' inefficiency factors (IF) for the posterior estimates of the parameters. Specifically, that is the inverse of the relative numerical efficiency measure of Geweke et al. (1991), i.e., the IF is an estimate of $(1 + 2\sum_{i=1}^{\infty} \rho_i)$, where ρ_i is the i-th autocorrelation of the chain. In this application, the estimate is performed using a Parzen window.[6] Figure 14 plots a complete description of the

[6] For inefficiency factors, see Section 6.1 of Giordani et al. (2011).



Notes: Joint distribution for posterior impulse responses of house prices after impact, five and fifteen quarters to a household expectation shock, comparing the periods 1984Q1 (horizontal axis) versus 2019Q1 (vertical axis), 19994Q1 (horizontal axis) versus 2022Q2 (vertical axis), 2007Q1 (horizontal axis) versus 2020Q2 (vertical axis).

Figure 11: Impulse Response functions of House Prices to a HH Expectation Shock



Notes: Joint distribution for posterior impulse responses of house prices after impact, five and fifteen quarters to a residual shock, comparing the periods 1984Q1 (horizontal axis) versus 2019Q1 (vertical axis), 19994Q1 (horizontal axis) versus 2022Q2 (vertical axis), 2007Q1 (horizontal axis) versus 2020Q2 (vertical axis).

Figure 12: Impulse Response functions of House Prices to a Residual Shock

characteristics of the chain, which is provided for the different sets of parameters. Θ_t: time-varying coefficients of the VAR; Ω: (hyperparameters) elements of the covariance matrix of Θ_t; λ_t: time varying simultaneous relations; σ_t: time varying volatilities; Ψ, Ξ: (hyperparameters) elements of the covariance matrix of λ_t and σ_t. As stressed by Primiceri (2005), values of the IFs below or around twenty are regarded as satisfactory. All the IFs are below 20, meaning that the densities for the parameters are well behaved. We made many robustness checks for prior specifications and the length of the chain with the main results not being affected significantly.

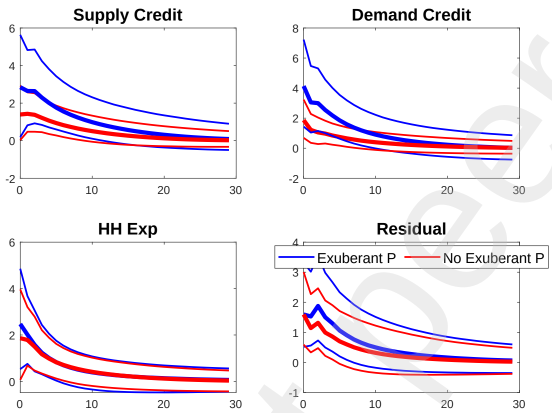


Figure 13: Average impulse response functions of exuberant and non-exuberant periods

Note: The figure shows average posterior distributions of impulse response functions of house prices of exuberant (blue) and non-exuberant (red) periods. Median (solid line) and 68% probability density intervals based on 500 draws.

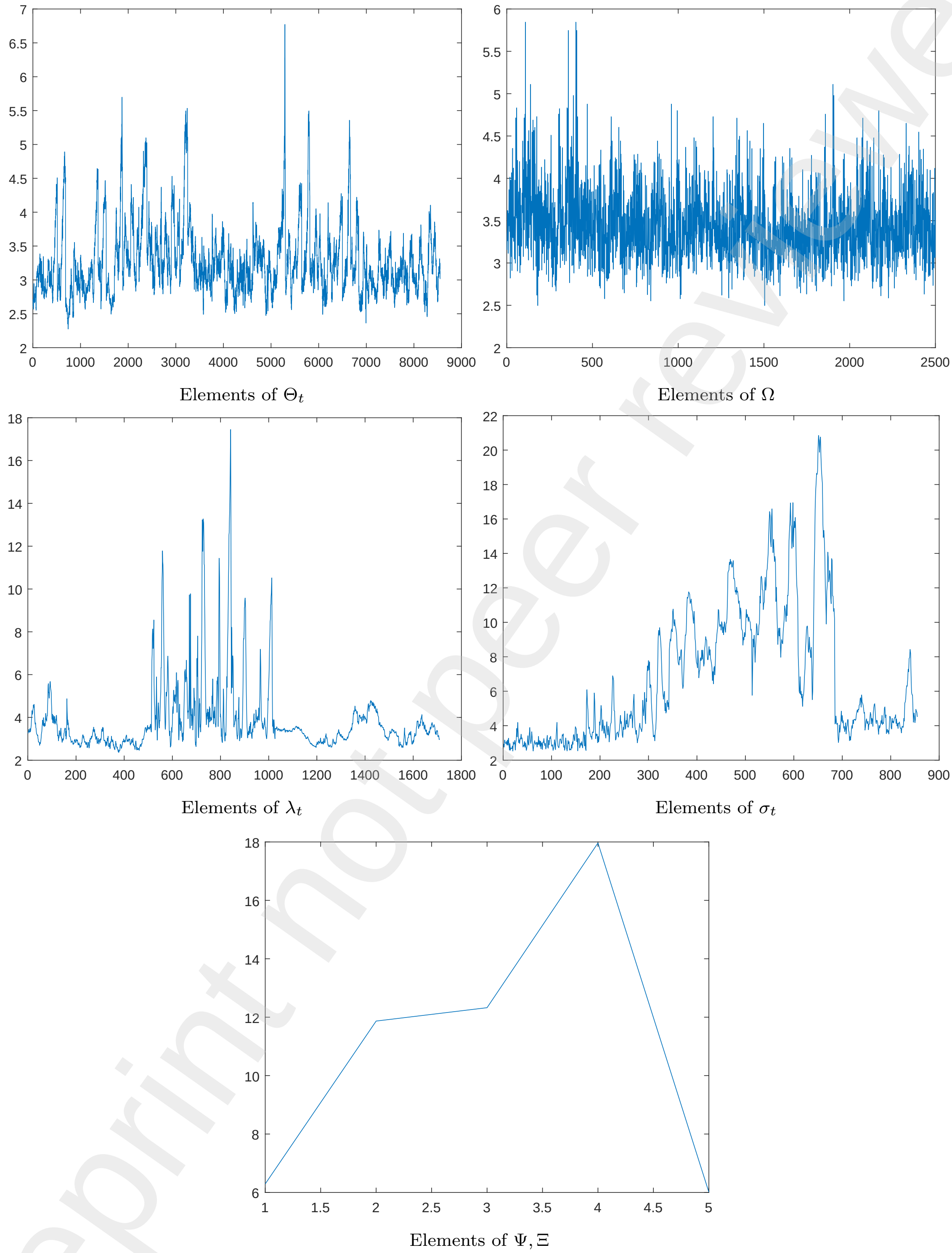


Figure 14: Summary of the distribution of the Inefficiency Factors for different sets of parameters and hyperparameters