Journal of
Risk and Financial Management

MDPI

Article

One Man's Bubble Is Another Man's Rational Behavior: Comparing Alternative Macroeconomic Hypotheses for the US Housing Market

Anastasios G. Malliaris [1,*], Mary Malliaris [1] and Mark S. Rzepczynski [2]

[1] Quinlan School of Business, Loyola University Chicago, 16 E. Pearson, Chicago, IL 60611, USA; mmallia@luc.edu
[2] AMPHI Research and Trading, LLC, Concord, MA 01742, USA; mrzepczynski@amphitrading.com
* Correspondence: tmallia@luc.edu

Abstract: Competing macroeconomic hypotheses have been developed to explain the US housing market and possible bubble behavior. We employ both seasonally adjusted (SA) and non-seasonally adjusted (NSA) monthly data for about 30 independent variables to examine alternative macro hypotheses for home prices. Using a neural network model as an atheoretical non-linear approach to capture the relative importance of alternative macro variables, we show that these hypotheses generate different macro relevance. As an alternative to testing housing time series, we focus on bubble identification being hypothesis dependent. Model forecast errors (residuals) identify the potential presence of bubbles through standardized residual CUSUM tests for structural breaks. By testing for housing bubbles from these unstructured models, we generate conclusions on the presence of bubbles prior to the Great Financial Crisis and the post-pandemic periods. Competing macro hypotheses or narratives will generate different conclusions on the presence of bubbles and create bubble identification issues.

Keywords: housing prices; Great Financial Crisis; quantitative easing; housing bubbles; neural network methodology

JEL Classification: E10; E32; E44; E58; E62; R31

Citation: Malliaris, Anastasios G., Mary Malliaris, and Mark S. Rzepczynski. 2024. One Man's Bubble Is Another Man's Rational Behavior: Comparing Alternative Macroeconomic Hypotheses for the US Housing Market. *Journal of Risk and Financial Management* 17: 349. https://doi.org/10.3390/jrfm17080349

Academic Editor: Susan Wachter

Received: 4 July 2024
Revised: 4 August 2024
Accepted: 8 August 2024
Published: 12 August 2024

1. Introduction

Housing dynamics has become a subject of intense interest since the Global Financial Crisis (GFC) via the potential for "bubbles" that may create macro financial instability. However, there is limited agreement on when housing bubbles occur, especially when framed by macro drivers or hypotheses. Any identification of a bubble based on macro drivers is dependent on the narrative and variables employed. Bubble identification is a joint test of the model used to explain housing price dynamics and the actual presence of a bubble. Two different models may draw different conclusions on the presence of a bubble.

Even with the knowledge gained since the GFC, we have seen significant housing price increases as measured by the S&P CoreLogic Case–Shiller U.S. National Home Price Index, which may represent another housing bubble. After the GFC, housing prices increased from February 2011 to March 2020 by over 55 percent during a period of relatively slow economic growth and near-zero short rates. The dramatic increases in liquidity by the Fed during and after March 2020 and the easy fiscal policies employed to counteract the COVID-19 recession offered further stimulus to housing. The housing index rapidly climbed by over 40% in just over 2 years. Housing prices have reached new highs with economic growth not significantly higher than the pre-GFC period even with new post-GFC macro-prudential policies to reduce speculative housing excess. A key housing question is whether this is a rational response to macro factors or an irrational bubble.

While significant research has been conducted on identifying housing bubbles and price extremes, these macro finance works have focused on time series (discounted present value) properties and have neglected the macro drivers of housing. We employ a different two-step approach by first testing a set of alternative narratives or theories concerning housing price dynamics using a non-linear atheoretical neural network model to compare narratives that can explain housing prices, and second, identifying housing bubbles based on these hypotheses.

From a set of competing macro hypotheses proposed to explain housing dynamics, we test for bubbles using a CUSUM test for structural breaks and conclude that the presence of asset bubbles is macro narrative dependent. While there is general agreement on a housing bubble preceding the GFC, our analysis extends through 2022 to determine whether prominent explanations from the GFC cycle are also applicable to the housing cycle during COVID-19.

We are not trying to definitively identify the presence of a bubble, but given that certain assets, such as housing, realize price booms and busts, can different competing macro hypotheses provide useful insights? If the residual CUSUM reaches an extreme, there is evidence that a bubble may have existed, conditional on the model employed. Conversely, if a model does not have significant positive CUSUM residuals, there is evidence that specific macro factors can explain the large price moves and there is no bubble.

From training and testing features across extended housing data, we draw inferences on: (1) the quality of hypotheses to describe housing prices, and (2) the potential presence of bubbles based on the structure of forecast errors. Our methodology of combining machine learning with tools for measuring structural breaks to identify bubbles can serve as an operational framework for problems with complex alternative hypotheses.

After a literature review on housing price dynamics during the GFC and the measurement of housing bubbles in Section 2, we propose a neural network (NN) methodology in Section 3 to investigate alternative hypotheses formulated in Section 4. These hypotheses and related analysis associated with several economic variables that impact house prices provide comparisons of conflicting views that promote different narratives used to explain housing price cycles. The main conclusions are summarized in the last section and focus on the presence of bubbles through competing macro housing hypotheses.

2. Literature Review

Duca et al. (2021) present a comprehensive literature survey of what drives house prices with an emphasis on papers written since 2007. Housing prices are determined by complex relationships with macroeconomic variables, financial and credit conditions, monetary policies, globalization, microeconomic supply and demand factors, regulation, and asset price bubbles, all playing roles. This work highlights the problem of competing hypotheses trying to explain housing dynamics.

Leamer (2015) establishes that housing belongs to the group of macroeconomic business cycle variables (GDP, consumption, investment, industrial productions, disposable income, and unemployment) linked to the business cycle. He offers evidence that from 1950 to 2000, 9 out of 11 recessions were preceded by housing price declines.

The impact of monetary policy on housing prices has been proposed by Taylor (2007, 2009, 2010), who argues that an easy monetary policy fueled the housing bubble. McDonald and Stokes (2013) also discuss the impact of monetary policy on housing, and Bhar and Malliaris (2021) compare the role of monetary policy on housing both during the GFC and COVID-19. Corsi and Sornette (2014) argue that asset bubbles usually occur during periods of excess liquidity. Bernanke (2010) disputes the thesis that the housing bubble during 2000–2006 was driven by an easy monetary policy. This easy money issue has not been addressed after 2010.

Bernanke (2005, 2007a, 2007b, 2009) proposes that the housing bubble was fueled by lower longer-term interest rates for 10-Year Treasury Notes and 30-Year Treasury Bonds. Such low longer-term interest rates also cause housing mortgage rates to decline. These lower rates were associated with a global saving glut. Sa and Wieladex (2015) and Steinberg (2019) investigate empirically the role of the global saving glut, and Evgenidis and Malliaris (2023) show that the global saving glut contributed to the housing bubble prior to the GFC but did not drive the rapid increases in housing prices during and after COVID-19. Beyond the impact of monetary policy and the global saving glut on mortgage rates, the housing micro bubble literature focuses not on whether prices rose too much but rather on why and what role borrower price expectations versus lender easing of underwriting played in enabling and separately contributing to excess prices. This micro approach is developed in Levitin et al. (2020), who show that as the volume of private-label mortgage-backed securitized loans increased and lending terms eased, risk premiums failed to price the increase in risk. This easy credit supply combined with bullish house price expectations contributed to the pre-GFC housing bubble and is a compelling argument. Also, the easy credit supply narrative on a micro level is consistent with the global saving glut macro argument.

Little is available in the literature comparing the housing bubble pre-GFC and post. Evgenidis and Malliaris (2023) study the role of monetary policy on housing price extremes, pre-GFC and during COVID-19, and find different drivers for each. Bhar et al. (2024) offer comparative analysis of housing prices pre-GFC and during COVID-19 by focusing on the stability of coefficients and its impact on housing forecasts without focusing on housing bubbles. Specifically, Bhar et al. (2024) propose 5 hypotheses to explain house prices using 15 economic variables and employ standard dynamic econometric techniques to test for significance of independent variables across regime changes. The general conclusion that emerges is that both SA and NSA house prices over a long period from 1987 to the end of COVID-19 were driven by the nonlinearity of coefficients of 15 economic variables, with varying impact across certain sub-periods.

The present paper extends Bhar et al. (2024) first by proposing 10 hypotheses entailing 30 independent variables to contribute towards a more complete understanding of house prices; second, by employing an NN methodology to provide an alternative approach not constrained by linear estimation; and third, by evaluating models to assess any evidence of the presence of bubbles. Instead of testing a formal structural linear model or a simple vector autocorrelated model, an NN framework is employed to find those variables that have the greatest impact on housing variability and the macro themes that have the highest predictive value. Using this common modeling methodology and sample periods allows us to make comparisons among key independent variables driving housing prices and draw conclusions on different strands of macro housing research.

The structure of forecast errors from our housing themes is used to test for bubbles. Any bubble discussion is dependent on the model used to explain price dynamics. Model errors trained on our data sets should have an expected value of zero and be iid. Systematic deviations of standardized residuals can identify potential model failure, structural breaks, and insights into the possibility of bubbles. The behavior of the residual CUSUM along with formal testing allows us to identify structured deviations from competing models as potential bubbles. Across different model themes, we find evidence for structural breaks surrounding the GFC, which suggests that these models or themes inadequately describe housing cycle dynamics. Those who use specific themes to describe housing market dynamics may inappropriately identify a housing bubble that may not exist based on alternative theses.

A bubble has been simply described by Kindleberger (1996, p. 13) as "an upward price movement over an extended range that then implodes". Similar definitions emphasize unsustainable excessive price increases. A bubble can also be defined as an asset price that exceeds an asset's fundamental value because current owners believe they can resell the asset at an even higher future price. A bubble cannot be separated from a model or valuation or from the drivers that impact valuation.

Books such as Kindleberger (1996) and Evanoff et al. (2012), and survey papers such as Scherbina and Schlusche (2014) give a detailed analysis of financial modeling of asset bubbles. These models provide alternative hypotheses based on asymmetric information between traders, the interaction between rational and behavioral traders, limits to arbitrage, investors holding heterogeneous beliefs, and disagreements about fundamental values.

Bubble research has often focused on finding extreme price movements by measuring forms of exponential growth. See, for example, Sornette and Cauwels (2014) for a review of the price-based approach to bubble identification. This strain of research uses techniques from operations research; see Sornette (2003), Corsi and Sornette (2014), Sornette et al. (2017), and Ziemba et al. (2017). Excess returns over compact timeframes, the focus of the exponential work, are less applicable when national housing price data with differences in quality are calculated monthly.

The study of housing price bubbles has been extensive with special emphasis on Phillips-type right-tailed unit root tests, such as the Supremum Augmented Dickey Fuller (SADF) and Generalized SADF (GSADF). Hu (2023) offers a review of this approach. The work of Phillips and Shi (2018), Martinez-Garcia and Grossman (2018), and Shi and Phillips (2020) has led to real-time monitoring of housing bubbles around the world by the Dallas Federal Reserve Bank.[1] However, these exuberance or bubble indicators focus on real house prices and price-to-rent fundamentals and do not address the question of whether macro fundamental hypotheses can be used to explain the price changes or exuberance.

Otero et al. (2022) undertake Monte Carlo simulation experiments to examine the effect of changing the frequency of observations and the data span and find that when a series is characterized by multiple bubbles, periodically collapsing, decreasing the frequency of observations is associated with profound power losses for the test. This motivates us to use a long series of data with the empirical observation of one collapsing housing bubble after the Global Financial Crisis. Holmes et al. (2011) investigate regional house price convergence in the United States, complementing our national house price bubble behavior.

West (1988) suggests that fads may contribute to bubbles, but in our analysis such fads do not play a critical role. The theoretical modeling of Kiselev and Ryzhik (2010) incorporates three main factors as components for asset price bubbles. These components are the tendency of mean reversion to a stable value, speculative social response triggered by trend following, and random fluctuations. The interplay of these three forces may lead to bubble formation and collapse. Tarlie et al. (2022) discuss explosive behavior of stocks relative to valuation. We do not test or look at a valuation model for house bubbles but rather focus on macro drivers as explanations of price change. LeRoy (2012) reminds us of the role of holding periods, with housing generally being a long hold.

Our premise is that any bubble discussion should be a two-step process of first identifying and testing alternative feature hypotheses as explanations of price extremes, and then testing whether price breaks from these explanatory features serve as a bubble identifier. Albeit more difficult to form definitive conclusions, this approach allows commentary on the value of alternative macro narratives.

3. A Neural Network Framework

A supervised learning approach using artificial neural networks as an alternative to linear regression is employed to rank the importance of a set of macro and market variables that may have complex non-linear relationships with housing prices.[2] Instead of forming a single structural model, we measure the relative importance of variables associated with specific narratives for the housing market. By focusing on the relative importance of variables and the ability of specific models to explain housing prices, we address core macro housing issues. Our atheoretical restriction-free approach compares specific hypotheses and measures relative validity and the importance of macro housing themes through differences in model prediction errors.[3]

The supervised neural network (NN) algorithm feeds data forward through layers of nodes or neurons. Neural networks adapt based on errors, and then improve by making small adjustments to weights. It is a repetitive process that continues until the error meets some pre-specified minimum. Our network is composed of three layers: nodes for each input, an intermediary layer, which is the "hidden" layer that contains nodes connected to both the input and output nodes, and a third layer consisting of a node for the output value. Each input node is connected to every node in the hidden layer and is multiplied by a weight. Each hidden layer node also has a weighted connection to the output node. Initial weights are assigned randomly and adjusted to minimize prediction error. The weighted connections that arrive at a node are summed and sent through a hyperbolic tangent function with the output from each hidden layer node serving as an input for the next layer. The final node sums the weighted inputs from the hidden layer nodes and applies a hyperbolic tangent function to this sum where this last layer node becomes the model's target value prediction. An illustration of this NN methodology is presented in Malliaris and Malliaris (2021). SPSS Modeler automatically computes the optimal size of the hidden layer by trying various sizes and selecting the one that results in the minimum test error. If multiple networks have the same error, the one with the fewest hidden nodes is retained. Since the objective in these hypotheses was to best model the variable relationships, all rows for each hypothesis were used in building that model. The specific architecture used in the network for each hypothesis varies depending on the input data. At the end of each figure description, the network architecture for that model is specified. For example, Figure 1 specifies: Network Architecture: 7 input nodes, 2 hidden layer nodes, 1 output node.

The model is trained through an error backpropagation algorithm to compute the first partial derivatives of the error function with respect to the weights. Weights are adjusted based on the error, using the gradient descent method and the generalized delta rule. A change to the weight calculated by the generalized delta rule would be:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left[w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)\right] + \eta\delta_j^{(l)}(n)y_i^{(l-1)}(n)$$

where $w_{ji}^{(l)}$ indicates weight w, in layer l, in neuron j, fed from neuron i in the previous layer. The iteration is represented by n, with a learning-rate parameter η and momentum of α. See Haykin (1994, p. 156) for a detailed discussion of this process. This procedure is repeated until either the total error is below a specified level or the number of data passes has exceeded a specified maximum.

A sensitivity analysis is conducted after training to determine the influence of each feature variable on the output (housing prices) through varying the input variable values while holding the other variables fixed. By observing the value of the mean squared error corresponding to each agitated input, the model can determine the output sensitivity to that input. The sensitivity analysis computes the decrease in variance of the target variable that can be attributed to each input variable. Saltelli et al. (2004) show that this normalized sensitivity is a good measure to rank the predictors in order of importance for any combination of interaction and non-orthogonality among predictors. The input variables are ranked by the effect of their changes on the output variable, which generates a predictor importance ranking. The sensitivity measure ranking the predictors is $S_i = V_i/V(Y) = V(E(Y|X_i))/V(Y)$ where V(Y) represents the output variance and X represents inputs. The predictor importance is the normalized sensitivity $VI_i = Si/\sum S_j$.

Methodology for Testing Bubbles

While significant work has focused on price data time series, the unit root problem, a bubble cannot be divorced from a valuation model. A perceived bubble may not be a bubble if we find exogenous variables that explain price behavior without any residual bias; however, a bubble may be identified by the deviations (prediction errors) away from a model, a structural break from model behavior. Homm and Breitung (2012) associated the structure of forecast errors as an identification of bubbles; however, most of this work has focused on price series and not specific models using exogenous variables. The pattern of time series residuals, deviations from a model's forecast, can be used as a bubble test. Hence, CUSUM tests can measure specific structural breaks in a model. Bubble identification is conditional on the model used. Ploberger and Krämer (1992) test OLS residuals to identify and locate breaks.

We explicitly link an atheoretical machine learning framework across different sets of features which represent different macro narratives to test the presence of housing market bubbles conditional on the model selected through tests of residuals. Inspection of the CUSUM time series from our atheoretical NN models, along with tests of critical values, can identify whether model failure is consistent with when bubbles are said to have existed. Cumulative deviations from a model over the training set is a strong test of bubbles because the model has all information prior to and after the bubble. This is not a test of a model's out-of-sample forecast ability but a focus on whether a set of variables can adequately find a fit that will generate forecast errors that are iid with an expected value of zero. A model can have high forecast errors but have an expected mean of zero; however, a CUSUM, recursive residual test can identify structural errors that can be viewed as bubbles. CUSUMQ test results are also available upon request.

4. Hypotheses and Analysis

We investigate the influence of macroeconomic variables on monthly housing prices from January 1987 to June 2022. The independent and macro variables are organized into two categories: variables that are Not Seasonally Adjusted (NSA) and variables that are Seasonally Adjusted (SA). There are both economic and statistical reasons for this distinction. All housing transactions occur with unadjusted prices. Anticipations and expectations are also not seasonally adjusted by builders, sellers, and buyers. Statistically, mixing NSA and SA impacts estimations since the SA data incorporates a filter with its own dynamics. By offering two sets of results, we enrich our understanding of the dynamics played by different independent variables. When important variables are available in only one mode, only NSA or only SA, we allow for some mixing with some caution in interpreting results. The target Case–Shiller home price variable is available as either NSA or SA.

Table 1 provides an overview for all our 10 major hypotheses and sets of variables. We generate the ranked feature importance within each hypothesis since all model variables are scaled between 0 and 1, as well as statistics on model errors. Hence, the values measure the amount of volatility explained by a given feature.

Table 1. Hypotheses and variables (features) for neural network tests. All data from FRED.

Hypotheses	**Variables**
Housing and Macroeconomic Variables	
H1 NSA Macroeconomic variables	Consumer Price Index All (CPI) annualized change, Consumer Price Index Rent annualized change (CPIR), Non-Farm payroll number (NFP), Industrial Production annualized change (IP), 30-year Mortgage Rate (MORT), macro news (MACRO), and Economic Policy Uncertainty Index (EPU)
H2 SA Macroeconomic variables	Durable goods (DGOOD), Disposable income (DINC), Trade balance (TBAL), Employment/population ratio (EMRATIO), Unemployment level (UNEMPLOY), Industrial production (IP)
Housing driven by monetary policy	
H3 NSA credit variables	30-year Mortgage Rate (MORT), Treasury 10-year/2-year spread (TSPREAD), Fed Funds (FFUND), EPU monetary index (EPUM)
H4 NSA credit with Fed assets	30-year Mortgage Rate (MORT), Treasury 10-year/2-year spread (TSPREAD), Fed Funds (FFUND), EPU monetary index (EPUM), FedAssets (FEDA)
Housing and global savings glut	
H5 NSA target variable	30-year Mortgage Rate (MORT), Trade balance (TBAL), Fed Funds (FFUND), FedAssets (FEDA)

Table 1. *Cont.*

Hypotheses	Variables
H6 SA target variable	30-year Mortgage Rate (MORT), Trade balance (TBAL), Fed Funds (FFUND), FedAssets (FEDA)
Housing supply and demand	
H7 NSA variables	Monthly supply of new houses (HSUPPLY), new single-family houses sold (HSOLD), single-family housing units completed (HCOMPL), industrial production (IP), non-farm payroll (NFP)
H8 SA variables	Monthly supply of new houses (HSUPPLY), new single-family houses sold (HSOLD), single-family housing units completed (HCOMPL), disposable income (DINC), durable goods (DGOOD), trade balance (TBAL)
H9 Extends H7 by adding expectations	Monthly supply of new houses (HSUPPLY), new single-family houses sold (HSOLD), single-family housing units completed (HCOMPL), industrial production (IP), non-farm payroll (NFP), KC Fed stress index (STRESS), University of Michigan consumer sentiment (MSCENT), single-family units started/population level (HPOP), housing authorized but not started (HAUTH)
Housing and price extrapolation	
H10 Price lags and momentum	Case–Shiller prices lagged 1 period (CSLAG1), Case–Shiller prices lagged 6 period (CSLAG6), Fed funds (FFUND), housing units authorized but not started (HAUTH), single-family housing units completed (HCOMPL), Chicago Fed financial conditions (CFINCON), University of Michigan consumer sentiment (MCSENT), Michigan inflation expectations (MINFEX)

Comparing the NSA and SA analysis, cyclical housing behavior is driven by traditional macroeconomic variables such as industrial production, durable goods, disposable income, non-farm payroll, and two special factors that are relevant to housing: CPI rent and trade balance. For NSA data, the three most important cyclical variables are the CPI rent, industrial production, and non-farm payroll while for SA data, durable goods, disposable income, and trade balance emerge as most important. The SA model has half the mean absolute error and half the standard deviation as the NSA test. Contemporaneous business cycle effects include a trade component.

These two hypotheses conclude that national US economic cycles play an important part in housing cycles. Both NSA and SA data confirm that different cyclical macroeconomic variables are connected to housing prices. Housing cycles, as expected, are congruent with the business cycle.

Hypothesis 1. *Case–Shiller National Home Price Index NSA is driven by macro variables. The non-seasonally adjusted (NSA) data set ranges from January 1987 through June 2022 and includes the consumer price all index NSA (CPI), consumer price rent index NSA (CPIR), Non-farm payroll NSA (NFP), industrial production NSA (IP), 30-year Mortgage Rate (MORT), macro news (MACRO), and the Economic Policy Uncertainty Index (EPU) to capture overall macro risk. These independent variables are chosen among a large set of macro data available to capture relationships between house prices and consumer prices, the consumer price index measuring rent as a relevant alternative opportunity cost to purchase, non-farm payroll, and industrial production are proxies for GDP. The 30-year mortgage rate is a primary variable that measures house financing and affordability. Macro news and the economic policy uncertainty index serve as proxies for the scope of financial conditions.*

The results in Figure 1 generate a notable surprise with the most important variable, the CPI rent component (weight 0.341), which proxies for the cost of overall housing but does not play a central role in business cycle aggregate demand analysis. Two important features, employment and industrial production, key business cycle variables, only account for approximately 40% of the housing price variability.

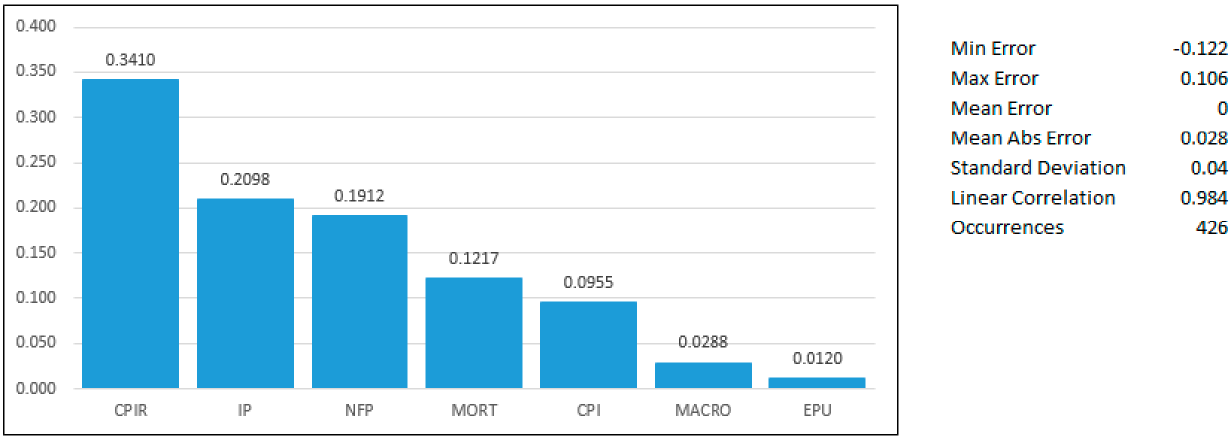


Figure 1. H1. Case-Shiller National Home Price Index NSA and macro variables sensitivity. Period: Jan 1987-June 2022. Source FRED database: Consumer price index all (CPI) annualized change, Consumer price index rent annualized change (CPIR), Non-Farm payroll number (NFP), Industrial Production annualized change (IP), 30-year mortgage rate (MORT), macro news (MACRO), and Economic policy uncertainty Index (EPU). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 7 input nodes, 2 hidden layer nodes, 1 output node.

Hypothesis 2. *Case–Shiller National Home Price Index SA is driven by different macro variables. Seasonally adjusted macroeconomic variables are introduced in this hypothesis for the period 1992-June 2022, and the dependent variable is also seasonally adjusted. Disposable income (DINC), durable goods (DGOOD), industrial production (IP), trade balance (TBAL), and unemployment (UNEMPLOY) are all proxies for the business cycles; employment to population ratio (EMRATIO) is introduced to adjust employment relative to population size. Durable goods, disposable income, and trade balance are the three most important drivers.*

Results are presented in Figure 2.

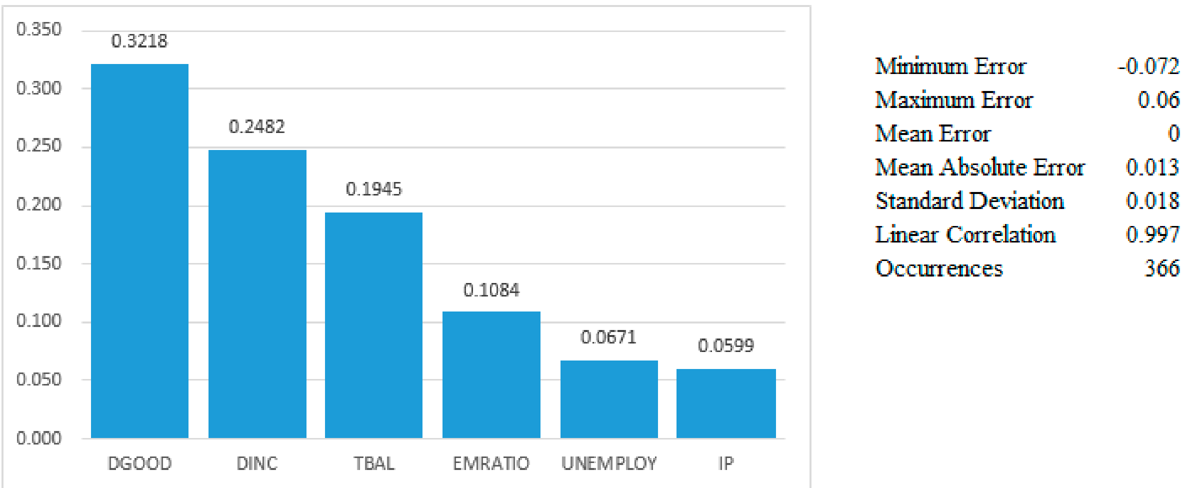


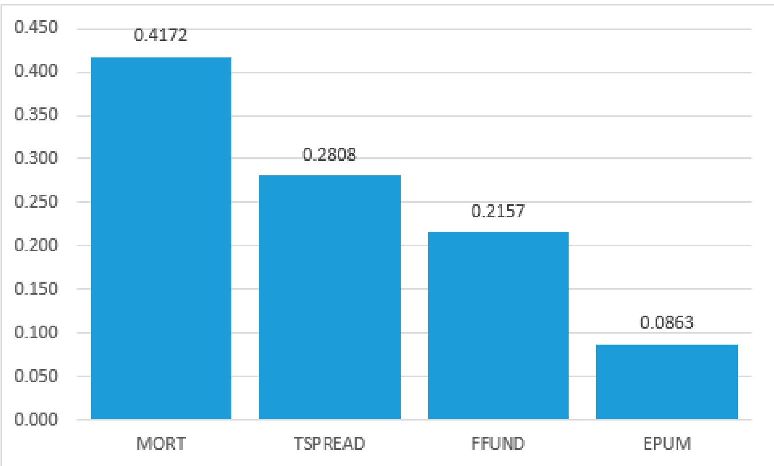
Figure 2. H2. Case-Shiller National Home Price Index SA and other macro variable sensitivity. Period: Jan 1992-June 2022. Source FRED database: Durable goods (DGOOD), Disposable income (DINC), Trade balance (TBAL), Employment/population ratio (EMRATIO), Unemployment level (UNEMPLOY), Industrial production (IP). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 6 input nodes, 3 hidden layer nodes, 1 output node.

Hypotheses 3 and 4 address the impact of monetary policy on house prices. In Hypothesis 3, we test the role of Fed funds with other financial variables, while in Hypothesis 4, we place an emphasis on Fed assets accumulated via QE. Sample periods differ since there is little movement in Fed's balance sheet (no QE) prior to the GFC.

NSA housing prices for the entire sample are driven by the 30-year mortgage rate and the difference between the 10-year and 2-Year Treasury rate, which measure the slope of the yield curve, while the Fed funds rate ranks as the third factor. When a similar exercise is performed for a shorter period of 2003 to June 2022, Fed assets become most important followed by Fed funds. These two variables dominate the 30-year mortgage rate as the key drivers of housing behavior. Hypotheses 3 and 4 confirm that the housing market is impacted by monetary policy, initially and up to the GFC through Fed funds policy and after the GFC by QE.

Hypothesis 3. *Housing prices NSA and monetary policy. The Case-Shiller National Home Price Index NSA is impacted by monetary policy expressed by the Fed funds, the 10-year Treasury minus 2-year spread, 30-year mortgage rate, and an economic policy uncertainty index to capture the changes in policy expectations from 1987 to June 2022.*

These results in Figure 3 conclude that NSA house prices are driven by the 30-year mortgage rate, the term structure of interest rates represented by the 10-year less the 2-year spread, and Fed funds rate. However, monetary policy variables have much less explanatory power than the macroeconomic variables of Hypotheses 1 and 2, with greater dispersion in errors as Figures 1–3 illustrate.



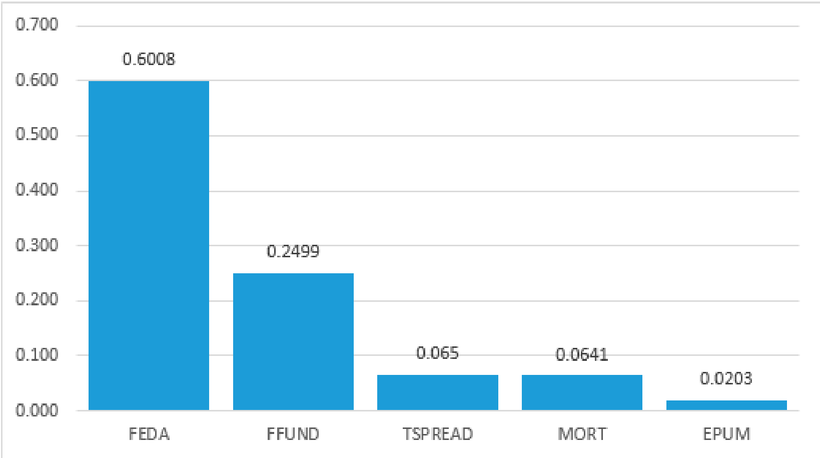
Minimum Error	-0.199
Maximum Error	0.256
Mean Error	0
Mean Absolute Error	0.044
Standard Deviation	0.062
Linear Correlation	0.96
Occurrences	426

Figure 3. H3. Case-Shiller National Home Price Index NSA monetary policy sensitivity. Period: Jan 1987-June 2022. Source FRED database: 30-year mortgage (MORT), Treasury 10-year/2-year spread (TSPREAD), Fed Funds (FFUND), EPU monetary index (EPUM). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 4 input nodes, 6 hidden layer nodes, 1 output node.

Hypothesis 4. *Housing prices and monetary policy including Fed assets. We study the behavior of the same dependent variable by introducing assets on the Fed balance sheet, which becomes the most important feature. The low mean absolute error for the post-GFC monetary model theme with Fed assets even with the Fed funds rate tied closely to zero is especially notable.*

The results from Hypothesis 4 are presented in Figure 4 that illustrate the important role of Fed assets.

Hypotheses 5 and 6 address the role of global saving glut. We compare drivers that are NSA as in Hypotheses 3 and 4 with the global savings glut using the trade balance as a proxy that is only available as SA. To moderate this statistical difficulty of mixing SA and NSA data, we use two models, expressed as H5 and H6.



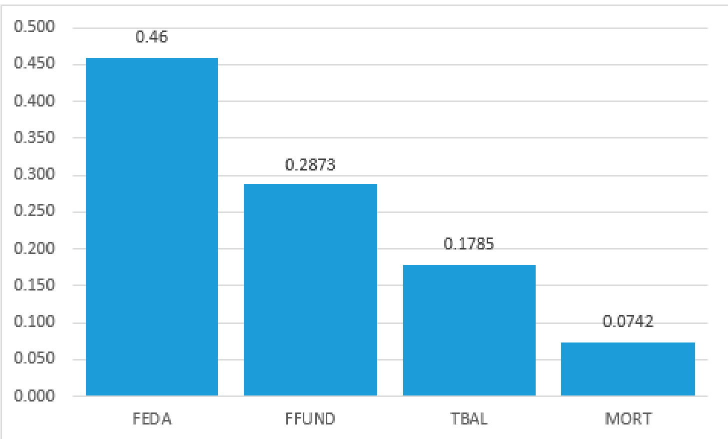
Minimum Error	-0.083
Maximum Error	0.102
Mean Error	0
Mean Absolute Error	0.017
Standard Deviation	0.023
Linear Correlation	0.988
Occurrences	234

Figure 4. H4. Case-Shiller National Home Price Index NSA monetary policy sensitivity. Period: Jan 1992-June 2022. Source FRED database: 30-year mortgage (MORT), Treasury 10-year/2-year spread (TSPREAD), Fed Funds (FFUND), EPU monetary index (EPUM), Fed assets (FEDA). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 5 input nodes, 2 hidden layer nodes, 1 output node.

Hypothesis 5. *Housing prices (NSA) with monetary policy and trade balance.*

Hypothesis 6. *Housing prices (SA) with monetary policy and trade balance.*

With H5, Case–Shiller NSA is explained in Figure 5 by Fed funds, Fed total assets, the 30-year mortgage rate (all three NSA), and the trade balance (SA). The second case, H6, considers the Case–Shiller SA dependent variable with the same independent variables to test whether the global saving glut (trade balance) emerges as an important variable. Adjusting for seasonality does not influence the results.

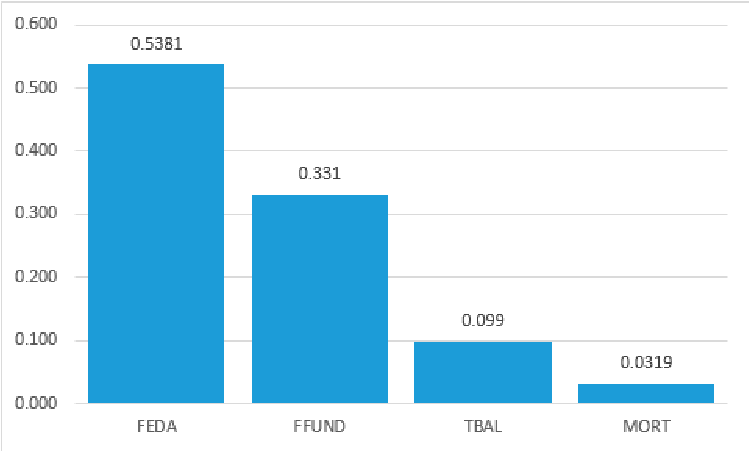


Minimum Error	-0.085
Maximum Error	0.152
Mean Error	0
Mean Absolute Error	0.022
Standard Deviation	0.028
Linear Correlation	0.99
Occurrences	234

Figure 5. H5. Case-Shiller National Home Price Index NSA monetary policy sensitivity. Period: Jan 2003-June 2022. Source FRED database: 30-year mortgage (MORT), Trade Balance (TBAL), Fed Funds (FFUND), EPU monetary index (EPUM), Fed assets (FEDA). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 4 input nodes, 4 hidden layer nodes, 1 output node.

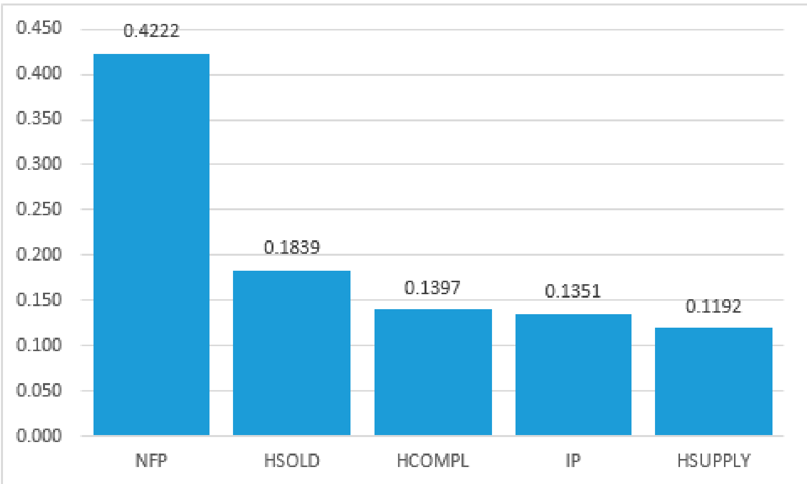
Figures 5 and 6 show the importance of Fed assets and Fed Funds as drivers of home prices.

We next examine the housing market with specific supply and demand information based on the recent housing research surveys of Glaeser and Gyourko (2018) and Duca et al. (2021). Erdmann (2023) focuses on supply and demand fundamentals in metropolitan areas. These results confirm the earlier analysis, where SA cyclical variables such as disposable income, trade balances, and durable goods spending drive housing prices. Supply variables represented by houses started, houses completed, and houses sold play a lesser role. The supply of housing appears less elastic, and housing prices are driven by cyclical factors caused by demand shifts. Figures 7 and 8 show the impact of the variables proposed in hypotheses 7 and 8.



Minimum Error	-0.125
Maximum Error	0.172
Mean Error	-0.001
Mean Absolute Error	0.029
Standard Deviation	0.038
Linear Correlation	0.983
Occurrences	234

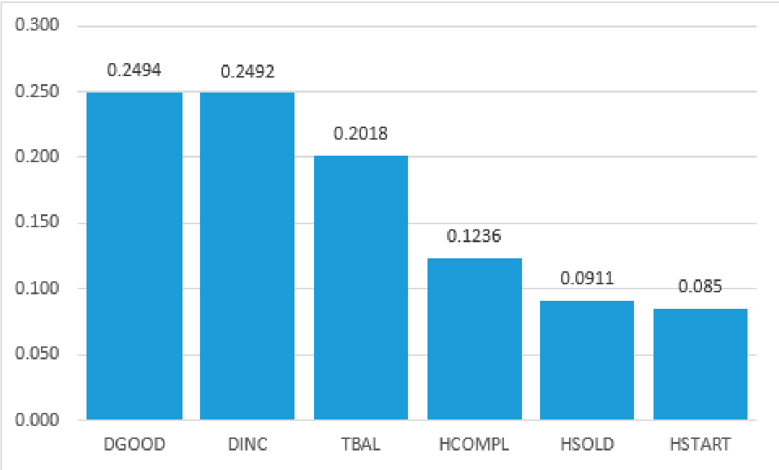
Figure 6. H6. Case-Shiller National Home Price Index SA monetary policy sensitivity. Period: Jan 2003-June 2022. Source FRED database: 30-year mortgage (MORT), Trade Balance (TBAL), Fed Funds (FFUND), Fed assets (FEDA). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 4 input nodes, 3 hidden layer nodes, 1 output node.



Minimum Error	-0.172
Maximum Error	0.166
Mean Error	0.001
Mean Absolute Error	0.026
Standard Deviation	0.038
Linear Correlation	0.985
Occurrences	426

Figure 7. H7. Housing prices (NSA), micro supply and macro demand factors. Period: Jan 1987- June 2022. Source FRED database: Monthly supply of new houses (HSUPPLY), new single-family houses sold (HSOLD), single-family housing units completed (HCOMPL), industrial production (IP), and non-farm payroll (NFP). Variables are NSA. Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 5 input nodes, 4 hidden layer nodes, 1 output node.

Hypothesis 7. *Housing prices (NSA), micro supply and macro demand factors. Case–Shiller NSA housing prices are explained by supply variables: monthly supply of new houses, new single-family houses sold, single-family housing units completed, as well as industrial production and non-farm payroll. There are no data for explicit housing demand other than proxies for aggregate demand which focus on the business cycle. Results using NSA variables suggest that housing fundamentals such as houses completed, houses supplied, and houses sold are important influences on prices, but the demand side through employment and, to a lesser extent, industrial production are also key drivers.*

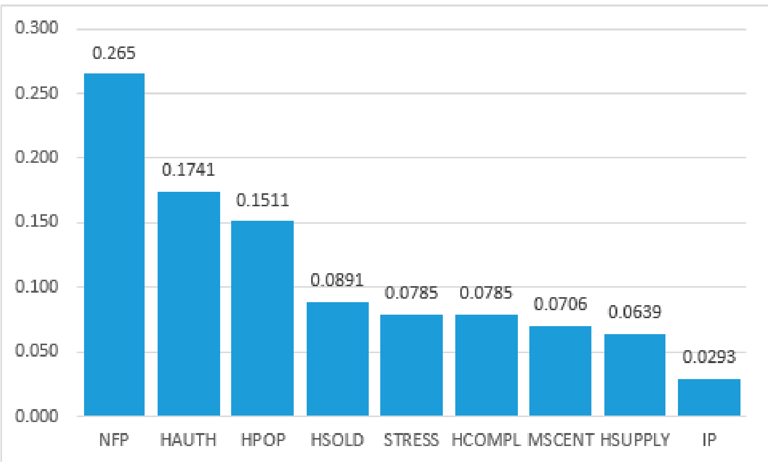


Minimum Error	-0.044
Maximum Error	0.085
Mean Error	0
Mean Absolute Error	0.012
Standard Deviation	0.016
Linear Correlation	0.997
Occurrences	366

Figure 8. H8. Housing Prices (SA) and micro supply and demand factors. Period: Jan 1992-Jun 2002. Source FRED database: Monthly new houses started (HSTART), new single-family houses sold (HSOLD), single-family housing units completed (HCOMPL), trade balance (TBAL), disposable income (DINC), and durable goods (DGOOD). Variables are NSA. Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 6 input nodes, 3 hidden layer nodes, 1 output node.

Hypothesis 8. *Housing prices (SA), micro supply and demand factors. For the Case-Shiller SA test, housing prices are explained by new single-family houses sold, single-family housing completed, single-family housing started, disposable income, durable goods, and trade balance (demand by foreigners). Data extends from 1992 through June 2022.*

Hypothesis 9. *Housing prices and expectations. This hypothesis is motivated by Piazzesi and Schneider (2016) and Kuchler et al. (2022) on housing expectation as measured by the Michigan Consumer Sentiment Index and its numerous components. H9 adds four new variables: housing units authorized but not started, single-family units started/population level, Michigan consumer sentiment, and the Kansas City financial stress index. We find significant improvement based on a decline of mean absolute error versus H7. See Figure 9.*



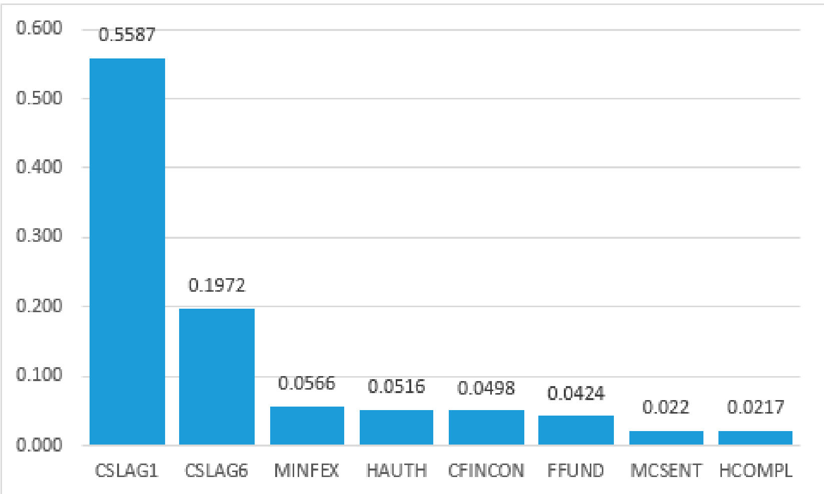
Minimum Error	-0.072
Maximum Error	0.103
Mean Error	0
Mean Absolute Error	0.015
Standard Deviation	0.021
Linear Correlation	0.996
Occurrences	389

Figure 9. H9. Housing Prices micro supply and demand factors with expectations. Period: Feb 1990-June 2022. Source FRED database: Monthly non-farm payroll (NFP), housing units authorized but not started (HAUTH), single-family units started divided by the population level (HPOP), single-family houses sold (HSOLD), Kansas City financial stress index (STRESS), single-family housing units completed (HCOMPL), Michigan consumer sentiment (MCSENT), housing supply (HSUPPLY) and industrial production (IP). Variables are NSA. Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 9 input nodes, 5 hidden layer nodes, 1 output node.

We next test the importance of past prices as a driver for housing price behavior relative to key exogenous macro and micro variables. If key macro variables represent most of the variation in housing prices, then the bubble question becomes more complex. Housing prices are responding to changes in the business cycle, monetary policy, and sector-specific variables. Housing is cyclical, but these cycles may not demonstrate bubble behavior. Alternatively, if extrapolative behavior explains most of the variation in housing prices, then we can say that a positive feedback loop from past trends drives price extremes and dominates any exogenous variables. This hypothesis is based on momentum and bubble work developed by Piazzesi and Schneider (2016), Piazzesi et al. (2020), Mayer (2011), Glaeser and Gyourko (2018), and other surveys. Basco and Schäfer-i-Paradís (2022) follow a different methodology by proposing a model-free test of rational bubbles applied to US housing and conclude that a bubble occurred only during 2002–06.

Hypothesis 10. *Price extrapolation as the key driver of housing prices. This hypothesis uses all NSA data: Case–Shiller lagged 1 period, Case–Shiller lagged 6 periods, with Fed funds, housing units authorized but not started, single-family housing completed, Chicago Fed financial conditions, Michigan consumer sentiment, and Michigan inflation expectations.*

Beyond short-term (1-lag) and longer-term (6-lag) momentum, we include variables for housing expectations, inflation expectations, indicators such as housing permits for housing not started, completed houses that may reduce or fuel current prices, financial conditions evaluated in surveys, and other factors. The results in Figure 10 show the importance of extrapolative expectations as a key driver of housing market behavior.



Minimum Error	-0.021
Maximum Error	0.03
Mean Error	0
Mean Absolute Error	0.005
Standard Deviation	0.007
Linear Correlation	1
Occurrences	420

Figure 10. H10. Housing prices are driven by lagged prices. Period Jan 1992-June 2022. Source FRED database: Case-Shiller prices lagged 1 period (CSLAG1), Case–Shiller prices lagged 6 periods (CSLAG6), Michigan inflation expectations (MINFEX), housing units authorized but not started (HAUTH), single-family housing units completed (HCOMPL), Chicago Fed Financial conditions (CFINCON), Fed funds (FFUND), Michigan consumer sentiment (MCSENT), and single-family housing units completed (HCOMPL). Data scaled between 0 and 1 and sensitivities sum to 1. Network Architecture: 8 input nodes, 6 hidden layer nodes, 1 output node.

The past price components with lag 1 and lag 6 dominate and explain about 80% of the housing price variation. Other than price lag effects, the other two important variables are inflation expectations and housing units authorized but not started, followed by Fed funds and financial conditions.

In summary, the most impactful variables using non-seasonally adjusted data are consumer price index rent, the 30-year mortgage rate, Fed assets, non-farm employment, and the lag of the Case–Shiller index. CPI Rent was the top variable in H1. CSLag1 was the top variable in H10, and Fed Assets was the top variable in H4, H5, and H6. The remaining hypotheses with NSA data (H3, H7, and H9) had either non-farm employment or the 30-year mortgage rate as the best independent variable. Running a single neural network on the most impactful non-seasonally adjusted variables, excluding the Case–Shiller lag, Fed assets is the most influential variable, as noted in H3, H5, and H6. For the hypotheses that use only seasonally adjusted data, H2 and H8, durable goods spending was the dominant variable.

Comparison of Results and Bubble Tests

Themes are presented in Table 2 with the first six hypotheses using NSA vs. SA data and the remaining four only using NSA data. The themes have different explanatory power based on the mean absolute error, the maximum and minimum error, and the standard error. The price extrapolation theme, which suggests the potential for a bubble through price expectations, dominates all models even with a restricted set of features. On a relative basis, the housing-specific information theme outperforms those that focus on macro variables, the business cycle, monetary policy, and the savings glut; yet, when testing over a shorter sample, we find the possibility of a bubble break for four hypotheses.

Table 2. Comparison of themes using neural network models.

Themes:	**Housing and the Business Cycle**		**Housing Driven by Monetary Policy**		**Housing and Global Savings Glut**		**Housing Supply and Demand**			**Housing and Price**
	H1	**H2**	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**	**H10**
Max Error	0.106	0.06	0.256	0.102	0.152	0.172	0.166	0.085	0.103	0.03
Min Error	−0.122	−0.072	−0.199	−0.083	−0.085	−0.125	−0.172	−0.044	−0.072	−0.021
Mean Abs Error	0.028	0.013	0.044	0.017	0.022	0.029	0.026	0.012	0.015	0.005
Std Dev	0.04	0.018	0.062	0.023	0.028	0.038	0.038	0.016	0.021	0.007
CUSUM test for each H; entire sample	reject *	accept	reject **	accept	accept	accept	accept	accept	accept	accept
CUSUM test for same sample Feb 2003–Jun 2022	reject *	reject *	reject **	accept	accept	accept	reject *	reject *	accept	accept
Bubble period above 0.05 critical level	5 Oct–22 Mar	7 Mar–8 Feb	None	None	None	None	4 May–6 Sep	7 Nov–9 Sep	None	None
Number of months above 0.05 critical level	78 months	12 months	None	None	None	None	29 months	19 months	None	None

* reject at 0.05 level, ** reject at 0.10 level, of no structural break (bubble) in the model.

The investigation of the first theme clearly shows that housing is closely tied to business cycles. Among various NSA macro variables, CPI rent and industrial production are the dominant drivers of housing variation, while durable goods and disposable income are the most important SA macro variables.

An analysis of the role of credit and monetary policy shows that among the NSA variables, the 30-year mortgage rate and the 10-year 2-year Treasury rate spread are the leading variables. However, the introduction of Fed assets after the GFC overtakes the 30-year mortgage rate as the key explanation for housing prices. The extensive availability of money and credit drove the surge in housing prices over the last decade. When monetary policy is compared with the global saving glut, SA factors such as the trade balance and disposable income still emerge as important housing price drivers.

Housing demand fundamentals such as durable goods and disposable income drive housing demand among SA variables. Non-farm employment, houses completed, and houses sold emerge among NSA variables as important features. New privately owned housing units scaled to the population level become an important measure of speculation; as housing prices increase, the number of adjusted single-family units also increases. Among the several financial variables considered, housing is closely associated with Fed funds and Fed assets.

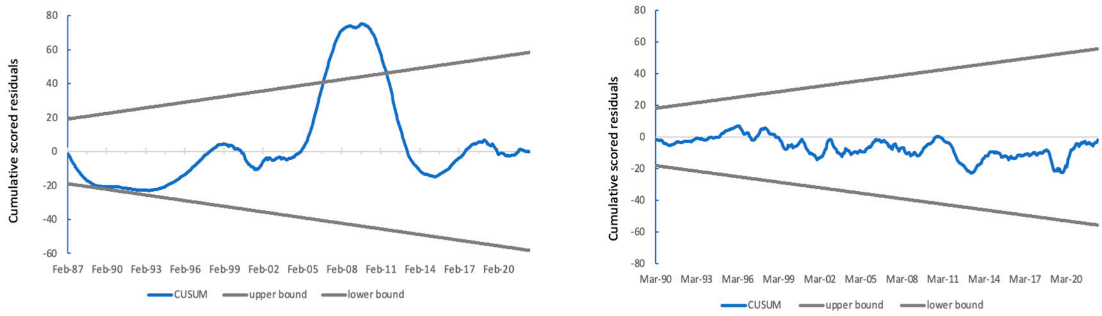
If, as some authors claim, there is a persistent deficit of several million houses in the US, the supply of housing is rather inelastic; however, we find good macro conditions, a global saving glut, and easy monetary policies drive housing price predictions over the past 25 years. Nonetheless, the University of Michigan sentiment index and the Kansas City financial condition stress index do not play any special role in housing price behavior. Lastly, using 1- and 6-period lags in the house price index to investigate the role of extrapolative forecasts, we find strong evidence that both lags dominate other features. Past prices play an important role in explaining the variation in housing prices. Extrapolative expectations fueled by quantitative easing, which provides excess credit, along with a savings glut story, cause more extreme home price changes. While all themes generate some validity, the dominance of extrapolative expectations with easy credit provides a theme consistent with bubble discussions.

To identify possible bubbles, we test for error dislocations or structural breaks, from the upper and lower band confidence regions for our ten model hypotheses. Although difficult to formally conclude given the problem of bubbles being a joint hypothesis, the residual extremes, which indicate a structural break, likely represent a bubble. The tests for whether residuals stay within the CUSUM bounds for all themes are reported for two different samples in Table 2.

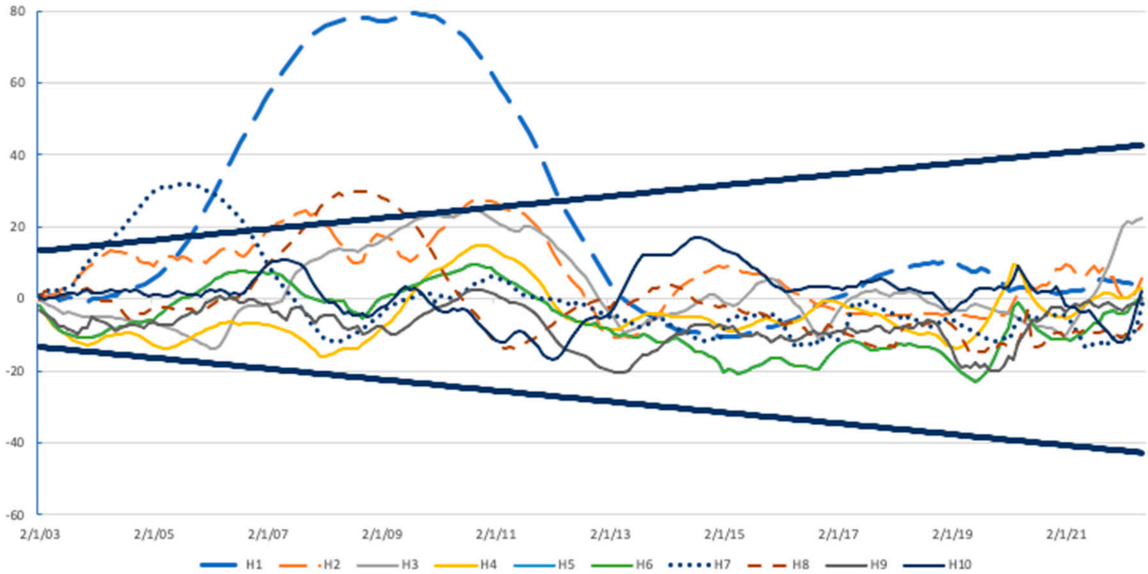
First, we test the null hypothesis of staying within the confidence band for the entire test period for each model. The sample size for each model test may differ, which means the confidence bounds will also change. In the case of a full sample for each model, we find two hypotheses reject the null of no structural break. However, in the case of H3, the rejection is caused by the CUSUM piercing the lower bound during the period prior to the tech bubble. That is, housing prices were too low relative to the monetary policy indicator model. In the case of H1, the CUSUM was consistent with a bubble prior to the GFC.

Second, we provide a set of tests where the start and end date are the same for all ten hypotheses and find the presence of potential bubbles in four cases. We include the start and end date of each break as well as the number of months the CUSUM of scored residuals (price > model) exceeded the upper confidence band. Although the timeframes for the possible presence of a break (bubble) differ in our four cases, all are consistent with the view that a housing bubble as defined by the CUSUM extremes, nonstationary mean or feature behavior, occurred prior to the Great Financial Crisis. Nonetheless, our tests also demonstrate that several models do not show the presence of any structural breaks and can thus explain the housing price extremes.

Bubble identification through structural breaks is highly model- or feature-dependent. For illustrative purposes, we show the CUSUM for two themes, H1 and H9. For H1, there is a clear positive CUSUM, actual greater than predicted, for the period prior to the GFC and then a switch to negative after the GFC, actual less than predicted, followed by a return to normal. See Scheme 1. In Scheme 2, the CUSUMs for each of the ten hypotheses are presented with the upper and lower bound for the average number of features with a start date when all data are available, February 2003 to June 2022. Note that the critical levels are based on the sample size and will be sensitive to the start date, and CUSUM tests will suffer from low power if the change point or bubble dislocation is close to the beginning or end of the sample.



Scheme 1. CUSUM chart examples for H1 and H9 with upper and lower bounds for critical 0.05 level.



Scheme 2. CUSUM for with upper and lower bounds for the 0.05 critical level with matching start date of February 2003.

This comparison shows a clear pattern for some models to reject the null hypothesis through piercing the upper confidence band only to return to normal. Notably, the SA and NSA business cycle models suggest a break, as well as the housing supply and demand models. Price extremes during the period of the perceived housing bubbles seem to be linked with monetary policy, the saving glut, and price extrapolation. In no case do we see extreme CUSUMs after the COVID-19 pandemic.

Different themes will have different CUSUM patterns as seen in Scheme 2, which suggest the possibility of structural breaks and misspecification of model narratives. For example, our business cycle theme shows that standardized residuals exceeded the predicted value only to then fall after the crisis. In this case, the macro narrative of just looking at the business cycle would lead to the belief in a housing bubble. The CUSUM pattern of a break and possible bubble is not found when we use an extrapolative price model or in our other macro hypotheses, especially when we account for the behavior of monetary policy.

5. Conclusions

We selected important features that can explain the long-run behavior of housing prices from January 1987 to June 2022, the emergence of the 2004–07 housing bubble, its bursting that led to the GFC, and the housing boom surrounding the COVID-19 pandemic. From these features, we developed ten hypotheses to study the US housing market for both SA and NSA house prices data over similar time periods and methodology. While the strong run-up in housing prices during COVID-19 may suggest a bubble, macro factors like easy fiscal and monetary policies stimulated housing prices and prevented a possible strong reversal. There is no evidence based on our CUSUM analysis to suggest a COVID-19 housing bubble. Additionally, without a large correction following the rapid rise of house prices during COVID-19, we cannot argue that housing has experienced a second bubble during 1987–2022.

Our NN methodology recognizes the relative value of certain macro drivers such as the Consumer Price Index Rent, the 30-Year mortgage rate, Fed assets, and non-farm payroll for explaining the NSA S&P Case–Shiller US National Home Price Index. When the NN methodology is applied to the SA National Home Price Index, durable goods, Fed assets, new single-family houses sold, and disposable income emerge as important features. Among financial variables, mortgage rates, Fed funds and Fed assets are key drivers of house prices.

Tests for housing bubbles (structural breaks) are applied to our NN predictions and find that some hypotheses suggest there were price deviations consistent with housing bubbles. The hypothesis that focuses on extrapolative prices does not show the presence of a bubble (structural break) but confirms that the formation of expectations based on past prices is a key housing market driver.[4] We do not dispute the results of others who find the presence of price extremes or bubbles; rather, we highlight the difficulty of identifying bubbles when there are competing hypotheses. A micro fundamental or price-based model may identify a bubble, yet a macro model may conclude that there are fundamental drivers that lead to high housing prices consistent with model parameters.

Any bubble is conditional on a model and the features used to describe the market environment. Comparing different hypotheses or housing narratives with an unstructured machine learning methodology using over 30 independent variables and explicit residual tests serves as an effective framework for broadly analyzing housing market extremes and bubbles. Using a single NN methodology applied to thematic model specifications coupled with tests for structural breaks (bubbles) advances our understanding of the housing market and supports the identification of different market themes. One man's bubble could be another man's rational behavior.

Author Contributions: All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by A.G.M., M.M. and M.S.R. All authors commented on all versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All data available from the St. Louis FRED database. Variables used are listed in the Appendix A.

Conflicts of Interest: Mark S. Rzepczynski was employed by the company AMPHI Research and Trading, LLC. The authors have no sources of funding or conflicting interests.

Appendix A. Data from the St. Louis FRED Database (Accessed 25 October 2022)

Type	FRED Identifier	Description	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
NSA	COMPUTNSA	New Privately Owned Housing Units Completed: Total Units, Thousands of Units, Monthly, Not Seasonally Adjusted							x		x	x
NSA	CSUSHPINSA	S&P/Case–Shiller U.S. National Home Price Index, Index Jan 2000 = 100, Monthly, Not Seasonally Adjusted	x		x	x	x		x		x	x
NSA	UMCSENT	University of Michigan: Consumer Sentiment, Index 1966: Q1 = 100, Monthly, Not Seasonally Adjusted									x	x

Type	FRED Identifier	Description	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
NSA	AUTHNOTT	New Privately Owned Housing Units Authorized but Not Started: Total Units, Thousands of Units, Monthly, Not Seasonally Adjusted									x	x
NSA	MICH	University of Michigan: Inflation Expectation, Percent, Monthly, Not Seasonally Adjusted										x
NSA	FEDFUNDS	Federal Funds Effective Rate, Percent, Monthly, Not Seasonally Adjusted			x	x	x	x				x
NSA	IPB50001N	Industrial Production: Total Index, Index 2017 = 100, Monthly, Not Seasonally Adjusted	x						x		x	
NSA	KCFSI	Kansas City Financial Stress Index, Index, Monthly, Not Seasonally Adjusted									x	
NSA	MSPNHSUS	Median Sales Price for New Houses Sold in the United States, Dollars, Monthly, Not Seasonally Adjusted							x		x	
NSA	PAYNSA	All Employees, Total Nonfarm, Thousands of Persons, Monthly, Not Seasonally Adjusted	x						x		x	
NSA	HOUST1FNSA	New Privately Owned Housing Units Started: Single-Family Units, Thousands of Units, Monthly, Not Seasonally Adjusted									x	
NSA	CNP16OV	Population Level, Thousands of Persons, Monthly, Not Seasonally Adjusted									x	
NSA	CUUR0000SEHA	Consumer Price Index for All Urban Consumers: Rent of Primary Residence in U.S. City Average, Index 1982–1984 = 100, Monthly, Not Seasonally Adjusted	x									
NSA	EMVMACRO-CONSUME	Equity Market Volatility Tracker: Macroeconomic News and Outlook: Consumer Spending and Sentiment, Index, Monthly, Not Seasonally Adjusted	x									
NSA	EPUMONETARY	Economic Policy Uncertainty Index: Categorical Index: Monetary policy, Index, Monthly, Not Seasonally Adjusted	x		x	x						
NSA	MORTGAGE30US	30-Year Fixed Rate Mortgage Average in the United States, Percent, Monthly, Not Seasonally Adjusted	x		x	x	x	x				
NSA	MSACSRNSA	Monthly Supply of New Houses in the United States, Months' Supply, Monthly, Not Seasonally Adjusted							x		x	
NSA	NFCI	Chicago Fed National Financial Conditions Index, Index, Monthly, Not Seasonally Adjusted										x
NSA	T10Y2YM	10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity, Percent, Monthly, Not Seasonally Adjusted			x	x						
NSA	USACPIALL-MINMEI	Consumer Price Index: All Items for the United States, Index 2015 = 100, Monthly, Not Seasonally Adjusted	x									

Type	FRED Identifier	Description	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
NSA	WALCL	Assets: Total Assets: Total Assets (Less Eliminations from Consolidation): Wednesday Level, Millions of U.S. Dollars, Monthly, Not Seasonally Adjusted			x		x	x				
SA	BOPGSTB	Trade Balance: Goods and Services, Balance of Payments Basis, Millions of Dollars, Monthly, Seasonally Adjusted		x			x	x		x		
SA	COMPU1USA	New Privately Owned Housing Units Completed: Single-Family Units, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate								x		
SA	CSUSHPISA	S&P/Case–Shiller U.S. National Home Price Index, Index Jan 2000 = 100, Monthly, Seasonally Adjusted		x				x		x		
SA	DSPI	Disposable Personal Income, Billions of Dollars, Monthly, Seasonally Adjusted Annual Rate		x						x		
SA	HOUST1F	New Privately Owned Housing Units Started: Single-Family Units, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate								x		
SA	HSN1F	New One Family Houses Sold: United States, Thousands, Monthly, Seasonally Adjusted Annual Rate								x		
SA	UNEMPLOY	Unemployment Level, Thousands of Persons, Monthly, Seasonally Adjusted		x								
SA	PCEDG	Personal Consumption Expenditures: Durable Goods, Billions of Dollars, Monthly, Seasonally Adjusted Annual Rate		x						x		
SA	EMRATIO	Employment-Population Ratio, Percent, Monthly, Seasonally Adjusted		x								
SA	INDPRO	Industrial Production: Total Index, Index 2017 = 100, Monthly, Seasonally Adjusted		x								

Notes

1. See the Dallas Fed's house price database, which updates quarterly exuberance indicators based on price-to-fundamentals and price-to-rent ratios, https://www.dallasfed.org/research/international/houseprice (accessed on 9 August 2023).
2. Machine learning has been applied to many housing market studies; see Xu and Zhang (2021) for a review of this work. Since bubble identification is a joint hypothesis, our approach is to use a model-free approach focused on using specific features associated with a macro narrative as a base for comparison.
3. We employ IBM Modeler; for details, see the Modeler 18 Algorithms Guide, p. 311.
4. A comparison of our macro results with the micro exuberance indicators using supremum augmented Dickey–Fuller (SADF) and generalized SADF (GSADF) reported by the Dallas Fed in their International House Price Database suggests that a macro model may provide useful information on the housing price extreme drivers. The SADF test shows exuberance or a bubble before the GFC based on price or price-to-fundamental ratios; however, it does not provide any insight on macro drivers or macro narratives that can explain a bubble.

References

Basco, Sergi, and Maximilian Schäfer-i-Paradís. 2022. A Model-Free Test of Rational Bubbles: An Application to the US Housing Market. Available online: https://ssrn.com/abstract=4161754 (accessed on 9 August 2023).

Bernanke, Ben. 2005. The Global Saving Glut and the U.S. Current Account Deficit. Paper presented at Remarks at the Sandridge Lecture, Virginia Association of Economics, Richmond, VA, USA, March 10. Available online: http://www.federalreserve.gov/boarddocs/speeches/2005/200503102/ (accessed on 9 August 2023).

Bernanke, Ben S. 2007a. Global Imbalances: Recent Developments and Prospects. Paper presented at the Bundesbank Lecture, Berlin, Germany, September 11.

Bernanke, Ben S. 2007b. Globalization and Monetary Policy. Paper presented at the Fourth Economic Summit, Stanford Institute for Economic Policy Research, Stanford, CA, USA, March 2.

Bernanke, Ben S. 2009. Asia and the Global Financial Crisis. Paper presented at the Federal Reserve Bank of San Francisco's Conference on Asia and the Global Financial Crisis, Santa Barbara, CA, USA, October 19.

Bernanke, Ben S. 2010. Monetary Policy and the Housing Bubble. Paper presented at the Annual Meetings of the American Economic Association, Atlanta, Georgia, January 3. Available online: https://www.federalreserve.gov/newsevents/speech/bernanke20100103a.htm (accessed on 9 August 2023).

Bhar, Ramaprasad, and Anastasios George Malliaris. 2021. Modeling U.S. Monetary Policy During the Great Financial Crisis and Lessons for COVID-19. *Journal of Policy Modeling* 43: 15–33. [CrossRef] [PubMed]

Bhar, Ramaprasad, Mary Malliaris, Mark Rzepczynski, and A. G. Malliaris. 2024. Five Themes of U.S. Home Prices Cycles: A Dynamic Modelling Approach. *Annals of Operations Research*. [CrossRef]

Corsi, Fulvio, and Didier Sornette. 2014. Follow the Money: The Monetary Roots of Bubbles and Crashes. *The International Review of Financial Analysis* 32: 47–59.

Duca, John, John Muellbauer, and Anthony Murphy. 2021. What Drives House Price Cycles? *International Experiences and Policy Issues Journal of Economic Literature* 59: 773–864.

Erdmann, Kevin. 2023. Reassessing the Role of Supply and Demand on Housing Bubble Prices. Available online: https://ssrn.com/abstract=4327414 (accessed on 9 August 2023).

Evanoff, Douglas D., George G. Kaufman, and Anastasios G. Malliaris, eds. 2012. *New Perspectives on Asset Price Bubbles*. New York: Oxford University Press.

Evgenidis, Anastasios, and Anastasios Malliaris. 2023. House Bubbles, Global Imbalances and Monetary Policy in the U.S. *Journal of International Money and Finance* 138: 102919. [CrossRef]

Glaeser, Edward, and Joseph Gyourko. 2018. The Economic Implications of Housing Supply. *Journal of Economic Perspectives* 32: 3–30. [CrossRef]

Haykin, Simon. 1994. *Neural Networks: A Comprehensive Foundation*. Englewood Cliffs: Macmillan Publishing Company.

Holmes, Mark J., Jesús Otero, and Theodore Panagiotidis. 2011. Investigating regional house price convergence in the United States: Evidence from a pair-wise approach. *Economic Modelling* 28: 2369–76. [CrossRef]

Homm, Ulrich, and Jorg Breitung. 2012. Testing for Speculative Bubbles in Stock Markets: A Comparison of Alternative Methods. *Journal of Financial Econometrics* 10: 198–231. [CrossRef]

Hu, Yang. 2023. A Review of Phillips-type Right-tailed Unit Root Bubble Detection Tests. *Journal of Economic Surveys* 37: 141–58. [CrossRef]

Kindleberger, Charles. 1996. *Manias, Panics and Crashes: A History of Financial Crises*, 3rd ed. New York: John Wiley and Sons.

Kiselev, Alexander, and Lenya Ryzhik. 2010. A simple model for asset price bubble formation and collapse. *arXiv* arXiv:1009.0299.

Kuchler, Theresa, Monika Piazzesi, and Johannes Stroebel. 2022. Housing Market Expectations. In *Handbook of Economic Expectations*. Cambridge: Academic Press.

Leamer, Edward E. 2015. Housing Really is the Business Cycles: What Survives the Lessons of 2008-09? *Journal of Money, Credit and Banking* 47: 43–50. [CrossRef]

LeRoy, Stephen F. 2012. Infinite Portfolio Strategies. *Contemporary Economics* 6: 54–60. [CrossRef]

Levitin, Adam J., Desen Lin, and Susan M. Wachter. 2020. Mortgage Risk Premiums during the Housing Bubble. *The Journal of Real Estate Finance and Economics* 60: 421–68. [CrossRef]

Malliaris, Anastasios, and Mary Malliaris. 2021. What Microeconomic Fundamentals Drove Global Oil Prices during 1986–2020? *Journal of Risk and Financial Management* 14: 391. [CrossRef]

Martinez-Garcia, Enrique, and Valerie Grossman. 2018. Explosive Dynamics in House Prices? An Exploration of Financial Market Spillovers in Housing Markets around the World. *Journal of International Money and Finance* 101: 102103. [CrossRef]

Mayer, Christopher J. 2011. Housing Bubbles: A Survey. *Annual Review of Economics* 3: 559–77. Available online: https://ssrn.com/abstract=1920051 (accessed on 9 August 2023). [CrossRef]

McDonald, John F., and Houston H. Stokes. 2013. Monetary Policy and the Housing Bubble. *Journal of Real Estate Finance and Economics* 46: 437–51. [CrossRef]

Otero, Jesús, Theodore Panagiotidis, and Georgios Papapanagiotou. 2022. Testing for exuberance in house prices using data sampled at different frequencies. *Studies in Nonlinear Dynamics & Econometrics* 26: 675–91.

Phillips, Peter C. B., and Shuping Shi. 2018. Real Time Monitoring of Asset Markets: Bubbles and Crises. In *Handbook of Statistics*. Cowles Foundation Discussion Paper No 2152. Amsterdam: Elsevier.

Piazzesi, Monika, and Martin Schneider. 2016. *Housing and Macroeconomics*. NBER Working Paper 22354. Chicago: University of Chicago Press.

Piazzesi, Monika, Martin Schneider, and Johannes Strobel. 2020. Segmented Housing Search. *American Economic Review* 110: 720–59. [CrossRef]

Ploberger, Werner, and Walter Krämer. 1992. The CUSUM test with OLS residuals. *Econometrica* 60: 271–85. [CrossRef]

Sa, Filipa, and Tomasz Wieladex. 2015. Capital Inflows and U.S. Housing Boom. *Journal of Money, Credit and Banking* 47: 221–56. [CrossRef]

Saltelli, Andrea, Stefano Tarantola, Francesca Campolongo, and Marco Ratto. 2004. *Sensitivity Analysis in Practice—A Guide to Assessing Scientific Models*. Hoboken: John Wiley & Sons Publishing.

Scherbina, Anna, and Bernd Schlusche. 2014. Asset price bubbles: A survey. *Quantitative Finance* 14: 589–604. [CrossRef]

Shi, Shuping, and Peter C. B. Phillips. 2020. Diagnosing Housing Fever with An Econometric Thermometer. *Journal of Economic Surveys* 37: 159–86. [CrossRef]

Sornette, Didier, and Peter Cauwels. 2014. Financial Bubbles: Mechanisms and Diagnostics. *arXiv* arXiv:1404.2140. [CrossRef]

Sornette, Didier. 2003. *Why Stock Markets Crash: Critical Events in Complex Financial Systems*. Princeton: Princeton University Press.

Sornette, Didier, Peter Cauwels, and Georgi Smilyanov. 2017. Can We Use Volatility to Diagnose Financial Bubbles? Lessons from 40 Historical Bubbles. *Quantitative Finance and Economics* 2: 486–594. Available online: https://ssrn.com/abstract=3006642 (accessed on 9 August 2023). [CrossRef]

Steinberg, Joseph. 2019. On the Source of the U.S. Trade Deficits: Global Saving Glut or Domestic Saving Drought? *Review of Economic Dynamics* 31: 200–23. [CrossRef]

Tarlie, Martin B., Georgios Sakoulis, and Roy Henriksson. 2022. Stock Market Bubbles and Anti-Bubbles. *International Review of Financial Analysis* 81: 101235. [CrossRef]

Taylor, John B. 2007. Housing and Monetary Policy. In *Federal Reserve Bank of Kansas City, Housing, Housing Finance and Monetary Policy*. Kansas City: Federal Reserve Bank of Kansas City, pp. 463–76.

Taylor, John B. 2009. *The Financial Crisis and the Policy Responses: An Empirical Analysis of What Went Wrong*. Working Paper, No.14631. Cambridge: National Bureau of Economic Research.

Taylor, John B. 2010. The Fed and the Crisis: A Reply to Ben Bernanke. *Wall Street Journal* 11: A19.

West, Kenneth D. 1988. Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation. *The Journal of Finance* 43: 639–56. [CrossRef]

Xu, Xiaojie, and Yun Zhang. 2021. Rent Index Forecasting Through Neural Networks. *Journal of Economic Studies* 49: 1321–39. [CrossRef]

Ziemba, William, Sebastien Lleo, and Mikhail Zhitlukhin. 2017. Other Bubble-testing Methodologies and Historical Bubbles. World Scientific Book Chapters. In *Stock Market Crashes Predictable and Unpredictable and What to Do about Them*. Singapore: World Scientific Publishing Company, chp. 11, pp. 247–57.