Macroeconomic Effects of Housing Market Equilibrium

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Abstract

This paper studies the response heterogeneity of equilibrium housing prices to macroeconomic variations from the demand and supply sides of housing. We refine a housing stock-flow model by allowing for long-memory error corrections in the housing - macroeconomic system to accommodate the possibility that the correction speed could be slow and vary between the demand and supply of housing. Using a long quarterly dataset for the U.S., our results supported by FCVAR estimation confirm the system-wide long-memory, indicating slow and distinct disequilibrium corrections following macroeconomic variations from the two sides of housing. We find that impacts of the macroeconomic factor that engages exclusively on the demand/supply side of housing would be biased if the one from the other side is neglected. As for the factor having differential impacts from both sides of housing, its net impact is negative and is dominated by the demand-side dynamics, indicating a relatively elastic housing demand. Moreover, the FCVAR estimation with zero restrictions is performed for identification purposes and lends robustness to our findings.

Key Words: Housing prices; Macroeconomic variations; Long memory error corrections; Fractionally cointegrated VAR

JEL Classifications: C32; R21; R31

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1 Introduction

The bitter lesson of the recent global financial crisis has revealed the importance of the housing market dynamics in business cycle fluctuations, centralizing the error-corrective role of macroeconomic variations toward housing equilibrium. Recently, an emerging body of literature has shown that macroeconomic variations drive the housing market dynamics, eventually determining the steady-state of housing prices in the long-run (Garriga et al., 2019). However, less is known about the way disequilibrium errors are corrected in demand and supply functions of housing following changes in macroeconomic conditions. Unlike an instant market clearing, the housing market is known to be inefficient with marked frictions on both the demand and supply sides of housing (Case and Shiller, 1989; Oikarinen et al., 2018).[1] Such an inefficiency is characterized by sluggish rate of error corrections driven by slow-convergent (viz., long-memory) shocks within the housing-macroeconomic interaction milieu. Accordingly, the potentially-distant correction speeds from the two sides of housing would therefore contribute differently to the formation of the overall housing price equilibrium. While under-representation of such distant and slow correction speeds of shocks may produce biased inferences, the literature by far is silent in the treatment of this issue. To this end, this paper analyzes the demand and supply channels of housing, through which distinct effects of macroeconomic factors from the two channels on equilibrium housing prices are captured in a long-memory cointegration framework.

So far, the extant literature has reported that the *same* macroeconomic shock, for instance, a change in interest rates, may exert heterogeneous impacts on equilibrium housing prices by shifting the demand and supply curves (McCarthy and Peach, 2002).[2] However, existing research has either considered macroeconomic impacts only on the housing demand side, ignoring the supply-side dynamics, or has failed to disentangle possibly heterogeneous impacts of the same macroeconomic factor on both demand and supply sides of housing.[3] The first gap to be filled in

[1]The housing market is often characterized by frictions that are largely due to long periods of searching and construction, as well as high costs of carrying and transactions (Case and Shiller, 1989; DiPasquale and Wheaton, 1994).

[2]It is known that the same macroeconomic variation can shift the housing demand or supply curve exclusively, or both of them simultaneously (e.g., Arestis and Gonzalez-Martinez, 2016; Duan et al., 2021).

[3]For example, the well-known strategy of the inverted demand function ignores the supply-side dynamics by assuming rigidity of the housing supply (e.g., Muellbauer and Murphy, 1997; Oikarinen et al., 2018). At the same time, directly including the demand and supply factors in the same function would under-represent the actual effects of the same macroeconomic variables. The literature seems to have been engaged with uncovering only aggregate impacts (e.g., Duan et al., 2019).

our paper, therefore, involves investigation of the mechanism through which equilibrium housing prices are determined by separately modelling distant responses of housing demand and supply functions to macroeconomic variations.

Moreover, an equally important issue that has also received little attention is the long-memory feature in the housing and macroeconomic system. Indeed, it is known that housing prices only adjust gradually to disequilibrium deviations from both the demand and supply sides of housing (Glaeser et al., 2014). Such a slow price adjustment may suggest the presence of a *long memory* shock in the interactive system, one that can be captured by the presence of fractional integration order (d) of the target series.[4] It indicates that disequilibrium deviations in the housing market can be highly persistent over time and dying out slowly. However, built on the strict assumption of the integer integration order, the conventional strategy assumes that shocks are either infinitely lived with *permanent memory* (i.e. I(1) series) or instantly died out with *short memory* (i.e. I(0) series). Clearly, this would lead to a failure in replicating the naturally gradual adjustment towards housing equilibrium, which could have been avoided by capturing the fractional integration order and the associated long-memory feature of target series within the system.

Recently, increasing evidence has emerged with regard to the presence of long memory in housing prices (e.g., Canarella et al., 2021) and macroeconomic time series (e.g., Jones et al., 2014). We further expand this domain of literature by quantifying the extent of system-wide memory within the housing price - macroeconomic interaction. Indeed, a shock never works alone and the assessment of its impact magnitude is very much contingent upon a complex web of interaction within the dynamic system, governing the path dependence of individual series in the system (Chen and Xu, 2021). Interpretation on the sluggish housing market clearing and the steady-state of the housing price - macroeconomic interaction would be biased unless we capture the long memory feature in the system by allowing for fractionality of d. Thus, the second part of our paper extends the literature by modelling the gradual (long-memory) error corrections towards equilibrium from the demand and supply sides of housing, respectively.

As a first step, we refine a housing stock-flow model by accommodating the long-memory error corrections where the determination processes of housing prices from the demand and supply

[4] A long-memory featured series indicates that the past shocks could last for a long time period and taper-off slowly towards a stable mean (Johansen and Nielsen, 2012). The slow price adjustment with a long memory is also indicative of the inefficiency of the housing market (Fu and Ng, 2001).

functions are separately modelled. Using a quarterly dataset for the U.S. over four decades, we derive a reduced form specification of the conceptual framework and estimate the same using the fractionally cointegrated vector autoregressive (FCVAR) approach proposed by Johansen and Nielsen (2012). Through this, we apply a separate estimation strategy where macroeconomic impacts from the demand and supply sides on equilibrium housing prices are respectively estimated. At the same time, different speeds of the long-memory featured error corrections on the two sides of housing are gauged. By solving the subsystem of the demand and supply functions in housing equilibrium, we eventually arrive at a clearer picture of the net impacts of macroeconomic factors. To ensure exact identification and offer robustness evaluation, the FCVAR model is re-estimated by imposing zero restrictions on insignificant coefficients.

Consistent with theoretical expectations, some important results emerge from our empirical investigation. First, the long memory feature of housing price and macroeconomic series contained in our dataset is found by capturing the presence of the fractional integration order. Second, macroeconomic impacts are shown to shift the demand or supply curve exclusively, or both of them simultaneously. We find that impacts of the factors with an exclusive role from the demand/supply side of housing would be mis-estimated if the ones from the other side are failed to be considered. With regard to the factors having different 'dual' impacts from both sides, the net impact of each factor is negative, implying that its negative impacts from the demand side are greater than its positive counterparts from the supply (in absolute terms). The dominance of the demand-side dynamics echoes with the existing viewpoint on an elastic demand against a relatively inelastic supply in the U.S. housing market (e.g., Saiz, 2010).

The above demonstrates the information loss suffered when estimating either a single function that aggregates demand and supply factors or an inverted demand function for housing prices, indicating the appropriateness of our separate estimation strategy. Through this, we confirm the long-memory featured error correction towards housing equilibrium, and the adjustment speeds from the demand and supply sides of housing are measured to be different. Eventually, the net macroeconomic impacts obtained by aggregating the separate impacts from the two sides of housing are in line with our expectations and extant literature. In addition, the restricted FCVAR estimation further ensures exact identification and reassures the robustness of our results. Our findings possess insightful implications for clear comprehension of the equilibrium housing price formation and the long-memory feature of the housing market dynamics.

The rest of paper is structured as follows. Section 2 reviews the existing related literature. Section 3 presents the theoretical framework. Section 4 introduces the empirical methodology. Section 5 presents data and preliminary observations. Section 6 discusses our empirical findings. Finally, Section 7 concludes and draws out policy implications.

2 Literature

While the literature on macroeconomic effects of housing price dynamics is growing, there still remain some gaps, especially in the way macroeconomic variables impact the demand and supply functions of housing, and the determination of the steady-state of housing prices in a long-memory featured environment. This section undertakes a review of existing related research.

Recent literature shows that the same macroeconomic fluctuations have distinct implications for the demand and supply of housing. As a clear demonstration, McCarthy and Peach (2002) find that after restructuring the housing finance system in the U.S. since the mid-1980s, the same tightening monetary policy (a positive shock to the federal funds rate) would together raise the financing cost of both house purchase and construction, shifting down both the demand and supply curves. They further point out that in the face of an increasing financing cost, housing prices could witness a decline in the long run due to the dominant negative impact of a slump in the housing demand against the relatively smaller positive impact from the supply side. The above motivates a separate identification of the housing price determination from the demand and supply sides, without which macroeconomic effects cannot be truly uncovered. We, therefore, summarize below the research on the macroeconomic impacts from the two sides of housing, as well as the long-memory in housing prices.

2.1 Macroeconomic effects on the housing demand

It has been long recognized that macroeconomic fundamentals can impact housing prices by shifting the demand curve. Building an inverted housing demand function in the context of the UK, Muellbauer and Murphy (1997) find that the historical housing boom and bust are largely driven by macroeconomic impacts on the demand side. Poterba (1984) points out that a negative shock of user financing costs, i.e., declining interest rates, raises housing prices given fixed housing stocks in the short-run. Afterwards, housing prices experience a gradual decline in the market adjustment with increasing housing supply until a new steady-state is reached. Anundsen and Jansen (2013) suggest that the interest rate along with inflation are an important part of the user cost of home ownership, and rising inflation would raise the cost of owning. Christensen et al. (2016) find that increases in the collateral value boost housing consumption and subsequently housing prices during the Canadian housing cycles. The important role of credit rationing in the demand side has also been embraced, at least in spirit, by the extant literature (e.g. Favara and Imbs, 2015; Ling et al., 2016).

Among others, Muellbauer and Murphy (1997) and McCarthy and Peach (2002) document that available housing stocks reveal the level of housing demand, which is proportional to the former. An increase in housing stocks indicates a rising housing demand that leads to heightening housing prices. Alternatively, housing stocks also represent the ability of the market supply to meet the required demand though there might exist a gap between them due to the slow housing adjustment (Heath, 2014). Recent studies, such as Arestis and Gonzalez-Martinez (2016), build a conceptual framework that attributes the housing price dynamics to forces on both the demand and supply functions. They find that macroeconomic factors, such as interest rates and credit availability, could affect housing prices through both the two functions. A series of relevant studies including Fitzpatrick and McQuinn (2007); Gerlach and Peng (2005) also confirm the above findings.

Moreover, the effect of uncertainty on the housing demand is also important (Xia et al., 2020). High exposure to uncertainty dampens households' intentions for house purchase, leading to a decline in the demand and price of housing (André et al., 2017). We will discuss in the next that, like interest rates, the uncertainty level could also exert differential 'dual' roles via not only the housing demand but also the supply side simultaneously (Miles, 2009).

2.2 Macroeconomic effects on the housing supply

Besides housing demand, macroeconomic fundamentals can also impact housing prices by shifting the supply curve, and a failure to consider the supply-side dynamics would mis-estimate the impacts (Anundsen and Jansen, 2013). A popular method to describe the housing market dynamics on both the demand and supply sides is the stock and flow model, where housing price is determined by an inverted demand function (i.e. 'stock' function); the 'flow' of housing is modelled by a function (i.e. 'flow' function) that includes housing prices (DiPasquale and Wheaton, 1994). The model is recently updated to accommodate the slow price adjustment and the forward-looking property of housing market participants by adding terms of the short-run dynamics and the error corrections (Murphy, 2018). However, it only considers the role of the demand side in housing price dynamics but fails to consider the supply-side.

In addition to the demand side dynamics, housing stock exerts a negative effect on the supply side due to the fact that an increase in housing stock indicates a heightening housing supply that, in turn, decreases housing prices (Anundsen and Jansen, 2013). Although bank credit and interest rate can affect housing prices from both the demand and supply sides (e.g., Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018, 2019), only their aggregate impacts are estimated, neglecting the heterogeneous roles of each factor on the two sides of housing. Furthermore, the role of input factors for the housing supply should also not be neglected. Poterba (1984) suggests that a buoyant demand for production factors, such as costs of construction, financing and land, can raise equilibrium housing prices due to a downward shift of the supply curve induced by a rising supply cost. DiPasquale and Wheaton (1994) document that an initial positive shock to housing prices would drop the land availability. Consequently, a rising land price would weaken the housing supply, leading to a rise in housing prices in the long-term. Recent literature also echoes the important role of the land price arguing that it drives most of the housing price fluctuations compared to the cost of structures (Davis and Heathcote, 2007; Davis et al., 2021). As for uncertainty, in addition to its role from the demand side, it can also shift the supply curve by affecting the construction incentive and then the stock of housing (Miles, 2009).

2.3 Long-memory in the housing market dynamics

The literature on the long-memory feature of a housing market is still nascent. The ongoing but limited research has mainly focused on testing long-memory in univariate series, rather than modeling its potential presence in a system-setting such as the housing price and macroeconomic interactive system in our case. Among others, Ngene et al. (2015) identify a significant long-memory feature in the U.S. regional housing prices, indicating a highly-persistent price moving pattern. Gupta et al. (2015) analyze the long-memory featured co-movement of housing prices among European countries by allowing fractional values of both integration and cointegration orders. They demonstrate that European housing prices are fractionally integrated, and the integration order is above one, indicating the non-mean-revision pattern. Similarly, Canarella et al. (2021) find significantly high persistence of the dynamics of housing prices in both the U.S. and UK. The long-range dependence of housing prices in the U.S. is also echoed by other extant literature (see, e.g., Segnon et al., 2021). In addition to housing prices, whether macroeconomic series possess long memory have also raised widespread attention. Notable work in this regard involves interest rates (e.g., Jones et al., 2014), inflation (e.g., Cogley and Sargent, 2005; Kumar and Okimoto, 2007), and commodity prices (e.g., Dolatabadi et al., 2018).

Overall, there is a clear dearth of research on how changes in macroeconomic conditions impact housing prices separately via the demand and supply functions, when shocks within the interactive system feature long-memory. This paper aims to fill the gap in the literature by introducing a theoretical construct - one that determines (equilibrium) housing prices from the demand and supply functions, respectively, in a long-memory error correction model. We discuss our theoretical framework in the next section.

3 Theoretical construct

The conventional housing stock-flow model, originally proposed by Smith (1969), applies the life-cycle model to the consumption of housing. In this section, we augment the basic model by updating the measure of user cost of home ownership (U). Moreover, the macroeconomic - housing price interaction is then built on the modified stock-flow model where long-memory shocks within the system are further considered. In our modified version of the stock-flow model, housing demand and supply functions are formulated as:

$$D(RHP, U, R, X_D) = HUC \tag{1}$$

$$\Delta HUC = C(X_S, RHP) - \delta HUC \tag{2}$$

where in Equation (1) the demand ($D(.)$) - assuming to be proportional to the housing stock (HUC) - depends on the house price (RHP), the user cost of owning (U), the imputed rental price of housing (R), and other factors that affect the demand (X_D). Modern demand theory suggests that U could be expressed by (See, e.g., Himmelberg et al., 2005):

$$U = LIR \pm DEF + \delta - E(\Delta RHP/RHP) + CD \tag{3}$$

where LIR is the interest rate, DEF is the inflation rate[5], δ is the depreciation rate or the rate of maintenance costs adjusting for property taxation, $E(\Delta RHP/RHP)$ is the expected appreciation rate of housing prices, and CD is the credit/mortgage rationing. The determination of equilibrium housing prices on the demand side (RHP^{D*}) is obtained by inverting the demand function (Equation (1)) and jointly considering Equation (3).[6]

$$RHP^{D*} = \alpha_0 + \alpha_1 DEF + \alpha_2 HUC + \alpha_3 LIR + \alpha_4 EPU + \alpha_5 CD \tag{4}$$

where $\alpha_1 <> 0$[7], $\alpha_2 > 0$, $\alpha_3 < 0$, $\alpha_4 < 0$, and $\alpha_5 > 0$; RHP^{D*} is the housing price level determined in the long-run demand function; EPU is the uncertainty level, which changes would shift the demand curve, and is included in X_D.[8]

Equation (4) describes a static long-run equilibrium status in the housing demand function, which is obtained when the stock of housing equates the current demand. It can be seen as a linearization of the theoretical formulations of Equations (1) and (3). Presuming that changes in housing stock can reflect the demand dynamics, an increase in the housing stock along with the

[5]Two strands of literature have discussed the role of inflation in affordability of homeownership with distant viewpoints. One centers on the 'user costs of homeownership' that inflationary expectations reduce the user costs and increase the homeownership rate (e.g., Martin and Hanson, 2016; Rosen and Rosen, 1980); another viewpoint lies in the role of unanticipated inflation in driving interest rates that further raise the cost of both mortgage and homeownership (e.g., Hedlund, 2019)

[6]We follow the literature (See, e.g., Anundsen and Jansen, 2013) by assuming that δ is constant, and the real R is unobservable and is represented by a function of disposable income in the household sector. Since both disposable income and inflation with the latter represented by the GDP deflator in our case are related to the GDP, considering both of them simultaneously may encounter the issue of multicollinearity. Our empirical analysis, therefore, chooses to include the latter, while the role of disposable income is captured by changes in the GDP.

[7]As discussed in Footnote 5, the effect of inflation on housing price dynamics could be either positive or negative depending on whether changes in inflation are anticipated or unanticipated.

[8]Recent research has reported the role of uncertainty in the housing price dynamics from the demand side by affecting housing consumption factors, such as the probability of owning, purchase decisions, and preferences of home attributes (e.g., Diaz-Serrano, 2005; Zheng et al., 2018). The role of uncertainty is also known to transmit from the supply side by affecting the construction incentive and then the housing stock (Miles, 2009). Therefore, we will consider the role of uncertainty in the formation of housing demand and supply functions, respectively.

credit for house purchase, can boost housing demand and then housing prices. Further, combined with growing financing costs, inflation can accelerate the user cost of home ownership, pushing the housing price down by dampening the demand for housing. Here, uncertainty and its persistence also exert a negative impact by shifting the demand curve and prices of housing.

A model of house price dynamics will not be complete without considering the supply-side of the housing market (Muellbauer and Murphy, 1997; Oikarinen et al., 2018). Unlike conventional research that merely relies on the inverted demand function but ignores the equally-important supply-side dynamics, we extend the existing research by separately modelling the macroeconomic effects from the demand and supply sides of housing on equilibrium housing prices. Akin to the demand side, the equilibrium housing price level on the supply side can be obtained when the supply function is in the steady-state with $\Delta HUC = 0$. This can be derived by inverting the supply function (Equation (2)).

$$RHP^{S*} = \lambda_0 + \lambda_1 RLV + \lambda_2 HUC + \lambda_3 LIR + \lambda_4 EPU + \lambda_5 CS \tag{5}$$

where $\lambda_1 > 0$, $\lambda_2 < 0$, $\lambda_3 > 0$, $\lambda_4 > 0$, and $\lambda_5 < 0$; RHP^{S*} is the housing price level determined in the long-run supply function; the land value (RLV), the financing cost for housing development (LIR), the uncertainty level (EPU), and credit rationing (CS) are factors that might shift the housing supply curve, and are included in X_S in the construction function (C(.)) in Equation (2).

Derived from a linearization of Equation (2), Equation (5) depicts the housing supply function in equilibrium. It defines a residential investment rate governed by the housing price to adjust the housing construction towards a long-run level.[9] The housing stock is expected to be negatively related to housing prices since a rise in the former signals an expanded supply, weakening the latter. A heightening credit rationing for housing development raises housing supply and then drops housing prices. The increasing cost for inputs of housing constructions, such as land and financing, is expected to raise the construction cost and the price level. A rising uncertainty would also weaken the supply level and then push the price up.

Overall, we regard Equations (4) and (5) as a subsystem where the long-run housing price level

[9] Since the market power of constructors is relatively limited given that new housing is much smaller than the existing housing stock. This is the reason that in the stock-flow model constructors are assumed to operate within a competitive environment (Beenstock and Felsenstein, 2015).

derived from the demand and supply functions can be defined. The market-clearing conditions are achieved when both demand and supply functions attain a steady-state where the quantity and price of housing obtained from these two functions intersect, respectively (McCarthy and Peach, 2002). Particularly, $RHP^* = RHP^{D*} = RHP^{S*}$. Using this equilibrium condition, we can map the net effects of macroeconomic variables on the equilibrium housing price. Accordingly, RHP^* is derived as:

$$RHP^* = \psi_0 + \psi_1 DEF + \psi_2 CD + \psi_3 HUC + \psi_4 CS + \psi_5 RLV + \psi_6 EPU + \psi_7 LIR \qquad (6)$$

where $\psi_0 = (\alpha_0 + \lambda_0)/2$; $\psi_1 = \alpha_1/2$; $\psi_2 = \alpha_5/2$; $\psi_3 = (\alpha_2 + \lambda_2)/2$; $\psi_4 = \lambda_5/2$; $\psi_5 = \lambda_1/2$; $\psi_6 = (\alpha_4 + \lambda_4)/2$; and $\psi_7 = (\alpha_3 + \lambda_3)/2$. According to Equations (4) and (5), expected signs of macroeconomic factors in Equation (6) are $\psi_1 < 0$, $\psi_2 > 0$, $\psi_3 \lesseqgtr 0$, $\psi_4 < 0$, $\psi_5 > 0$, $\psi_6 \lesseqgtr 0$, $\psi_7 \lesseqgtr 0$. While signs of the factors that impact housing prices exclusively from the demand or supply functions are definite as previously defined, there also exist specific factors, such as the housing stock, uncertainty, and interest rate, that play different roles in the formation of the two functions simultaneously. Thus, their net impacts could theoretically be either sign depending on whether the impacts from the demand or the supply side is dominating.

In line with existing literature (See, e.g., Duan et al., 2019), it can be argued that the same macroeconomic factors can have varied effects on housing demand and supply functions. Directly aggregating the demand and supply factors in a single function would, otherwise, mask the true macroeconomic effects with potential 'dual' roles, leading to information loss and unreliable inferences. To uncover such distinct effects, we separately estimate demand and supply functions of housing in the equilibrium status (Equations (4) and (5)), respectively.[10] The specific and separate impacts of macroeconomic variables on the demand and supply of housing, and their overall impacts on equilibrium housing prices can be then gauged by the coefficients in Equation (6).

The above discussion concerns the 'long-run' that refers to the occasion when the price and

[10]It is worth noting that although the formation of the demand and supply functions is featured by a large difference, due to the inclusion of 'dual'-role factors in both functions, it may still raise a concern of simultaneous equations issue typically shown by correlated residuals of the two functions. This concern is handled in our empirical analysis that the steady-state of the demand and supply functions are respectively identified by capturing independent (linear) cointegrating vectors from the two different functions through the FCVAR model. Residual diagnostics will further examine that residuals of these two functions are free of both heteroskedasticity and autocorrelation, indicating that both functions are correctly specified (Anundsen and Jansen, 2013).

quantity of housing would *adjust to shocks immediately*. However, unlike an instant (market) clearing state that is characterised by frictionless and efficient market conditions, the shock adjustment process towards housing equilibrium is highly sluggish due to the presence of market frictions in both the demand and supply of housing, including long-construction duration, high searching and transaction costs, and in-liquidity (Oikarinen et al., 2018). Such a feature of informational inefficiency of a housing market has been widely studied by depicting patterns of the price series that is far from a 'random walk' (See, e.g., Case and Shiller, 1989; Larsen and Weum, 2008). In our work, we extend the conventional modelling strategy by introducing the role of housing market inefficiency - a feature that can be envisaged by high degree of serial correlation in the housing price series. Autocorrelated housing prices are mainly attributed to irrational market participants who form price forecasts by using extrapolative beliefs, i.e. backward-looking expectations, and behavioral factors such as feedback effects (Dusansky and Koç, 2007). Moreover, while efficient markets operating with rational expectations indicate that forward forecasts are made using all available market information, i.e., forward-looking expectations, prices can still depict an autoregressive pattern, thanks to the presence of gradual (error) adjustments (Glaeser et al., 2014). At the same time, the housing market inefficiency further suggests that prices are not a sufficient statistic, underlying the importance of incorporating market-related factors in the analysis (DiPasquale and Wheaton, 1994). By fully considering these short-term features of housing market adjustment, we extend our model for housing price dynamics (on the demand and supply sides) in the following error-correction form:

$$\begin{aligned}\Delta^{d1} RHP_t = \Pi_D L_{d1}(RHP_t - RHP_t^{D*}) + \beta_1 \Delta^{d1} L_{d1} HUC_t + \beta_2 \Delta^{d1} L_{d1} DEF_t \\ + \beta_3 \Delta^{d1} L_{d1} LIR_t + \beta_4 \Delta^{d1} L_{d1} EPU_t + \beta_5 \Delta^{d1} L_{d1} CD_t + \varepsilon_D\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta^{d2} RHP_t = \Pi_S L_{d2}(RHP_t - RHP_t^{S*}) + \gamma_1 \Delta^{d2} L_{d2} HUC_t + \gamma_2 \Delta^{d2} L_{d2} EPU_t \\ + \gamma_3 \Delta^{d2} L_{d2} LIR_t + \gamma_4 \Delta^{d2} L_{d2} RLV_t + \gamma_5 \Delta^{d2} L_{d2} CS_t + \varepsilon_S\end{aligned} \tag{8}$$

where Equations (7) and (8) are typical in empirical analyses of housing price movements (See, e.g., Harter-Dreiman, 2004). On both the demand and supply sides, the housing price change at the current period is determined by the lagged changes in prices and market fundamentals, and by the deviation of the price level from its long-term equilibrium level at the previous period. On these two sides, $L_{d1}(RHP_t - RHP_t^{D*})$ and $L_{d2}(RHP_t - RHP_t^{S*})$ respectively capture the sluggish and nonlinear price adjustment towards equilibrium where d_1 and d_2 can be any real numbers (i.e., an integer or a fraction); L_d and Δ^d denotes the difference and lag operators with an order d where $L_d X_t = X_{t-d}, L_d = 1 - \Delta^d$;[11] Π_D and Π_S are the parameter matrices where the adjustment speed and the equilibrium price determination (i.e., Equations (4) and (5)) are defined; ε_D and ε_S are assumed to be white noise series with a zero mean.

Conventionally, the error correction term is founded on the strict assumption that the integration order (d) can be only an integer, failing to embed the full picture of various rates of convergence of shocks (or varying degrees of 'memory') on governing the housing adjustment speed. In an I(0), or short-memory, series, past shocks are short-lived and died out quickly; in an I(1), or permanent, series, past shocks persist infinitely. However, in reality, d of the house price and macroeconomic series can be far from an integer; instead, being as a fraction (See, e.g., Canarella et al., 2021; Segnon et al., 2021). In an I(d), or long memory, series with $d \in (0, 1)$, shocks are distinct with the ones in an I(0) and I(1) series, demonstrating a hyperbolically decaying impact pattern. Thus, it is evident that the gradual housing adjustment towards equilibrium cannot be accurately modelled without capturing the long-memory featured correction speed. This representation determines the way equilibrium price is achieved and for the time length it takes to arrive at the same (Johansen and Nielsen, 2012). To summarise, we extend the conventional framework by allowing for fractional error corrections in the demand and supply functions of housing. In the following section, we present the methodological details regarding our employed long-memory cointegration approach.

4 Methodology

In this section, we identify the long memory feature of a time series by quantifying its fractional integration order. Instead of building on a conventional I(0)/I(1) framework like a cointegrated vector autoregressive (CVAR) model, we then introduce a fractionally cointegrated VAR (FCVAR) model that accounts for the long memory featured error-corrections within the macroeconomic-

[11] Shocks to the demand and supply functions will generate wedges between the actual price (i.e., RHP_{t-d1} and RHP_{t-d2}) and equilibrium prices (i.e. $RHP^{D*}_{t-d_1}$ and $RHP^{S*}_{t-d_2}$). The short-run disequilibrium in a housing market implied by those wedges will correct slowly if no other shocks occur in the system.

housing price system.

(a) Characterizing long-memory in the data

Defining that the individual time series at time t in our macroeconomic-housing price system is denoted by y_t. We model y_t (for $t = 1, \ldots, T$) as an integrated process of order d such that:

$$(1-L)^d y_t = \psi(L)\varepsilon_t \tag{9}$$

where $(1-L)^d$ is the difference operator of order d. For example, if $d = 1$, $(1-L)^1 y_t = y_t - y_{t-1} = \Delta y_t$. $\psi(L^j)$ is the coefficient of the error term (ε) at each specific time period $t - j$ with $\sum_{j=0}^{\infty} |\psi(L^j)| < \infty$, $j = 0, 1, 2, \ldots$, and the error term (ε_t) is a white noise process with zero mean and constant variance, viz. $\varepsilon_t \sim iid(0, \sigma^2)$. Instead of abiding by the conventional assumption that d is an integer, following Granger and Joyeux (1980), we assume a fractionally integrated process that allows d to be fraction values, thus enriching the dynamics of shock convergence processes. Equation (9) can be re-written in the following form:[12]

$$y_t = (1-L)^{-d}\psi(L)\varepsilon_t \tag{10}$$

Based on a power series expansion, $(1-L)^{-d}$ can be formulated as

$$(1-L)^{-d} = \sum_{j=0}^{\infty} \gamma_j L^j \tag{11}$$

$$\gamma_j = \frac{(d+j-1)(d+j-2)\cdots(d+2)(d+1)(d)}{j!} \tag{12}$$

where $\gamma_j \cong (j+1)^{d-1}$ given that $d < 1$ and j is large, and $\gamma_0 \equiv 1$. Thus, subject to Equation (11), a fractionally integrated process (shown as Equation (10)) can be re-formulated as the following infinite moving average (MA(∞)) process.[13]

$$y_t = (1-L)^{-d}\varepsilon_t = \gamma_0\varepsilon_t + \gamma_1\varepsilon_{t-1} + \gamma_2\varepsilon_{t-2} + \cdots \tag{13}$$

[12] As documented by Hamilton (1994), the inverse value of $(1-L)^d$ exists subject to $d < 1/2$; if $d > 1/2$, y_t will no longer be stationary as the inverse of $(1-L)^d$ approaches infinity.

[13] $\psi(L^j)$ in Equation (10) is replaced by γ_j in Equation (13) to represent coefficient of each $L^j\varepsilon_t$.

where impulse response coefficients of y_t, i.e. γ_j, reveal a slowly-decayed pattern of shocks to the lagged values of the error term ($L^j \varepsilon_t$). Following this, γ_j captures the potential 'long-memory' property of y_t, indicating that impacts of past shocks of y_t on its current value could be highly-persistent and display slow convergence in the form of a hyperbolic rate of decline with increases in temporal lags. In contrast, impulse response coefficients of a 'short-memory' time series decay more quickly as a geometric pattern, such as ρ^i in a covariance-stationary AR(1) process, i.e., $y_t = \sum_{i=0}^{\infty} \rho^i \varepsilon_{t-i}$. Concerning the statistical properties of a fractionally integrated series (y_t), y_t in Equation (13) is a mean-reverting process when the superscript of γ_j is less than 0, i.e., $d < 1$. It indicates that impacts of past shocks on y_t diminish gradually over time. Moreover, y_t can have a finite variance only when $d < 1/2$, implying a square-summable γ_j. Thus, y_t can be a covariance-stationary series only when $d < 1/2$ instead of $d = 0$. A summary of 'memory properties' of a series y_t with different integration orders (d) can be seen in Table 1. We will empirically estimate d using several semi-parametric estimators in both static and rolling-window setting.

Table 1: **Memory properties of y_t with different d values**

d Value	Memory	Stationarity	Mean	Variance	Shock Duration
$d < 0$	Long	Stationary	Mean-reversion	Finite	Long-lived
$d = 0$	Short	Stationary	Mean-reversion	Finite	Short-lived
$0 < d < 0.5$	Long	Stationary	Mean-reversion	Finite	Long-lived
$0.5 \leq d < 1$	Long	Non-stationary	Mean-reversion	Infinite	Long-lived
$d = 1$	Permanent	Non-stationary, unit root process	No Mean-Reversion	Infinite	Permanent
$d > 1$	Permanent	Non-stationary	No Mean-Reversion	Infinite	Permanent, the effects increase over time

(b) System memory and slow error corrections: Fractionally cointegrated VAR model

To uncover the macroeconomy - housing price interaction in equilibrium by accommodating slow error corrections, we employ a fractionally cointegrated vector autoregressive (FCVAR) model proposed by Johansen and Nielsen (2012). FCVAR model establishes a long-memory cointegration framework that allows fractionality in both the integration order of univariate series and the cointegration order. From a conventional CVAR model, our employed FCVAR model is formulated as

$$\Delta^d(Y_t - \rho) = \alpha\beta' L_d(Y_t - \rho) + \sum_{i=1}^{p} \Gamma_i \Delta^d L_d^i (Y_t - \rho) + \varepsilon_t \tag{14}$$

where Y_t is a K-dimensional $I(d)$ time series with $t = 1, 2, \ldots, T$; i stands for numbers of short-run dynamics with $i = 1, 2, \ldots, p$; Γ_i is the coefficient of each temporal lagged Y_t; Π is a parameter matrix identified by two parameters, viz. $\Pi = \alpha\beta'$. α and β are $K \times r$ matrices, β identifies the cointegrating relationship(s) among variables in Y_t, and α defines the adjustment speed towards the long-run equilibrium of each variable in Y_t. r is the rank of Y_t, and its value indicates the number of cointegration(s) in the model with $0 \leq r \leq K$. Δ^d and L_b stand for the fractional difference operator with order d and the fractional lag operator with b respectively where $\Delta^d = 1 - L_d = (1 - L)^d$ and $L_b = 1 - \Delta^b$. d and b could be either integer or fractional and positive values. ε_t is a K-dimensional identically independent distributed error term with zero mean and constant variance-covariance matrix ($\varepsilon_t \sim iid(0, \Omega)$).

While assuming zero values of Y_t before the start of the data sample allows for the calculation of fractional difference, it is far from the reality and would bias the estimation results. Therefore, we follow Johansen and Nielsen (2016) to correct for this bias by introducing a drift term (ρ) that shifts each series in Y_t by a constant value. The inclusion of a constant, i.e. $\beta'\rho$, in the long-run relationship(s) in $\beta' L_b \Delta^{d-b} Y_t$ can further capture unobserved explanatory powers in the identified relationship(s). The general FCVAR model allows multiple time series to be fractionally integrated with order d and cointegrated to a fractional order $d - b$. In our case, d is particularly set to be equal to b to ensure a short-memory stationarity in our obtained cointegrating relationship(s). For estimation, maximum likelihood (ML) estimators can provide reliable estimates of the FCVAR model parameters (Johansen and Nielsen, 2012).[14]

Similar to the CVAR model, significance of FCVAR model parameters can be tested by hypothesis testing (Jones et al., 2014). The framework of hypothesis testing on long-run parameters, i.e., β and α, can be formulated as

[14]ML estimates, such as $\hat{d}, \hat{\alpha}$ and $\hat{\Gamma}_i$, follow an asymptotically normal distribution, while $\hat{\beta}$ and $\hat{\delta}$ follow an asymptotically normal distribution when $d < 1/2$ and an asymptotically mixed normal distribution when $d > 1/2$. Moreover, the above properties imply that asymptotic χ^2 inferences can be used to test for significance of model parameters through likelihood ratio (LR) tests. Although the distribution property of $\hat{\rho}$ is still unknown, it is not crucial for the estimation as $\hat{\rho}$ is only used to correct for the fact that all initial values of Y_t are not observed (Jones et al., 2014).

$$\beta = \omega\lambda \tag{15}$$

$$\alpha = \tau\theta \tag{16}$$

With regard to the test on β in Equation (15), ω is a $K \times q$ matrix of identifying restriction(s) on cointegrating relationship(s), and λ is a $q \times r$ matrix defining free varying parameter(s). q is the number of restriction(s) associated with β-related hypothesis tests. In a context when each cointegrating relationship is imposed with the same restriction, the degree of freedom of the hypothesis test is equal to $(K-q)r$. If the number of cointegrating relationships is greater than one, viz. $r > 1$, different restrictions could be imposed on different columns of β. β can then be re-expressed as a row vector, i.e., $\beta = (\omega_1\lambda_1, \omega_2\lambda_2, \ldots, \omega_r\lambda_r)$. Each column of β is the product between ω_i and λ_i, where ω_i is a $K \times q_i$ matrix and defines the imposed restriction on the column i of β; λ_i is a $q_i \times 1$ matrix and defines the free varying parameter on the column i of β. In that case, degrees of freedom of the hypothesis test is $\sum_{i=1}^{r}(K-r-q_i+1)$. Concerning the test on α as in Equation (16), τ is a $K \times l$ matrix that defines restriction(s) on disequilibrium error corrections of target variables, and θ is a $l \times r$ matrix representing free varying parameter(s) with $l \geq r$. l stands for the number of restriction(s) associated with α-related hypothesis tests. Its degree of freedom is $(K-l)r$.

Moreover, building on a VAR structure, the FCVAR model deals with the endogeneity concern that emerges from possibly bi-directional relationships in the macroeconomic-housing price system. When deriving the long-run relationship in the system, the inclusion of a constant term further addresses the issue of omitted variables bias. Furthermore, exact identification of parameters of both housing demand and supply functions within the FCVAR setting can be accomplished in the following ways. First, exact identification of the cointegrating relationship between variables is achieved by normalizing a target variable, the housing prices in our case. Second, the concern regarding overidentification issues can be addressed by examining the significance of model parameters and then imposing zero restrictions on insignificant ones. Particularly, the weak-exogeneity of each variable is studied by testing for the zero restriction on its feedback coefficient in the α-matrix. If α coefficient of the variable appears insignificant, we term this as weakly-exogenous, indicating that it contributes nothing to restore the long-run equilibrium after disequilibrium errors have pervaded the system. At the same time, whether a variable in the system forms long-run cointegrating relationship(s) is arrived at by testing for zero restrictions on its feedback coefficient in the β-matrix. If β coefficient of the variable is restricted to zero, the variable would not enter the cointegrating relation(s). In addition, to further alleviate the issue of parameter identification raised by Carlini and Santucci de Magistris (2019), we follow Nielsen and Popiel (2018) by allowing the grid search in the FCVAR estimation.

5 Data and preliminary observations

5.1 Data

We use a quarterly dataset for the U.S. spanning more than four decades (1975Q1-2016Q1). The following variables are considered in our estimation of the housing demand and supply functions, viz., residential housing prices (RHP), credit to the housing demand (CD), credit to the housing supply (CS), residential land value (RLV), long-term interest rate (LIR), inflation (DEF), residential housing stocks (HUC), and economic policy uncertainty (EPU). The description of these variables and sources of data are reported in Table 2.[15]

Table 2: **Data description**

Variable Name and Abbreviation	Detailed Series	Time Period	Data Source
Credit to the Housing Demand (CD)	Mortgage debt outstanding for the residence purchase	1951Q3-2017Q2	Board of Governors of the Federal Reserve System (U.S.)
Credit to the Housing Supply (CS)	Private residential fixed investment	1946Q4-2017Q2	U.S. Bureau of Economic Analysis
Residential Land Value (RLV)	Aggregate market value of residential land	1975Q1-2016Q1	Lincoln Institute of Land Policy
Long-term Interest Rate (LIR)	10-year treasury constant maturity rate	1954Q2-2017Q3	Board of Governors of the Federal Reserve System
Inflation (DEF)	GDP deflator	1946Q4Q1-2017Q3	U.S. Bureau of Economic Analysis
Residential Housing Stocks (HUC)	Stock of privately-owned housing units	1967Q4-2017Q4	U.S. Bureau of Census & U.S. Department of Housing and Urban Development
Economic Policy Uncertainty (EPU)	U.S. historical news-based policy index	1940Q1-2017Q4	Baker et al. (2016)
Residential Housing Prices (RHP)	S&P/Case-Shiller U.S. National Home Price Index	1975Q1-2017Q3	S&P Dow Jones Indices LLC

[15] A detailed description of each variable with its corresponding data source is in Appendix A.

5.2 Cyclical and trend adjustments

The presence of periodic fluctuations, such as seasonality and cyclicality, would bias interpretation of the dynamics of the time series data and mask the presence of potential long-memory.[16] To mitigate the impact of short-run periodic disturbances, we have seasonally adjusted all variables by using the X-13ARIMA-SEATS package. Further, to adjust for cyclical movements in the mid/long-runs, we remove business cycles from our raw data. To this end, we employ the recently developed Hamilton filter, which decomposes a time series into cyclical and trend components.

While an alternative and the more conventional approach is to employ Hodrick-Prescott (H-P) filterr, despite its popularity, it is questioned for inheriting flaws that can be addressed by Hamilton filter.[17] In our analysis, we have illustrated and compared the data dynamics over time after business cycle removal by using Hamilton and H-P filters. Figures B.1 to B.3 in the Appendix B[18] present those graphs for seasonally-adjusted data in levels. Each variable is demeaned to remove common characteristics and lend comparisons to the observations from each cumulative series over time. Intuitively, the Hamilton filter accommodates depth of fluctuations in both cyclical and trend components, and it mimics the underlying data generating process well. In contrast, the H-P filter imposes a relatively smooth-varying moving pattern that is far from the reality. Therefore, we choose to use Hamilton filtered data in our empirical analysis.

As for the existing findings on boom-bust cycles of our target variables, Cesa-Bianchi (2013) regards five-year as the cycle length of housing prices and GDP for both advanced and emerging market economies. Igan and Loungani (2012) suggest that duration of housing cycles in the US is varying, and can be 5.25 years (Peak: 1973Q4; Trough: 1975Q3) and 10.75 years (Peak: 1979Q1; Trough: 1982Q4). Length of debt cycles on the demand side is suggested to be five years (Hamilton, 2018). Overall, considering the findings from the extant literature and our data characteristics,

[16]For example, *business cycles* describe repeated fluctuations and periodic behaviours of a time series that first increases/decreases from a reference time point until a peak point/trough point, and then decreases/increases until the end of a downturn/upturn (Hodrick and Prescott, 1997).

[17]The main criticism of the H-P filter lies in the strong autocorrelation of its decomposed trend and cyclical components (e.g., Hamilton, 2018). The highly-predictable feature of the two components is an artifact of the H-P filter itself instead of the characteristic of the underlying data generating process (DGP), leading to spurious interpretation of the data dynamics. Moreover, values of the H-P filter at the end of the data sample are usually very different from the observations in the middle, and its smoothing parameter values are largely inconsistent with common practice, raising issues of spuriousness in data dynamics. It is also known that the de-cycled series filtered by the H-P method always would produce 'abnormal' integration orders that are difficult to explain.

[18]To plot these figures, a two-year benchmark length has been used as suggested by Hamilton (2018).

the length of cycles for credit to the housing demand (CD), housing stocks (HUC), land values (RLV), and housing prices (RHP) are identified as 5 years. For the rest of the variables such as credit for housing supply (CS), interest rate (LIR), inflation (DEF), and uncertainty level (EPU), the business cycle lengths are set to 10-years period.[19]

6 Results and discussions

Our results are presented in two steps. First, we provide a detailed discussions on the presence of the long-memory in our dataset. Having the long-memory in univariate series is a prerequisite to verify whether the FCVAR model is an appropriate estimation strategy for our data. Second, we discuss results of the FCVAR estimation with and without restrictions for both demand and supply equations of housing as well as the equilibrium housing price determination.

6.1 Univariate analysis of long memory in housing price and macroeconomic series

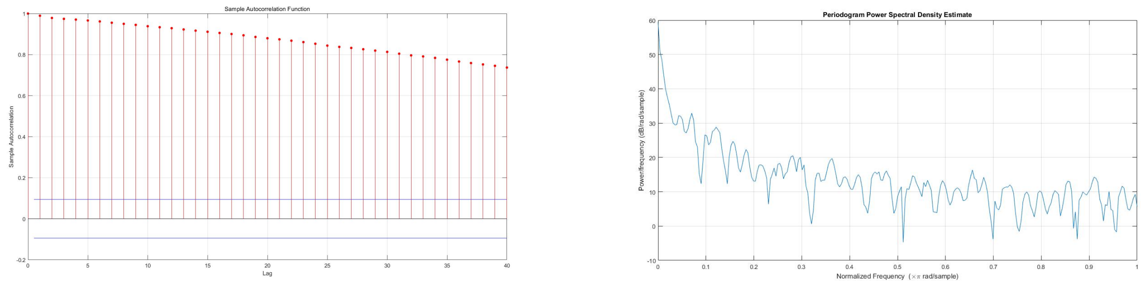
(i) Visual evidence of a long memory

As described in Equation (12), the long memory is featured in a fractionally integrated series, of which the autocorrelation is highly persistent and decays slowly in a hyperbolic pattern. To obtain visual evidence of the long memory feature, we plot the autocorrelation function (ACF) and the spectral density of each series. With regard to housing prices, the left panel of Figure 1 indicates that its ACF decays slowly and is significantly different from zero even after 100 lags. Its spectral density plot also indicates the same finding of the long memory in housing price series, which depicts a mass density near the zero frequency that are proportional to f^{-2d} where f stands for the frequency.

At the same time, the presence of the long memory feature in other included variables is also demonstrated via plots of the ACF and spectural density with the results shown in Figures C.1 and C.2 in Appendix C. It is worth noting that while the autocorrelation of residential housing stocks first drops to zero only after around 12 lags (i.e., 3 years), it then witnesses a periodic fluctuation from that point onwards, and can still be significantly different from zero even after 36

[19] Cycles of the included variables in our analysis are also identified by using higher or lower time lengths. Qualitatively similar results in the following analysis are obtained, and they are available from the authors upon request.

Figure 1: **ACF and spectral density figures of housing prices**



lags (i.e., 9 years). The spectral density plot further confirms the long memory of the housing stock, which has a mass density at the zero frequency. Our obtained visual evidence of long memory in housing prices and macroeconomic series is consistent with findings from the existing literature (e.g. Kumar and Okimoto, 2007).

(ii) Stationarity and unit root tests

It is known that a time series may be fractionally integrated if we reject the null hypothesis of both stationary and unit root tests at the same time. This is due to the fact that a fractionally integrated series does not possess a unit root, while it is still likely to be non-stationary. Thus, we conduct the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and the Augmented Dickey-Fuller (ADF) test to examine the stationarity and the unit root of each series, respectively. Corresponding results are reported in Table 3. As expected, all series reject the null hypothesis of the KPSS test, indicating the non-stationarity feature. In terms of the ADF test, except for credit to the housing demand side (LCD) and inflation ($LDEF$), all the other variables significantly reject its null hypothesis, indicating no unit root. It is clear that a given variable that rejects the above two null hypotheses implies a fractional integration order (d) with $0 < d < 1$. Although for LCD and $LDEF$ we do not reject the null of the ADF test, the estimated values of their d will be shortly shown to be not equal to one; instead, above one.

Table 3: **Stationarity and unit root tests**

	LCD	LCS	RHP	LHUC	LIR	LDEF	RLV	EPU
KPSS Test	0.201**	0.154**	0.255***	0.165**	0.694***	0.222***	0.129*	1.260***
ADF Test	-1.313	-3.785**	-4.032***	-3.959**	-3.247*	1.798	-3.242*	-3.722**

Note: (a) * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level; (b) the logarithmic variables begin with a prefix 'L'; (c) numbers of lags for both tests are selected based on the information criteria (IC).

(iii) Estimation of the fractional integration order (d)

We further estimate d by using the following three estimators, i.e., local Whittle estimator (LW) (Shimotsu et al., 2005), the two-step exact local Whittle estimator (2ELW), and '2ELW' estimator with demeaned and detrended data (Shimotsu, 2010), respectively. The d estimation of each series is conducted in both static and dynamic rolling window settings.

(a) ***Static estimation***

We now proceed to estimation of the fractional parameter d for each univariate series using the whole sample size, i.e., static estimation. The results are summarized in Table 4 where d values are estimated by using the above three estimators with various bandwidths, e.g., $B = T^{0.60}, B = T^{0.65}, \cdots, B = T^{0.80}$. Overall, the static estimation of d speaks in favor of the presence of the fractional integration order in our included variables where values of d broadly range between 0.5 and 1 except for credit for the housing demand (LCD) and inflation ($LDEF$).[20] As for LCD, its d estimates are between 1 and 2, i.e., $1 < d < 2$, except at extremely high or low estimation bandwidths (B).[21] Moreover, $LDEF$ is found to be fractionally integrated with $0.5 < d < 1$ when using most of the bandwidths except for extreme ones, although its d is approaching to 1.

In a nutshell, our static d estimation is consistent with the findings presented in the preceding section. A fractionally integrated series would be non-stationary (i.e., rejection of the KPSS test) if its d is greater than 0.5, while it would not have a unit root (i.e. rejection of the ADF test) if its d value is also less than 1. At the same time, even if a series does not reject the null hypothesis of the ADF test, it can still be fractionally integrated when its d value is either greater than 1 or very close but not equal to 1.[22]

[20]To well present the long-memory feature in our dataset, we transform credit to the housing demand (CD), credit to the housing supply (CS), housing stocks (HUC), and inflation (DEF) in a logarithmic format. They are denoted as LCD, LCS, $LHUC$, and $LDEF$, respectively. The other variables are applied in levels.

[21]To keep d of all the included variables within the same range (i.e. $0 < d < 1$) in the following FCVAR analysis, we, therefore, first differentiate the series LCD to remove its contained unit root.

[22]The ADF test previously employed is built based on a standard left-sided unit root test where the null hypothesis suggests unit root (i.e., $d = 1$) against the alternative hypothesis of $d < 1$. Corresponding inferences might be unreliable in the condition when $d > 1$.

Table 4: **The univariate *d* estimates**

Bandwidth	$B = T^{0.60}$				$B = T^{0.65}$				$B = T^{0.70}$			
Variable	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD
LCD	1.183	1.584	1.510	0.096	0.988	1.244	1.246	0.084	1.016	1.189	1.205	0.073
LCS	1.117	1.079	1.043	0.097	1.081	1.222	1.223	0.084	0.921	1.019	0.989	0.073
RHP	0.575	0.703	0.575	0.080	0.768	0.813	0.772	0.069	0.756	0.801	0.774	0.059
LHUC	0.590	0.647	0.624	0.106	0.532	0.592	0.568	0.093	0.507	0.580	0.558	0.082
LIR	0.825	0.833	0.837	0.071	0.750	0.758	0.762	0.061	0.664	0.676	0.680	0.052
LDEF	0.642	0.912	0.797	0.096	0.744	0.950	0.877	0.084	0.816	1.031	1.000	0.073
RLV	0.722	0.933	0.939	0.114	0.718	0.838	0.829	0.100	0.661	0.766	0.752	0.088
EPU	0.677	0.671	0.627	0.067	0.763	0.748	0.733	0.057	0.659	0.633	0.623	0.048
Bandwidth	$B = T^{0.75}$				$B = T^{0.80}$							
Variable	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD				
LCD	1.020	1.175	1.182	0.064	0.886	1.015	1.050	0.057				
LCS	0.823	0.937	0.874	0.064	0.684	0.870	0.780	0.058				
RHP	0.850	0.896	0.889	0.051	0.833	0.913	0.909	0.044				
LHUC	0.623	0.698	0.697	0.072	0.745	0.859	0.859	0.063				
LIR	0.689	0.712	0.715	0.044	0.745	0.791	0.792	0.037				
LDEF	0.915	1.169	1.165	0.064	0.922	1.257	1.258	0.056				
RLV	0.590	0.729	0.713	0.078	0.608	0.717	0.697	0.069				
EPU	0.736	0.710	0.700	0.040	0.788	0.787	0.782	0.034				

Note: (a) the logarithmic transformed variables begin with a prefix 'L'; (b) 'LW' stands for the local Whittle estimator, '2ELW' stands for the two-step ELW estimator, '2ELWdm' stands for 2ELW estimator conducted using the demeaned and detrended data; (c) standard errors of the estimates with different bandwidths (B) are saved in the column named 'SD'. SD is calculated by $(4\psi)^{-1/2}$ where $\psi = N^B$ and N is the number of observations.

(b) *Dynamic rolling window estimation*

To capture the potential time-varying feature of d of each variable and jointly examine the robustness of the static estimation results, we further perform a dynamic rolling window estimation of d. We use the same estimators as employed in the static d estimation, viz., LW, 2ELW, and 2ELWdm, based on a 10-year setting.[23] For each variable in our macroeconomic-housing price system, the estimates of d are obtained on a rolling basis until approaching the end of the sample. The gap between each adjacent window is four quarters. We accordingly generate d series for each variable with the annual frequency where each observation denotes the d estimate of the corresponding window. A complete illustration of the time-varying d for all variables using different estimators are reported in Figures D.1 to D.3 in Appendix D. It is evident that both dynamic and static estimations of d are consistent, depicting the presence of fractional integration and thus the presence

[23]The window setting closely follows the extant literature (see, e.g., Kumar and Okimoto, 2007). For sensitivity check, we also apply different window sizes, e.g., 5- and 15-year, to study if the dynamic d estimation results remain qualitatively the same. They are available from the authors upon request.

of a long memory in our data. As an illustration, we present results for the housing price series, which is one of the key variables in our analysis. The dynamics of its d values estimated by the 2ELW estimator is shown in Figure 2 with various bandwidths (B) from 0.6 to 0.8.

Figure 2: **Dynamics of rolling-window d estimates for housing prices**

Overall, the temporal variation of d of the US housing price is consistent with both our expectation and existing findings. It is known that fractional order (d) of the target series and the associated long-memory are related to the predictability and volatility of the series, which are in turn linked with economic conditions (see, e.g., Nguyen et al., 2020). With regard to the housing price, since d governs persistence of the impact of past shocks, a lower d suggests a smaller auto-correlation featured by a lower memory, indicating a higher housing price volatility; the latter is accompanied by an expectation of high housing returns that normally occurs during the period of economic expansion (see, e.g., Miller and Peng, 2006). As depicted in Figure 2, d of the housing price series experienced an evident drop during 2001-2002, indicating a lower memory degree and higher volatility of housing prices during 1991-1992[24] where the U.S. economy was in a stage of recovery after the cyclical crisis in 1990-1991. Moreover, d values witnessed a gradual decline during 2011-2017, coinciding with the expansion of the U.S. economy from the trough of the business cycle at the start of the Millennium. This further speaks in favor of the viewpoint that higher price

[24]Such a lead-lag structure is due to the fact that the series of d is built based on a 10-year rolling window setting where each observation is estimated by using the housing price data from the last 10 years. Therefore, the dynamics of d of the housing price at time t reflects the feature of the price from $t - 9$ to t.

volatility of housing that is represented by lower d of the housing price requires higher expected returns normally associated with boom economic conditions.

In addition to housing prices, the dynamics of fractional integration order (d) of other included variables are also consistent with findings in the existing research. In particular, as for inflation (DEF), its d value; alternatively, the long-memory degree, witnessed a gradual decline after the 1990s with small fluctuations over time. This resonates with existing findings (see, e.g., Cogley and Sargent, 2005). Regarding interest rates (LIR), our results also conform to the extant literature (see, e.g., Caporale and Gil-Alana, 2016). Among others, using U.S. and Canadian data, Jones et al. (2014) find that the d estimate of LIR could be close to 1; we confirm this result and further find that its d value tends to experience a gradual decline in recent periods.

6.2 FCVAR estimation: Long-memory driven interaction in the housing market

Having identified the long-memory feature in our target variables, we proceed with estimations of housing demand and supply functions (i.e., Equations (7) and (8)) using the FCVAR model (Equation (14)). Then, aggregate effects of macroeconomic factors, especially the one with differential 'dual' roles, on equilibrium housing price dynamics, are then gauged by solving the subsystem of demand and supply functions in the long run.

6.2.1 Determination of model specification

The primary step for the FCVAR estimation involves selections of the system lag order and the model rank. To determine the number of system lag order (p), we follow Jones et al. (2014) to select the optimal number using a series of Likelihood Ratio (LR) tests through a '*general to specific*' strategy. Specifically, the LR test starts from a generous lag order, viz. $p = 8$, by assuming that the short-run data dynamics exist within eight quarters. For each LR test, the null hypothesis is that the coefficient of the highest lag order (p) is insignificant ($H_0 : \Gamma_p = 0$), against the alternative hypothesis of the significance of Γ_p ($H_1 : \Gamma_p \neq 0$). If H_0 associated with a specified p is accepted, that p should be dropped, and the model will be re-estimated with a smaller p until H_0 of the new p is rejected. In each LR test, the Ljung-Box Q-test is applied to examine if the residuals are serially correlated.[25] If its null hypothesis of no autocorrelation is rejected, we will also have to drop that specified p and move one step back in the model specification. The optimal p is therefore selected in the *three-pronged* strategy. That is, a significant coefficient of p, no autocorrelation in the model residual, a minimum value of the information criteria (IC) of the model estimate.

After choosing an optimal p, we then determine the number of ranks ($rank$) in the FCVAR system. $rank$ is selected using a series of Likelihood Ratio (LR) tests where we sequentially test null hypotheses $H_0^r : rank = k$ for $k = 0, 1, \ldots, K$ against the same alternative hypothesis indicating the *full rank*, i.e. $H_1^r : rank = K$. K is the total number of variables and equals to the *full rank* in the system. The selected rank order is the one that first accepts its corresponding H_0^r. Moreover, it is known that parameters of cointegrating relationship(s), viz. α and β, cannot be separately identified without normalization restrictions for the matrix Π in Equation (14). To characterize equilibrium housing prices, we impose an identification restriction that normalizes β with regard to housing prices when modelling the housing demand and supply functions, respectively. In a situation when $rank$ is greater than one, the second variable imposed for β normalization is residential housing stocks (HUC), through which the long-run dynamics of housing stocks is gauged. We begin with the demand side estimation.[26]

6.2.2 Equilibrium housing price determination: Demand function

As defined in Equations (4) and (7), the housing demand function is built by the variables including, housing prices (RHP), residential housing stocks ($LHUC$), inflation ($LDEF$), interest rates (LIR), credit to the housing demand (LCD), and uncertainty (EPU). To specify the demand function using the FCVAR model, we first select the system lag order (p). The results are reported in Table 5, suggesting that the optimal $p = 4$ given its significant coefficient, no serial correlation in the corresponding residuals, and the lowest Akaike information criteria (AIC) value.

With our chosen system lag order, we then test the rank in the demand function by conducting a series of LR tests. The results are presented in Table 6 where the first two null hypotheses (i.e., $rank = 0$ and $rank = 1$) are significantly rejected against the same alternative hypothesis of

[25]The number of lags in the Ljung-Box Q test is chosen as 12. We also tried other lag orders such as 4, 8, and 16, and the test results are qualitatively the same.

[26]As explained in Footnote 10, our empirical strategy addresses the concern of simultaneous equations issue, and well specifies the demand and supply functions. Moreover, as explained in the methodological section, our employed FCVAR estimation deals with the concern of parameter overidentification.

Table 5: **Lag-order selection - FCVAR (Demand function)**

p	K	$\hat{d}$	$LogL$	LR	$P\text{-}value$	AIC	$PmvQ$
8	6	1.404	-2138.50	63.21	0.003	4938.99	1.00
7	6	1.508	-2170.10	40.31	0.285	4930.20	1.00
6	6	1.401	-2190.25	71.70	0.000	4898.51	1.00
5	6	1.294	-2226.10	50.18	0.059	4898.21	1.00
4	6	0.624	-2251.19	87.40	0.000	4876.38*	0.98
3	6	1.224	-2294.89	87.11	0.000	4891.78	1.00
2	6	1.209	-2338.45	83.69	0.000	4906.89	0.40
1	6	0.856	-2380.29	86.39	0.000	4918.58	0.00
0	6	0.784	-2423.48	0.00	0.000	4932.96	0.00

Table 6: **Rank tests - FCVAR (Demand function)**

$Rank$	$\hat{d}$	$LogL$	$LRstatistic$	$P\text{-}value$
0	0.770	-2316.228	130.073	0.000
1	0.687	-2288.641	74.899	0.001
2	0.680	-2271.028	39.672	0.045
3	0.641	-2254.864	7.344	0.926
4	0.616	-2252.225	2.067	0.945
5	0.625	-2251.194	0.004	0.998
6	0.624	-2251.192	—-	—-

$rank = 6$, viz. the *full rank*. Then, updated null hypotheses with higher ranks continue to be tested. Given that our main focus is the determination of equilibrium housing prices (RHP), we would like to keep as many demand factors as possible in the cointegrating relationship normalized by RHP. We eventually accept the null hypothesis of $rank = 2$ with $P = 0.045$, indicating two cointegrating relationships in the demand function. Thus, the FCVAR model for the demand function is specified as 4 short-run terms and 2 ranks. The corresponding estimates are reported in Equation (17) with the cointegrating relations identified by Equations (18) and (19).

Specifically, estimated parameters of each variable for the error adjustment speed (α) in each of the two cointegrating relationships are shown in matrix form on the right hand side of Equation (17). The column vector ν_t, i.e., $[\nu_{1t} \ \ \nu_{2t}]'$, stands for the two long-run cointegrating relations, which are normalized with regard to housing prices (RHP) and housing stocks ($LHUC$), respectively. The two relations are defined by $\nu_t = \beta' L_d(Y_t - \rho) = 0$ and presented in Equations 18 and 19.[27] A striking feature of our FCVAR estimation for the demand function is that the cointegration

[27] Estimated coefficients of the short-run terms ($\{\hat{\Gamma}_i\}_{i=1}^{4}$) are suppressed as our research focus is the long-run relationships. They are available from the authors upon request.

order, i.e. system d, is a fraction of 0.680 with standard error of 0.039, demonstrating gradual price adjustment on the housing demand-side featured by long-memory. If we had imposed an I(1)/I(0) assumption, the role of long-memory featured shocks in forming the equilibrium housing price -macroeconomic interaction would have been overlooked, leading to unreliable conclusions. The fractional d in the demand function further confirms inefficiency of the housing market, showing a predictable pattern of its price dynamics with strong autocorrelation (e.g., Case and Shiller, 1989; Larsen and Weum, 2008). Based on the Ljung-Box Q-test statistic ($Q_{\hat{\varepsilon}}$), it appears that the residuals are white noise, indicating that FCVAR estimation of the demand function is well specified.

FCVAR estimation: Housing demand function:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP \\ LHUC \\ LDEF \\ LIR \\ EPU \\ LCD \end{bmatrix} - \begin{bmatrix} 3.709 \\ 0.050 \\ -0.127 \\ -11.004 \\ -20.442 \\ -31.173 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.142 & 2.161 \\ 0.036 & -3.117 \\ -0.143 & 0.788 \\ 0.148 & -0.192 \\ 0.074 & 1.838 \\ -0.056 & 2.335 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^{i}(Y_t - \hat{\rho}) + \hat{\varepsilon}_t \quad (17)$$

$$\hat{d} = \underset{(0.039)}{0.680},\ Q_{\varepsilon}(12) = \underset{(0.996)}{358.611},\ LogL = -2271.028$$

The determination of equilibrium housing prices and stocks on the demand side:

$$RHP^{*} = -2.4548 - 14.238 \times LDEF_t - 2.415 \times LIR_t - 0.865 \times EPU_t + 1.280 \times LCD_t + \nu_{1t} \quad (18)$$

$$LHUC_t^{*} = 0.0837 - 0.279 \times LDEF_t - 0.024 \times LIR_t - 0.002 \times EPU_t + 0.012 \times LCD_t + \nu_{2t} \quad (19)$$

The cointegrating relations, normalized in Equations (18) and (19) respectively, demonstrate the determination of housing prices (RHP) and housing stocks ($LHUC$) by macroeconomic factors in the long-run steady state of the demand function. As shown in Equation (18), credit to the housing demand side (LCD) exerts a positive impact (1.280) on RHP, while coefficients of inflation ($LDEF$), interest rate (LIR), and economic policy uncertainty (EPU) are all negative, viz. -14.238, -2.415, and -0.865, respectively. Similarly, in Equation (19), signs of the macroeconomic impacts are the same as their counterparts in Equation (18). This is in line with our expectation that the demand is proportional to the housing stock (e.g., McCarthy and Peach, 2002; Muellbauer and Murphy, 1997); therefore, macroeconomic impacts that alter the demand and prices of housing would change the stock in the same direction. We further find that those impacts on prices are relatively greater than that on the stock.

Overall, our results for the demand side estimation are in line with a theoretical viewpoint in the extant literature. An increase in financing costs (LIR) and inflation ($LDEF$) raises the user cost of home-ownership, and then drops the demand and prices of housing (e.g., Himmelberg et al., 2005). Instead, loose mortgage rationing/debt (LCD) lowers the user cost of owning, raising housing prices (RPH) (e.g., Anundsen and Jansen, 2013; Oikarinen et al., 2018). As also supported by the literature (e.g., Duan et al., 2021; Zheng et al., 2018), a heightening uncertain degree (EPU) dampens the demand through various housing consumption factors, and then decreases the house price level. It is worth mentioning that, in addition to the impacts on the demand side, LIR and EPU can also impact the house price on the supply side with a possibly different magnitude. To be discussed in the next section, LIR would also govern the level of financing costs for housing constructions, shifting the supply curve and the price level (Arestis and Gonzalez-Martinez, 2016). A varying EPU could affect the supply incentive, and then fluctuate the supply and prices of housing (Miles, 2009).

As for the dynamics of housing stocks in the long-run on the demand side, the signs of the macroeconomic impacts would be the same as the counterparts on the price dynamics, given that the stocks are proportional to the demand. As expected, an increase in LIR, $LDEF$ would raise the financing cost of home owning, and a rising EPU would weaken the home purchase intention, subsequently dropping the demand and then the stock of housing (e.g., Diaz-Serrano, 2005; Duan et al., 2019). Increasing delivery of mortgage debt would raise available housing stocks by stimulating the demand for housing (e.g., Anundsen and Jansen, 2013).

6.2.3 Equilibrium housing price determination: Supply function

In this section, we proceed with the FCVAR estimation for the housing supply function, which is specified by housing prices (RHP), housing stocks ($LHUC$), uncertainty (EPU), interest rates

(LIR), residential land value (RLV), and credit to the housing supply (LCS) as previously defined in Equations (5) and (8). To determine the supply function, we first select the system lag order (p) following a three-pronged strategy as previously introduced. The corresponding results shown in Table 7 suggest that the optimal $p = 5$ given its significant coefficient, no serial correlation in the estimated residuals, and minimum AIC value. Results of the model rank test reported in Table 8 demonstrate that the first null hypothesis of $rank = 0$ is rejected, while we fail to reject the second null of $rank = 1$ with a P value of 0.263 against the same alternative hypothesis of $rank = 6$.

Table 7: **Lag-order selection - FCVAR (Housing supply)**

p	K	$\hat{d}$	$LogL$	LR	P-$value$	AIC	BIC	$PmvQ$
8	6	1.577	-2162.43	52.12	0.040	4986.86	5965.24	1.00
7	6	1.070	-2188.49	88.47	0.000	4966.98	5838.95	1.00
6	6	1.340	-2232.73	50.71	0.053	4983.45	5749.01	1.00
5	6	0.876	-2258.08	91.94	0.000	4962.16*	5621.31	1.00
4	6	1.129	-2304.05	98.29	0.000	4982.10	5534.84	0.96
3	6	0.927	-2353.19	37.52	0.399	5008.38	5454.71	0.59
2	6	0.010	-2371.95	125.13	0.000	4973.90	5313.82	0.00
1	6	0.066	-2434.52	220.35	0.000	5027.04	5260.55*	0.00
0	6	0.860	-2544.69	0.000	0.000	5175.39	5302.49	0.00

Table 8: **Rank tests - FCVAR (Housing supply)**

$Rank$	$\hat{d}$	$LogL$	$LRstatistic$	P-$value$
0	0.873	-2305.240	94.318	0.040
1	0.872	-2287.005	57.849	0.263
2	0.907	-2274.238	32.313	0.676
3	0.827	-2263.226	10.290	0.962
4	0.874	-2259.783	3.404	0.984
5	0.877	-2258.085	0.007	1.000
6	0.876	-2258.081	—-	—-

The above specifies the FCVAR model for the housing supply function as 5 short-run terms and 1 cointegrating relationship. We then proceed with the FCVAR estimation with corresponding results reported in Equation (20) and the steady-state cointegrating relationship shown in Equation (21). Error adjustment speed of each variable towards equilibrium is reported in the α coefficient matrix on the right-hand side of Equation (20). Vector ν_t defines the long-run cointegrating relationship normalized with regard to RHP, and such the steady-state relation is achieved when

$\nu_t = \beta' L_d(Y_t - \rho) = 0$. Similar to that in the housing demand function, the cointegraton order, i.e. system d, in the supply function is also found to be a fraction of 0.872 with standard error of 0.025. This demonstrates that the housing price adjustment is gradual and featured by long-memory in both the demand and supply functions, although the persistence of shocks that induce disequilibrium in the supply function is greater than that in the demand function. Such the greater persistence of disequilibrium is exhibited by a higher fractional cointegration order in the supply function than that in the demand function. It is worth noting that fractionality of the cointegration order in both the demand and supply systems further supports the existing viewpoint on the inefficiency of the housing market (e.g., Larsen and Weum, 2008). Model residuals do not have serial correlation demonstrated by a significant rejection of the Ljung-Box Q test with a P value of 0.999, indicating that the FCVAR estimation is well specified.

The determination of equilibrium housing prices by macroeconomic factors on the supply side is presented in Equation (21). As expected, the housing stock ($LHUC$) and credit to the supply side (LCS) depict negative impacts that their 1% increase induces 0.827 and 0.174 units decrease in housing prices (RHP), respectively. Uncertainty (EPU), interest rate (LIR), and (RLV) positively affect housing prices (RHP) with coefficients of 0.065, 0.143, and 1.312, respectively.

FCVAR estimation: Housing supply function:

$$\Delta^{\hat{d}} \left(\begin{bmatrix} RHP \\ LHUC \\ EPU \\ LIR \\ RLV \\ LCS \end{bmatrix} - \begin{bmatrix} 6.234 \\ -1.509 \\ -14.985 \\ -9.547 \\ 3.446 \\ -19.121 \end{bmatrix} \right) = L_{\hat{d}} \begin{bmatrix} -0.020 \\ -0.259 \\ 0.509 \\ 0.811 \\ 0.271 \\ -0.719 \end{bmatrix} \nu_t + \sum_{i=1}^{5} \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}} (Y_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{20}$$

$\hat{d} = \underset{(0.025)}{0.872}$, $Q_\varepsilon(12) = \underset{(0.999)}{347.802}$, $LogL = -2287.005$

The determination of equilibrium housing prices on the supply side:

$$\begin{aligned} RHP^*_t = -0.5229 - 0.827 \times LHUC_t + 0.065 \times EPU_t + 0.143 \times LIR_t + 1.312 \times RLV_t \\ -0.174 \times LCS_t + \nu_t \end{aligned} \tag{21}$$

Overall, our results of the long-run housing price determination are consistent with our expectations and the extant literature. As discussed in the preceding section, some macroeconomic factors, such as the interest rate (LIR) and uncertainty (EPU), affect housing prices from both the demand and supply sides, albeit in varying magnitudes. On the supply side, an increasing financing cost for housing constructions deters the supply and then raises the price level of housing (e.g., Duan et al., 2021; Fitzpatrick and McQuinn, 2007). A high-level uncertainty on the supply side would dampen the incentive of housing constructions and increase housing prices (e.g., Miles, 2009). Similarly, as an important input for construction, increases in land market value (RLV) diminish the housing supply, subsequently leading to a rise in housing prices (e.g., Knoll et al., 2017). At the same time, changes in the housing stock ($LHUC$) and credit rationing to housing suppliers (LCS) drive the dynamics of housing prices in an opposite direction. An increase in $LHUC$ indicates the heightening housing supply in circulation; this would discourage home builders' supply intentions and push the housing price level down (e.g., Beenstock and Felsenstein, 2015). Expanded credit provisions to the housing supply (LCS) could stimulate the supply level and then drop house prices (e.g., Arestis and Gonzalez-Martinez, 2016).

6.2.4 Net macroeconomic effects on equilibrium housing prices

So far, we have estimated demand and supply functions of housing. Through this, we can not only elicit the impacts of macroeconomic factors exclusively on either the demand or supply side of housing but also map out the heterogeneous and simultaneous impacts of the same macroeconomic factor on the two sides. Given that the housing market equilibrium is conditioned by $RHP^* = RHP^{*D} = RHP^{*S}$ (e.g., McCarthy and Peach, 2002; Oikarinen et al., 2018), adding the obtained cointegrating relations normalized by housing prices from the demand and supply functions together (i.e., Equations (18) and (21)), we then derive Equation (22). The latter not only measures net macroeconomic impacts on equilibrium housing prices, but also compares the impact of each 'dual'-role factor from the demand side against that from the supply side.

At the equilibrium, the net impacts of macroeconomic factors on housing prices can be derived as follows:

$$RHP_t^* = -1.48885 - 7.119 \times LDEF_t + 0.640 \times LCD_t - 0.4135 \times LHUC_t - 0.087 \times LCS_t + \\ 0.656 \times RLV_t - 0.400 \times EPU_t - 1.136 \times LIR_t + \nu_t^* \tag{22}$$

where the long-run steady-state of the housing market achieves when both the demand and supply functions are in the equilibrium condition. For the ease of presentation of the macroeconomic impacts on equilibrium housing prices from the demand and supply sides, we respectively report Equations (18) and (21) in the first two rows of Table 9. The derived aggregate impacts shown in Equation (22) are further exhibited in the final row of the table.

Table 9: **Macroeconomic impacts on equilibrium housing prices**

	Demand factors		Supply factors		Factors with impacts on both sides		
	LCD	LDEF	RLV	LCS	LIR	EPU	LHUC
Demand side (Equation (18))	1.280	-14.238	-	-	-2.415	-0.865	-
Supply side (Equation (21))	-	-	1.312	-0.174	0.143	0.065	-0.827
Net impacts (Equation (22))	0.640	-7.119	0.656	-0.087	-1.136	-0.400	-0.4135

Note: (a) LIR, EPU, and $LHUC$ are the factors having different impacts on the demand and supply sides; LCD and $LDEF$ are the factors that impact housing prices only through the demand side; RLV, and LCS are the factors that impact only through the supply side. (b) $LHUC$ is not included in Equation (18) since it is used to specify the second cointegration relationship in the demand function.

Lessons from separate estimation strategy

What lessons do we learn from the separate estimation strategy? It is now clear that directly estimating a housing function that aggregates macroeconomic impacts from the demand and supply sides may fail to disentangle possibly heterogeneous roles of the same macroeconomic factor on the two sides of housing. This would suppress detailed information on potential 'dual' effects of a specific macroeconomic factor that are different from the demand- and supply-side dynamics, leading to elusive inferences on the equilibrium housing price determination. Further, our results have also shown that the role of the supply-side dynamics cannot be ignored, indicating that the currently-popular inverted demand function for housing price dynamics would lead to a partial representation of the true effects of macroeconomic variables.

Accordingly, we have extended the conventional strategy by separately estimating demand and supply functions of housing. Once we have respectively identified the cointegration relationship between macroeconomic factors and housing prices on the demand and supply functions, we then solve the subsystem simultaneously to derive the net macroeconomic effects in equilibrium. The corresponding results are presented in Table 9. We observe that the computed net macroeconomic impacts are consistent with our expectations as discussed in Equation (6). With regard to the factors that impact housing prices exclusively through the demand or supply side, directions of their impacts are in line with theoretical explanations in Equations (4) and (5). We further find that impacts of those factors with the 'exclusive' role in the demand/supply side dynamics would be over-estimated (in absolute terms) if the factors from the supply/demand side are neglected.

As for the factors having different impacts on both demand and supply functions, e.g., interest rate (LIR) and uncertainty (EPU), the absolute magnitude of their negative impacts from the demand side is greater than their positive impacts from the supply side. Therefore, each of their net impacts is found to be negative and dominated by the demand-side dynamics. The corresponding magnitude (in absolute terms) is between its impacts from the supply side and that from the demand side, as a result of the interaction between the two sides of housing (Duan et al., 2019). Again, our findings are consistent with extant literature that reports an elastic demand against a relatively inelastic supply in the U.S. housing market (Murphy, 2018). It is known that the provision of housing supply entails a long period of planning and construction, inducing the supply to be unresponsive to changes in housing prices, while the response of the demand is relatively greater (Glaeser et al., 2012). In addition, housing construction largely depends on intrinsic supply inputs, such as land availability, further leading to a less elastic housing supply (Saiz, 2010).

Overall, as demonstrated above, our separate estimation/identification strategy extends the literature by avoiding the information loss from estimating a single aggregate function or an inverted demand function for housing prices. At the same time, it reconciles inconclusive findings so far regarding the macroeconomic impacts on housing price dynamics, especially the ones with different roles in shifting the demand and supply functions. In addition, through such a separate identification, possibly different persistence of shocks that induce disequilibrium in the demand and supply functions can be gauged by respectively estimating the different fractional cointegration orders in the two functions. Otherwise, true information on the system long-memory degree that governs the gradual adjustment on the demand and supply sides would be masked.

6.3 Identification of parameters: FCVAR estimation with restrictions

Having identified the cointegrating parameters by normalizing the vector with respect to a target variable, in this section, we further address the potential overidentification issue by examining the significance of FCVAR model parameters and then imposing zero restrictions on insignificant ones. Specifically, significance of α and β parameters in Equation (14) that form the long-run equilibrium relationship can be examined by using the hypothesis testing defined in Equations (15) and (16). FCVAR estimation is then re-conducted with zero restrictions on insignificant parameters. At the same time, estimating the FCVAR model with restrictions can also examine the robustness of our main findings obtained by the unrestricted model regarding the determination of equilibrium housing prices from the demand and supply functions, respectively.[28]

6.3.1 Restricted FCVAR estimation on the housing demand function

For the restricted FCVAR estimation of the demand function, the null hypotheses of α and β parameters associated with each variable are defined in Table 10. The first hypothesis is H_D^d, which tests a null hypothesis of $d = 1$ favoring the absence of long-memory and the choice of CVAR model. The rest of the hypotheses can be classified into tests on the cointegrating vectors (β) and tests for the weak exogeneity of variables on α. Corresponding test results are reported in Table 11. Specifically, a significant rejection of H_D^d demonstrates that FCVAR model is a more appropirate specification than the alternative CVAR model. The majority of the variables are shown to have significant β and α parameters in addition to the following exceptions. β of the uncertainty (EPU) is restricted to zero according to the rejection of H_{D5}^{β}, indicating that EPU does not enter the long-run equilibrium relation. While H_{D1}^{α} is not rejected, implying that the house price (RHP) appears to be weakly exogenous, we choose to not impose this restriction given that RHP is the key variable in the determination of equilibrium housing prices.

Overall, we re-conduct the FCVAR estimation with the imposition of the above parameter restrictions. The corresponding estimation results are shown in Equation (23) with two obtained cointegrating relations presented in Equations (24) and (25). With regard to both signs and mag-

[28]To further examine robustness of our findings, we have performed a thorough forecasting exercise for demand and supply functions of housing comparing performance of the FCVAR model against a competing CVAR model. The results are presented in the Appendix E. Our results show that FCVAR outperforms CVAR in various specifications.

nitudes of coefficient estimates, results of the restricted FCVAR estimation are consistent with our main findings drawn by using its unrestricted specification. Through this, the identification of model parameters is further enhanced, while the robustness of our main findings is examined.

Table 10: **Hypothesis tests: Demand function**

H_D^d	The fractional order, d, equals to one.	H_{D1}^{α}	RHP is weakly exogenous.
H_{D1}^{β}	HPI and LHUC do not enter the cointegrating relationships.	H_{D2}^{α}	LHUC is weakly exogenous.
H_{D2}^{β}	All demand-driven variables except HUC do not enter the cointegrating relationships.	H_{D3}^{α}	LDEF is weakly exogenous.
H_{D3}^{β}	LDEF does not enter the cointegrating relationships.	H_{D4}^{α}	LIR is weakly exogenous.
H_{D4}^{β}	LIR does not enter the cointegrating relationships.	H_{D5}^{α}	EPU is weakly exogenous.
H_{D5}^{β}	EPU does not enter the cointegrating relationships.	H_{D6}^{α}	LCD is weakly exogenous.
H_{D6}^{β}	LCD does not enter the cointegrating relationships.		

Table 11: **Results of hypothesis: Demand function**

	H_D^d	H_{D1}^{β}	H_{D2}^{β}	H_{D3}^{β}	H_{D4}^{β}	H_{D5}^{β}	H_{D6}^{β}
df	1	4	8	2	2	2	2
LR Statistic	35.228	38.878	19.136	8.136	38.037	3.751	107.991
P-Value	0.000***	0.000***	0.014**	0.017**	0.000***	0.153	0.000***
	H_{D1}^{α}	H_{D2}^{α}	H_{D3}^{α}	H_{D4}^{α}	H_{D5}^{α}	H_{D6}^{α}	
df	2	2	2	2	2	2	
LR Statistic	6.098	108.636	16.580	228.568	278.629	192.560	
P-Value	0.192	0.000***	0.002***	0.000***	0.000***	0.000***	

Note: (a) *: significant at the 10% level, **: significant at the 5% level, ***: significant at 1% level; (b) df denotes the degree of freedom; (c) LR is the abbreviation for the Likelihood Ratio test.

Restricted FCVAR estimation: Housing demand function

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP \\ LHUC \\ LDEF \\ LIR \\ EPU \\ LCD \end{bmatrix} - \begin{bmatrix} 2.948 \\ 0.135 \\ -0.307 \\ -9.655 \\ -21.971 \\ -30.672 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.032 & 2.056 \\ 0.053 & -2.868 \\ -0.049 & 1.103 \\ 0.039 & -0.615 \\ 0.002 & 0.860 \\ -0.018 & 2.054 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^{i}(X_t - \hat{\rho}) + \hat{\varepsilon}_t \quad (23)$$

$\hat{d} = \underset{(0.037)}{0.693}$, $Q_{\varepsilon}(12) = \underset{(0.998)}{351.949}$, $LogL = -2272.903$

Equiliibrium relationships on the demand side (with restrictions)

$$RHP_t^* = -3.130 - 61.142 \times LDEF_t - 8.219 \times LIR_t + 3.001 \times LCD_t + \nu_{1t} \tag{24}$$

$$LHUC_t^* = 0.069 - 1.074 \times LDEF_t - 0.122 \times LIR_t + 0.047 \times LCD_t + \nu_{2t} \tag{25}$$

6.3.2 Restricted FCVAR estimation on the housing supply function

We proceed with the FCVAR estimation with restrictions for the supply function. Similar to the case in the restricted FCVAR demand function, we present various null hypotheses in Table 12 for the supply function. The corresponding results are presented in Table 13. It is clear that H_S^d is strongly rejected indicating that the cointegrating order is not an integer 1; this further suggests the appropriateness of employing the FCVAR model against the alternative CVAR model. Most of the included variables are found to have significant β and α parameters, showing their important role in forming the cointegrating vector and correcting for disequilibrium in the supply function. As for few exceptions, α of the land market value (RLV) is restricted to be zero due to the non-rejection of the null of H_{S5}^{α}, indicating that RLV is weakly exogenous to error corrections that push the supply system back to equilibrium. The null of H_{S3}^{β} is weakly not rejected with a P value of 0.120, suggesting that the housing stock ($LHUC$) does not enter the long-run equilibrium relation obtained in the supply function. We nevertheless do not impose this restriction given that $LHUC$ along with the house price (RPH) are the key variables to interact the demand with supply sides of housing, and then form the determination process of equilibrium housing prices.

Overall, our results for the restricted version of the Supply function are presented in the Equation (26). The cointegrating relation is presented in Equation (27). Clearly, both signs and magnitudes of coefficient estimates in the restricted FCVAR mimic that from the unrestricted FCVAR estimation. Therefore, imposing restrictions on the FCVAR estimation not only enhances the exact model identification but also reassures the robustness of our main findings.

Table 12: **Hypothesis tests: Supply function**

H_S^d	The fractional order, d, equals to one.	H_{S1}^{α}	RHP is weakly exogenous.
H_{S1}^{β}	RHP does not enter the cointegrating relationship.	H_{S2}^{α}	LHUC is weakly exogenous.
H_{S2}^{β}	All supply-driven variables do not enter the cointegrating relationship.	H_{S3}^{α}	EPU is weakly exogenous.
H_{S3}^{β}	LHUC does not enter the cointegrating relationship.	H_{S4}^{α}	LIR is weakly exogenous.
H_{S4}^{β}	EPU does not enter the cointegrating relationship.	H_{S5}^{α}	RLV is weakly exogenous.
H_{S5}^{β}	LIR does not enter the cointegrating relationship.	H_{S6}^{α}	LCS is weakly exogenous.
H_{S6}^{β}	RLV does not enter the cointegrating relationship.		
H_{S7}^{β}	LCS does not enter the cointegrating relationship.		

Table 13: **Results of hypothesis test: Supply function**

	H_S^d	H_{S1}^{β}	H_{S2}^{β}	H_{S3}^{β}	H_{S4}^{β}	H_{S5}^{β}	H_{S6}^{β}	H_{S7}^{β}
df	1	1	5	1	1	1	1	1
LR Statistic	16.757	3.053	24.124	2.418	43.997	68.836	70.016	118.443
P-Value	0.000***	0.081*	0.000***	0.120	0.000***	0.000***	0.000***	0.000***
	H_{S1}^{α}	H_{S2}^{α}	H_{S3}^{α}	H_{S4}^{α}	H_{S5}^{α}	H_{S6}^{α}		
df	1	1	1	1	1	1		
LR Statistic	18.736	6.961	37.494	18.479	2.635	38.463		
P-Value	0.000***	0.031**	0.000***	0.000***	0.268	0.000***		

Note: (a) *: significant at the 10% level, **: significant at the 5% level, ***: significant at 1% level; (b) df denotes the degree of freedom; (c) LR is the abbreviation for the Likelihood Ratio test;

Restricted FCVAR estimation: Housing supply function

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP \\ LHUC \\ EPU \\ LIR \\ RLV \\ LCS \end{bmatrix} - \begin{bmatrix} 6.273 \\ -1.558 \\ -15.197 \\ -9.981 \\ 3.584 \\ -18.961 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.204 \\ -0.288 \\ 0.506 \\ 0.811 \\ 0.000 \\ -0.672 \end{bmatrix} \nu_t + \sum_{i=1}^{5} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^i (X_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{26}$$

$\hat{d} = \underset{(0.025)}{0.868}$, $Q_{\varepsilon}(12) = \underset{(0.998)}{350.796}$, $LogL = -2288.045$

Equilibrium relationships on the supply side (with restrictions)

$$\begin{aligned} RHP_t^* = -0.631 - 0.816 \times LHUC_t + 0.060 \times EPU_t + 0.156 \times LIR_t + 1.282 \times RLV_t \\ -0.184 \times LCS_t + \nu_t \end{aligned} \tag{27}$$

6.3.3 Equilibrium housing price determination from restricted models

We now derive the overall impact of macroeconomic variables in the housing equilibrium. We do so by solving the simultaneous demand and supply functions of housing with restrictions, i.e., Equations (24) and (27). Overall, the net macroeconomic impacts obtained by the restricted FCVAR estimation are consistent with our main results from the unrestricted FCVAR estimation (Equation (22)) and theoretical expectations (Equation (6)).

$$\begin{aligned} RHP_t^* = -1.8805 - 30.571 \times LDEF_t + 1.5005 \times LCD_t - 0.408 \times LHUC_t - 0.092 \times LCS_t + \\ 0.641 \times RLV_t + 0.03 \times EPU_t - 4.0315 \times LIR_t + \nu_t^* \end{aligned} \tag{28}$$

What lessons have we learnt so far? We outlined the importance of separately estimating housing price equilibrium from both the demand and supply channels. This helps us disentangle the possibly heterogeneous impacts of the same macroeconomic factor on demand and supply sides of housing, further uncovering the impact from which side is dominating. We found that impacts of the above factor with heterogeneous impacts in the demand function are greater than that in the supply functions, suggesting the elastic demand and relatively inelastic supply in the U.S. housing market. On the other hand, it confirms that the currently-popular approach of the inverted demand function for housing price dynamics would ignore the supply side dynamics, leading to misestimation of the results. Thus, the above manifests effectiveness of our separate estimation strategy in capturing the 'micro-level' information of macroeconomic impacts from demand and supply functions on housing price dynamics.

7 Conclusions

Changes in macroeconomic conditions can shift both the demand and supply curves of housing, eventually producing a different class of housing market equilibrium. This paper studies the equilibrium housing price dynamics driven by macroeconomic variations from the demand and supply sides through a long-memory cointegration approach. We have advanced a conceptual framework that disentangles net effects of macroeconomic variables on demand and supply functions of housing. Further, within such a setting, attention is given to the convergence of potential long-memory shocks in the two functions, the presence of which would lead to different and sluggish error correction speeds from the demand and supply sides of housing toward market clearing. A reduced form specification of our framework is then empirically estimated by using the FCVAR method, through which macroeconomic impacts from the two sides of housing are respectively uncovered.

A number of policy-relevant results emerge. First, macroeconomic impacts are found to shift either the demand/supply curve exclusively or both of them simultaneously in the formation of equilibrium housing prices. With respect to the factor with an 'exclusive' role from the demand/supply side, its impact estimation would be biased if factors from the other side are neglected. As for the factor with different 'dual' roles from the two sides, its net impact is negative due to its stronger negative impact from the demand side against a smaller positive one from the supply side, demonstrating an elastic housing demand against a relatively inelastic supply. The above reveals that unless the impact of macroeconomic variables is disentangled between the demand and supply functions of housing, serious information loss for the true macroeconomic impacts would otherwise arise.

Second, our FCVAR estimation of the housing - macroeconomic system evinces a long and mean-convergent system-memory on both the demand and supply sides of housing. Although individual series in the interactive system depict varying magnitudes of the long memory persistence, the system-memory estimate indicates that the system can be asymptotically stable towards housing equilibrium, given that the effective policy intervention is introduced at the right time. During the process of long-memory featured error corrections, the arrival of an exogenous shock in macroeconomic conditions can alter the nature of stability of the interactive system differently through channels of the demand and supply of housing. Exact identification can be achieved particularly through zero restrictions on insignificant parameters when conducting the FCVAR estimation, which further reassures robustness of our findings.

Our findings reveal that policy-effective strategy would be a separate estimation, through which the role of macroeconomic interventions from the demand and supply sides in the equilibrium housing price dynamics is uncovered. At the same time, our estimation offers precise guidance on the relative speed of convergence and timing of policy intervention aiming at stabilizing the macro-economy-housing market system. In particular, our approach to accommodate possibilities of slow (viz., long-memory) error corrections suggests that policy effectiveness would be enhanced by exploiting the memory feature of the target series to be regulated.

Generally, a series with a long memory has a tendency to be highly persistent. It indicates that tendency of the series would not easily change or even reverse unless an effective policy intervention is in place. In contrast, a moderate strategy would be more appropriate when regulating the dynamics of a short-memory series with low persistence. In our case, since the housing price in the U.S. is found to be a long-memory process, policymakers may adopt a relatively aggressive strategy in the case when they perceive that the current price is either rising or dropping too fast, and would like to control for such 'abnormal' changes.

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Appendix A Variable descriptions and data sources

This section explains our employed variables and their data sources. Broadly speaking, bank credit stands for the net lending claimed by money issuers, while it also denotes the outstanding amounts that borrowers are liable to repay. Bank credit can be collected from the asset side of consolidate balance sheets of monetary financial institutions (MFIs). As the money issuers, MFIs are depository institutions whose businesses are to receive deposits and grant credit from their own account to non-MFIs, such as households, non-profit institutions serving households, private non-financial corporations and other financial corporations (OFCs).[29] In the paper, we extract credit flowing to the residential real estate market and further segregate it following credit circulation channels on the demand and supply sides.

Credit to the housing demand (CD) represents the outstanding mortgage debts issued by the MFIs for the home purchase (including one- to four-family, and multifamily residences). It measures the amount of money used to finance the housing demand, and also indicates the purchasing power with regard to housing on the demand side. It is available from the Board of Governors of the Federal Reserve System (U.S.) covering the period 1951Q3-2017Q2.

Credit to the housing supply (CS) stands for the money lending issued by MFIs for the provision of housing supply. Due to a lack of data for credit lending to the housing industry, in the light of the NIPA Handbook (2020), CS can be alternatively represented by the private residential fixed investment. The latter describes the amount of money spent by private sectors for the construction of residential properties, such as a creation of new houses, an improvement of existing houses, and a replacement of worn out or obsolete houses, in the form of fixed investments.[30] The data are from the U.S. Bureau of Economic Analysis covering the period of 1946Q4-2017Q2.

Residential land value (RLV) stands for the market value of land for residential construction (Davis and Heathcote, 2007). It is known as an important input for the housing supply and describes the supply expenditure. The data of RLV are from the Lincoln Institute of Land Policy

[29] According to the European Central Bank (ECB), the Bank of England (BOE), and the International Monetary Fund (IMF), under the System of National Accounts (United Nations, 2008), MFIs stand for the depository corporations involving central bank and other deposit-taking corporations, such as commercial banks, credit unions, saving institutions and money market mutual funds, at the broadest level.

[30] In addition to a proxy of credit to the housing supply, the investment also represents the housing stock through the capital value. Following the literature (e.g., DiPasquale and Wheaton, 1994), it along with units of the housing stock (HUC) are used to reflect the stock in different aspects to form the supply function. HUC is known as a factor with differential roles, which also forms the demand function to reflect household formation decisions and tenure choice.

in the period 1975Q1 - 2016Q1 and its series is constructed based on the S&P/Case-Shiller U.S. National Home Price Index.

Long-term interest rate *(LIR)* stands for the borrowing cost of housing market participants for the home purchase or construction, and it is represented by the 10-year treasury constant maturity rate. The data are collected from the Board of Governors of the Federal Reserve System (U.S.) ranging from 1953Q1 to 2017Q4.

Inflation *(DEF)* describes the U.S. price level of all domestic-produced final goods and services in a given time period. We proxy it using the GDP deflator, through which the inflationary and deflationary periods in the U.S. economy can be well depicted. The data are from the U.S. Bureau of Economic Analysis over the period of 1946Q4 - 2017Q3.

Residential housing stock *(HUC)* stands for the stock of completions of the U.S. residential properties. HUC depicts amounts of housing units required by housing buyers, and it also describes amounts that are provided by housing suppliers. It is represented by a series named 'the completion of new privately-owned housing units' from the U.S. Bureau of Census and the U.S. Department of Housing and Urban Development. Its data are available from 1967Q4 to 2017Q4.

Economic policy uncertainty *(EPU)* depicts the uncertainty level that can affect investment intentions on both the demand and supply sides of the housing market. Following Baker et al. (2016), the index is constructed to measure the uncertainty on three aspects, viz. newspaper coverage of policy and economic related uncertainty, the number of federal tax code provisions set to expire in forthcoming years, and the disagreement among economic forecasters. EPU is represented by the U.S. historical news-based policy index and ranges from 1900Q1 to 2017Q4.[31]

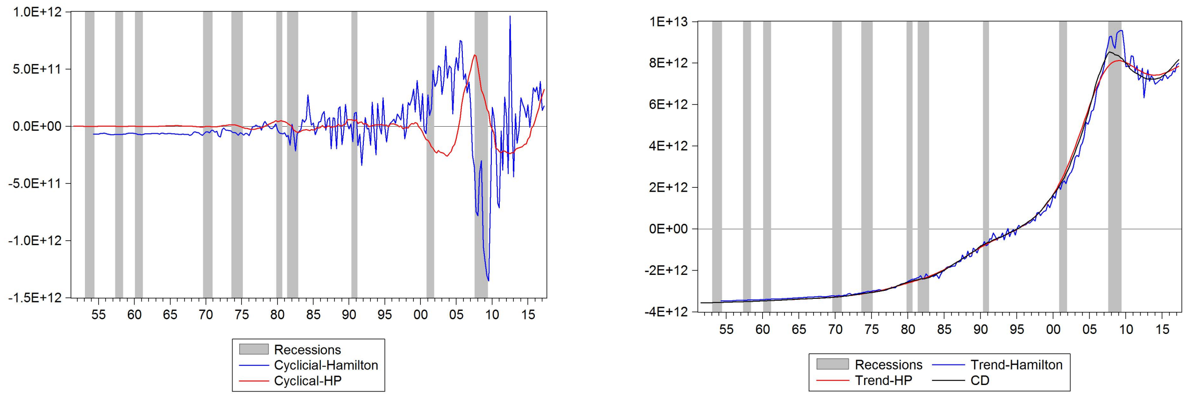
Residential housing prices *(RHP)* depicts the dynamics of national housing prices in the U.S.. It is represented by the well-known S&P/Case-Shiller U.S. National Home Price Index and is consistent with the price series used in the construction of RLV. Data are from S&P Dow Jones Indices LLC covering the period of 1975Q1 - 2017Q3. In addition, except for RLV and EPU, all the included variables are retrieved from the Federal Reserve of St. Louis (FRED), U.S..

[31]Data can be accessed through www.policyuncertainty.com/index.html

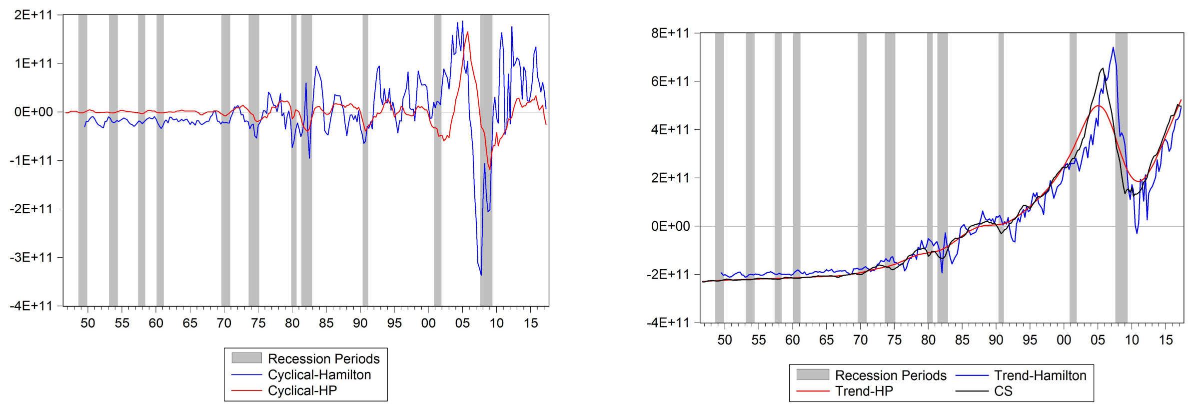
Appendix B Cycles and trends of target variables

Figure B.1: **Cycles and trends of variables in levels (1)**

(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices

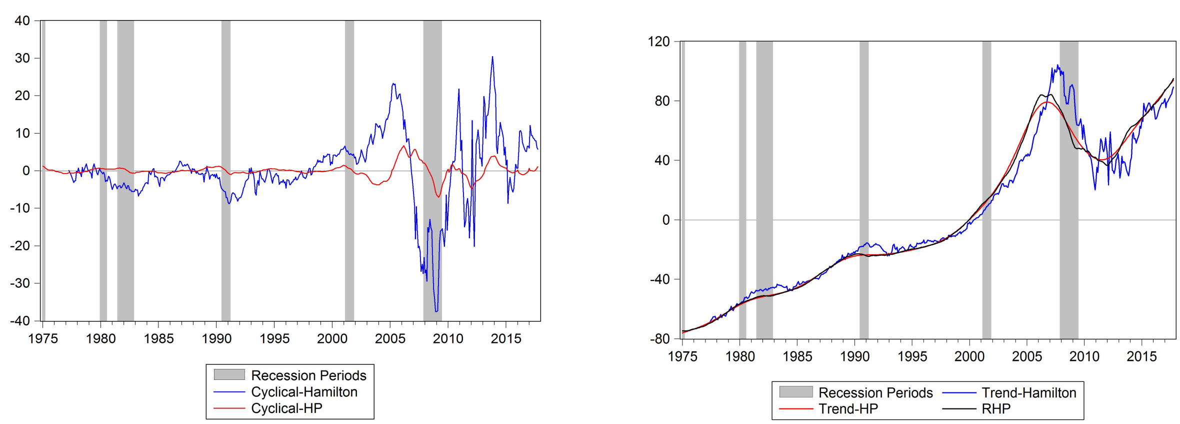
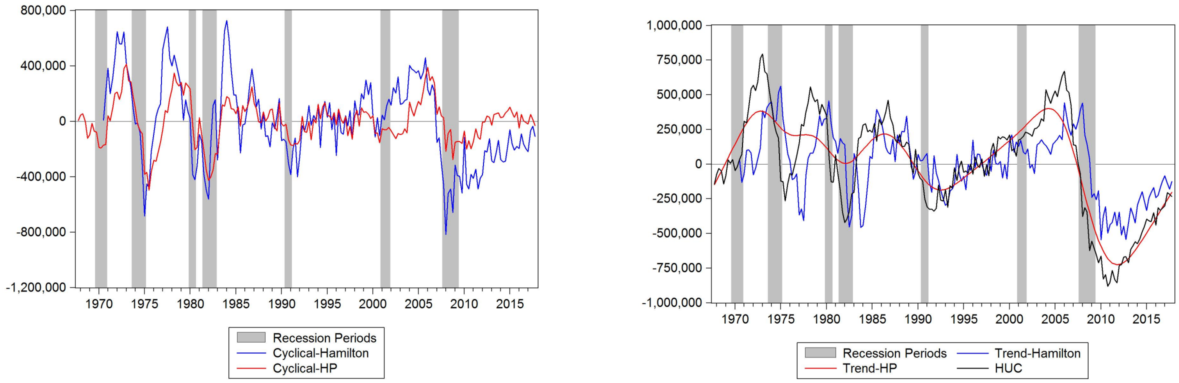
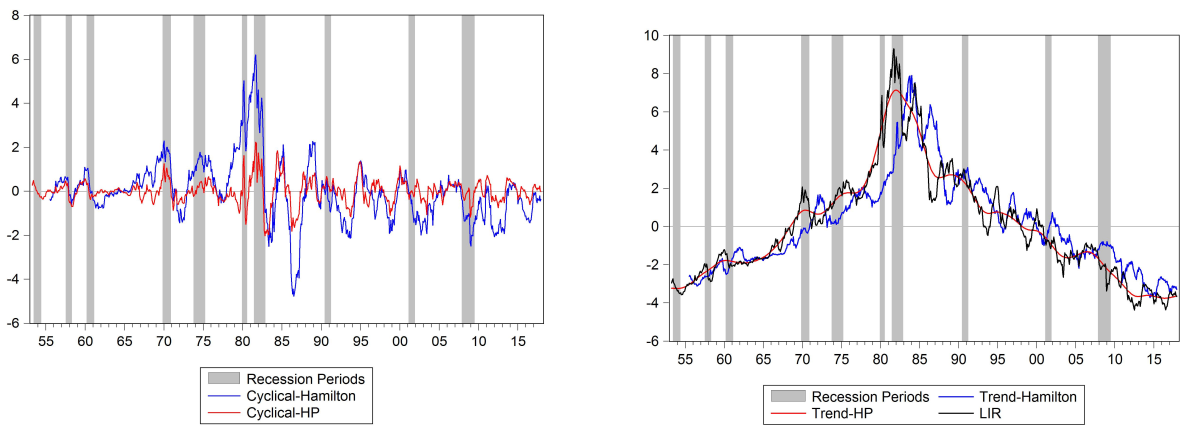


Figure B.2: **Cycles and trends of variables in levels (2)**

(a) Residential housing stocks



(b) Long-term interest rate



(c) Inflation

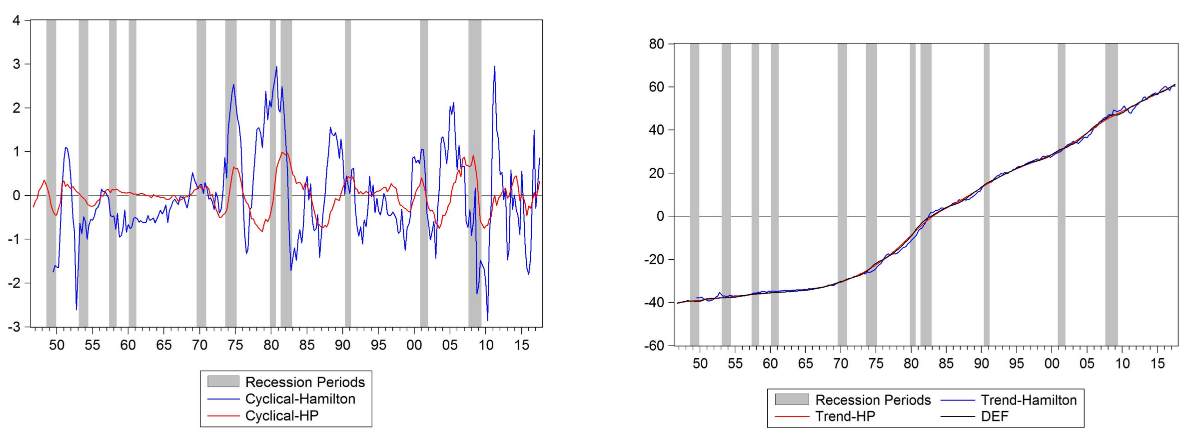
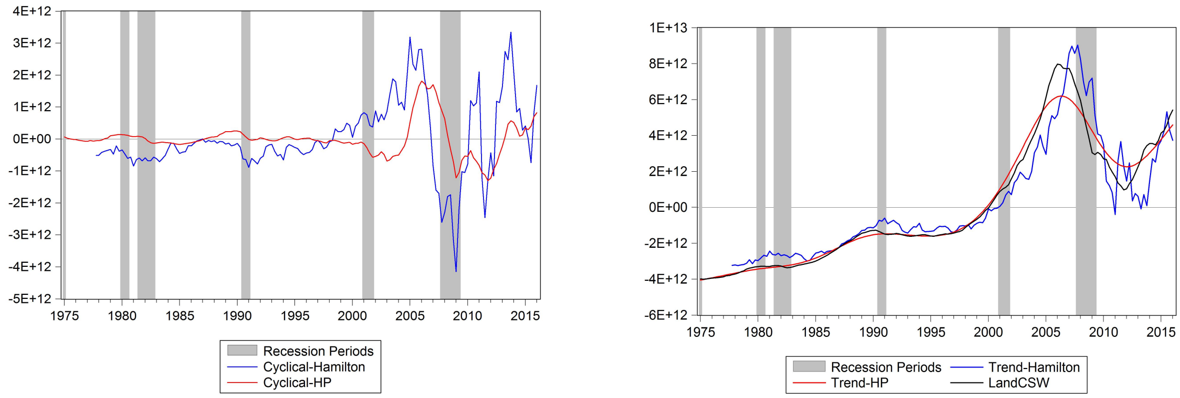
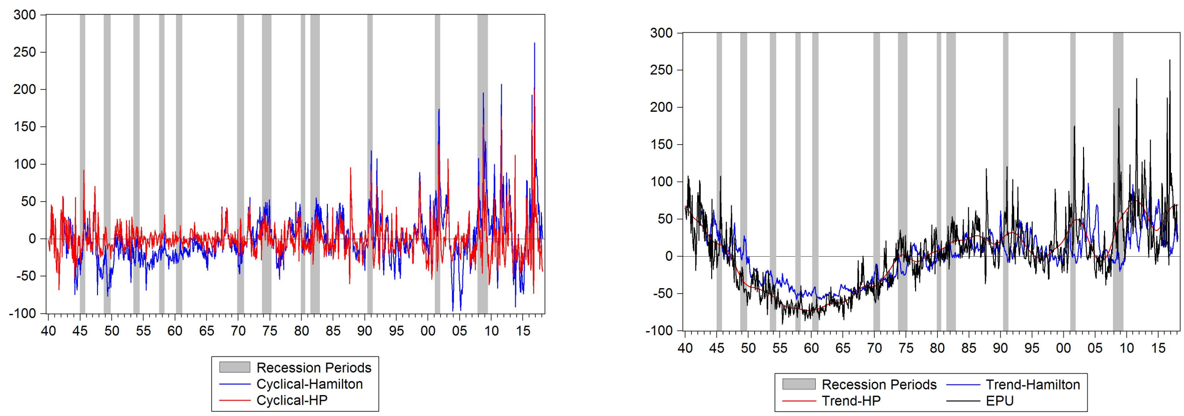


Figure B.3: **Cycles and trends of variables in levels (3)**

(a) Residential land value



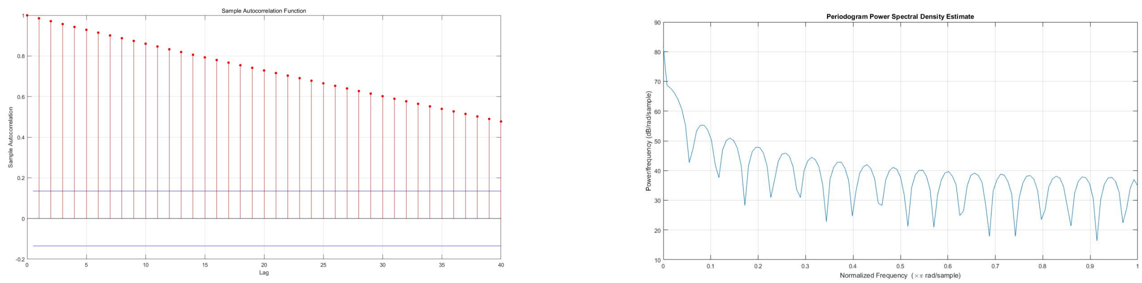
(b) Economic policy uncertainty



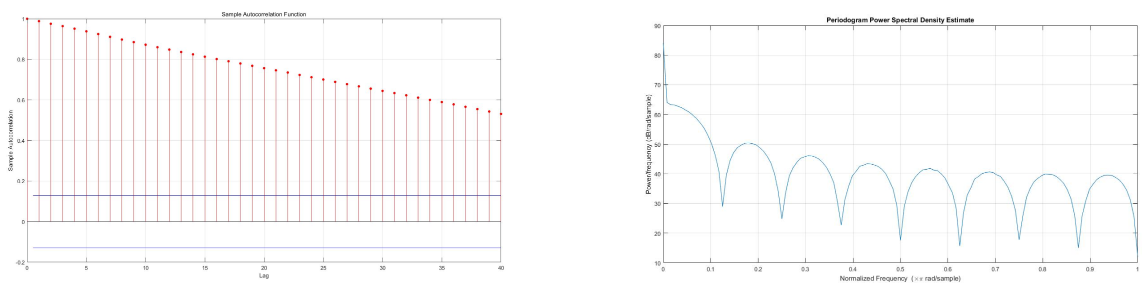
Appendix C ACF and Spectral Density Plots

Figure C.1: **ACF and spectral density figures (1)**

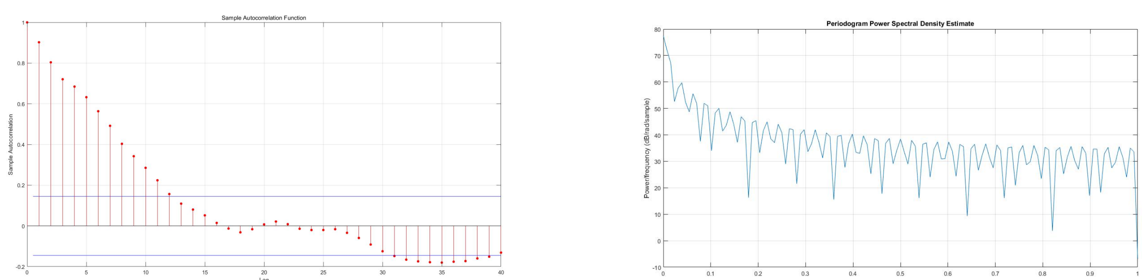
(a) Credit to the demand side



(b) Credit to the supply side



(c) Residential housing stocks



(d) Long interest rate

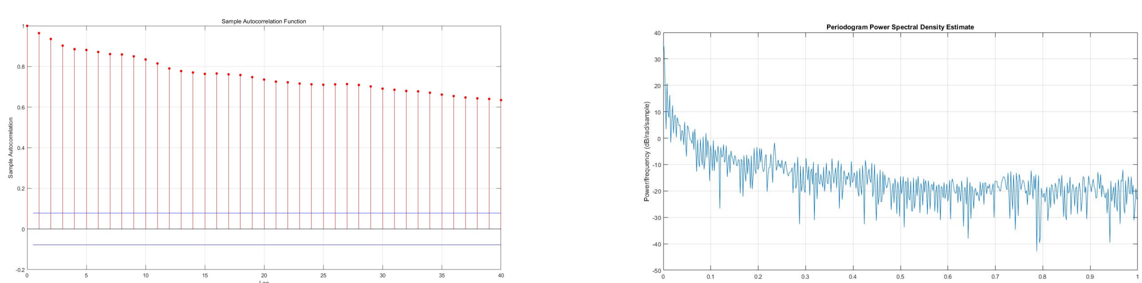
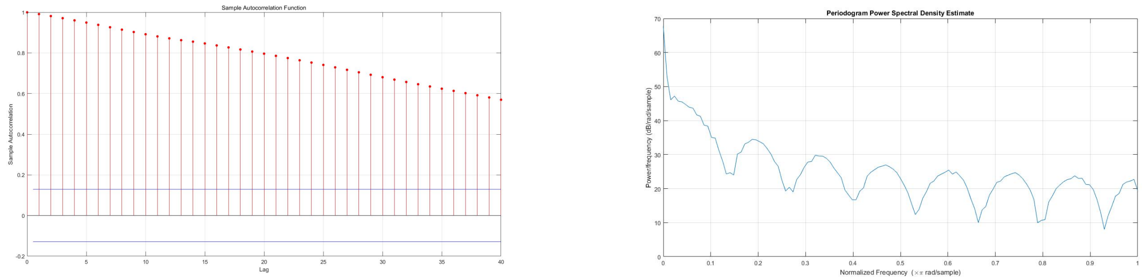
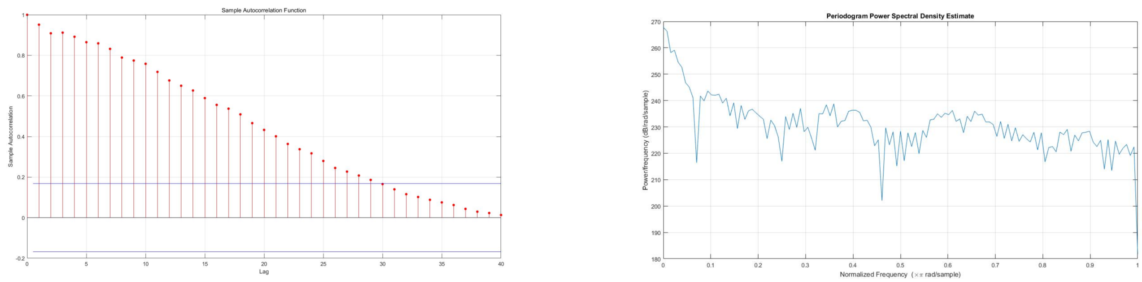


Figure C.2: **ACF and spectral density figures (2)**

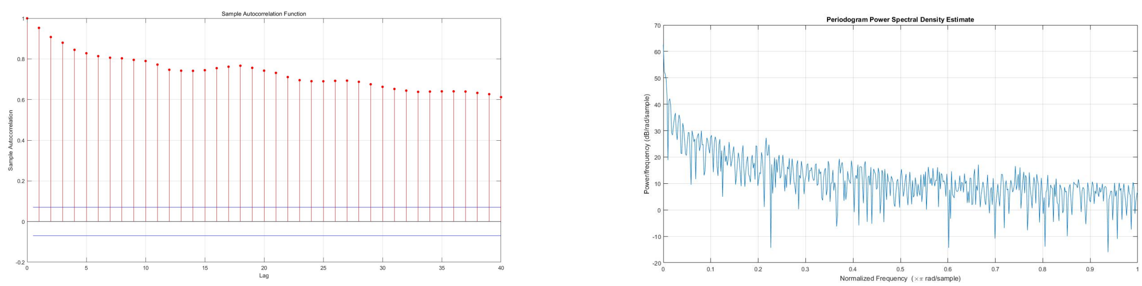
(a) Inflation



(b) Residential land value



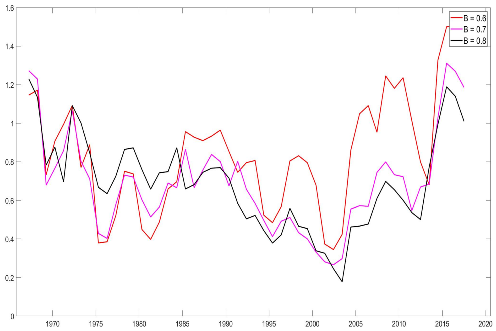
(c) Economic policy uncertainty



Appendix D Dynamic Rolling Window Estimation of d

Figure D.1: **Dynamics of rolling-window d estimates - LW estimator**

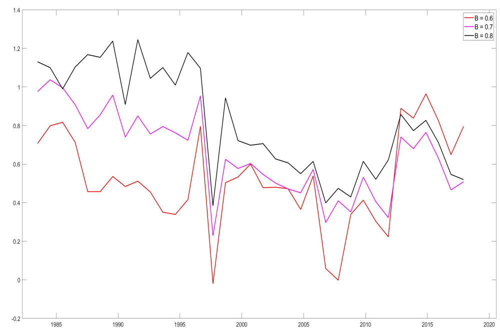
(a) Credit to the housing demand



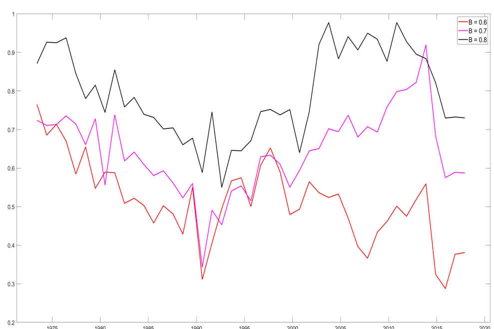
(b) Credit to the housing supply

(c) Residential housing prices

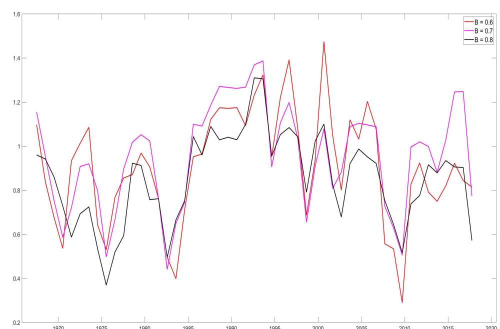
(d) Residential housing stocks



(e) Long-run interest rate



(f) Inflation



(g) Residential land value

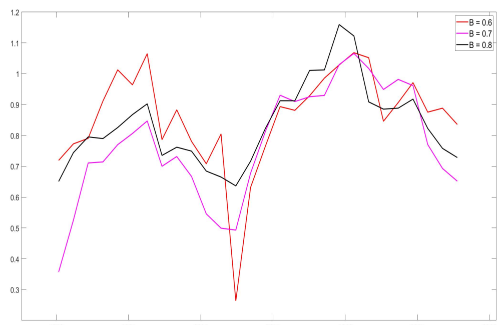
(h) Economic policy uncertainty

Figure D.2: **Dynamics of rolling-window d estimates - 2ELW estimator**

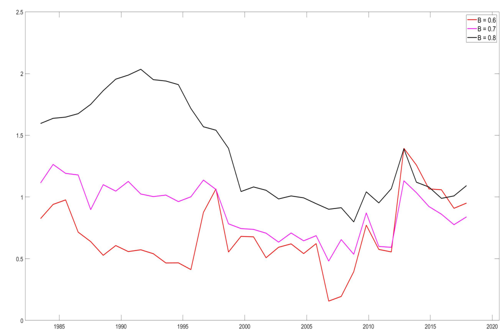
(a) Credit to the housing demand

(b) Credit to the housing supply

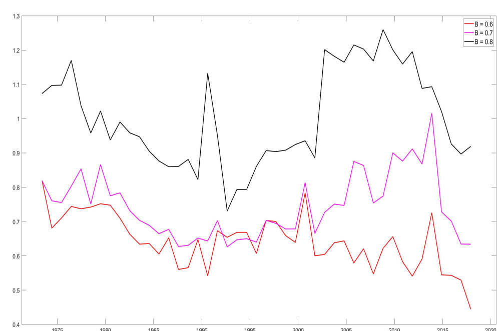
(c) Residential housing prices



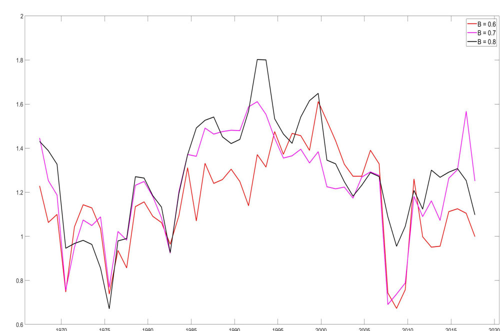
(d) Residential housing stocks



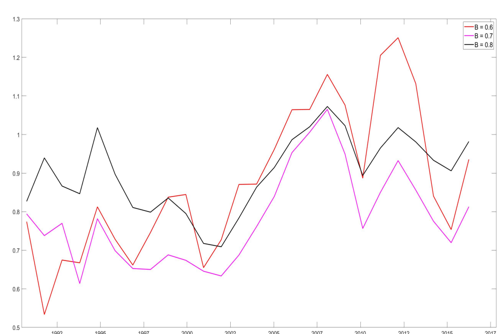
(e) Long-run interest rate



(f) Inflation



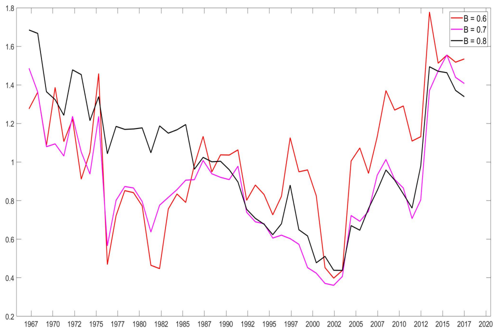
(g) Residential land value



(h) Economic policy uncertainty

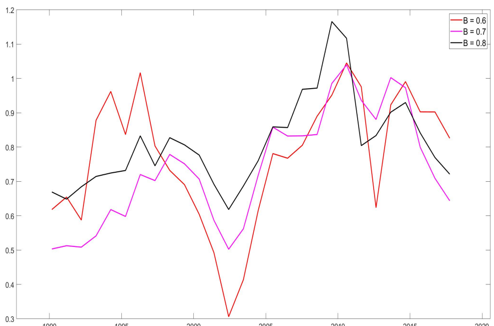
Figure D.3: **Dynamics of rolling-window d estimates - 2ELWdm estimator**

(a) Credit to the housing demand

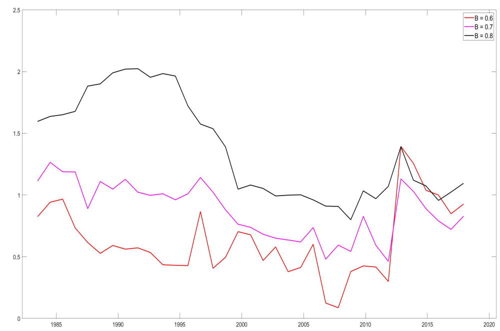


(b) Credit to the housing supply

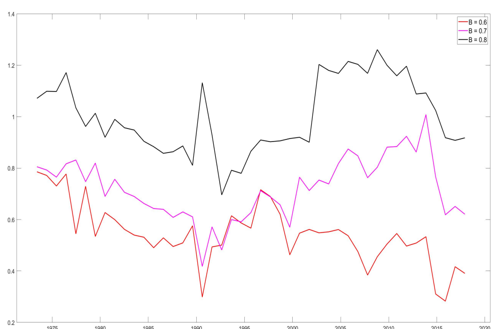
(c) Residential housing prices



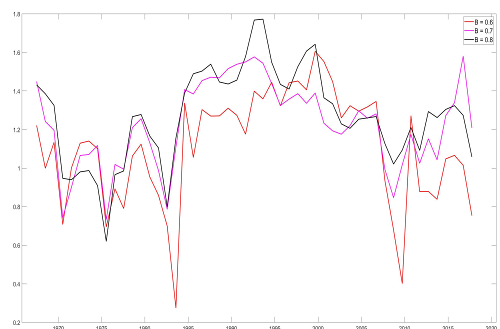
(d) Residential housing stocks



(e) Long-run interest rate



(f) Inflation



(g) Residential land value

(h) Economic policy uncertainty

Appendix E Further evaluation of the FCVAR estimation: Forecasting exercises

To further evaluate performance of our modelling strategy, we perform forecasting exercises for the demand and supply functions of housing within our FCVAR setting. The predictive superiority of the FCVAR model is examined against the conventional cointegrated VAR (CVAR) model.

(1) Forecasting: Housing demand function

To evaluate performance of our obtained housing price-macroeconomic system from the demand function by the FCVAR estimation, a forecasting exercise is conducted as follows. We compute RMSFE values of FCVAR and CVAR models in h-step ahead forecasting horizons where $h = 1, 5, 10, 15, 20,\ 25, 30, 35, 40$. The results are shown in Table E.1. Better predictive performance of the FCVAR model against the CAR model is examined by showing lower RMSFE values.

Table E.1: **RMSFE calculations (Housing demand function)**

Model	Forecast horizon (h)								
	1 step	5 step	10 step	15 step	20 step	25 step	30 step	35 step	40 step
Panel A: The magnitudes of RMSFE values									
FCVAR	0.0069	0.0059	0.0148	0.0256	0.0302	0.0617	0.0466	0.0321	0.0184
CVAR	0.0046	0.0067	0.0284	0.0630	0.2075	0.1743	0.0633	0.2514	0.1449
Panel B: Percentage change in RMSFE values									
FCVAR versus CVAR	50.2906	-12.2085	-47.7410	-59.3619	-85.4452	-64.5979	-26.3334	-87.2188	-87.3032

Note: (a) Panel A reports the values of RMSFE for the multivariate model system of the FCVAR and CVAR. (b) Panel B reports comparisons of RMSFE values between the FCVAR and CVAR. (c) Negative values favour the FCVAR model.

As reported in Panel A of Table E.1, magnitudes of RMSFE of the FCVAR model are consistently smaller than that of the CVAR model in all the nine horizons except the 1-step ahead horizion where RMSFE values of both models are highly similar. It clearly demonstrates that the FCVAR model outperforms the CVAR model with regard to RMSFE values. Moreover, difference in RMSFE values between the two models is gradually enlarged with increases in forecasting horizons, indicating better predictability of the FCVAR model in a relatively longer-term. We further examine the predictive performance of the FCVAR model over the CVAR model by measuring the difference between a ratio of their RMSFE values and 1 through

$$100 \times \left\{ \frac{RMSFE_{FCVAR}}{RMSFE_{CVAR}} - 1 \right\} \tag{29}$$

where negative values indicate more accurate predictions of the FCVAR model given its smaller RMSFE than the CVAR model; and positive values favor an opposite conclusion. Corresponding results in Panel B of Table E.1 show that RMSFE values of the FCVAR model can be as lower as 87% than that of the CVAR model. Hence, results exhibited in Table E.1 demonstrate that the FCVAR model outperforms the CVAR model in terms of prediction in the housing demand function.

(2) Forecasting: Housing supply function

At the same time, to evaluate predictive performance of the FCVAR model in the housing supply function, magnitudes of RMSFE of the FCVAR and CVAR models in h-step ahead forecasting horizons are calculated and presented in Panel A of Table E.2 where $h = 1, 5, 10, 15, 20, 25, 30, 35, 40$. Intuitively, the FCVAR model outperforms the CVAR model in all the horizons except the 25-step and 30-step ahead ones where the two models possess similar RMSFE values. The gap in RMSFE values between the two models witnesses an increasing pattern with increases in the horizons, indicating more precise forecasting using the FCVAR model in a relatively longer-term.

Moreover, we measure the difference between a ratio of RMSFE values of the FCVAR model to that of the CVAR model and 1 following Equation (29). Results shown in Panel B of Table E.2 indicate that RMSFE values of the FCVAR model can be as lower as 99% than that of the CVAR model. Thus, results from Table E.2 indicate better predictive performance of the FCVAR model against the CVAR model in terms of forecasting in the housing supply function.

Table E.2: **RMSFE calculations (Housing supply function)**

Model	Forecast horizon (h)								
	1 step	5 step	10 step	15 step	20 step	25 step	30 step	35 step	40 step
Panel A: The magnitudes of RMSFE values									
FCVAR	0.0073	0.0084	0.0261	0.0532	0.0269	0.0900	0.0421	0.0273	0.0129
CVAR	0.0091	0.0227	0.0667	0.0579	0.0300	0.0457	0.0346	0.1552	1.5336
Panel B: Percentage change in RMSFE values									
FCVAR versus CVAR	-19.9531	-63.1356	-60.9260	-8.0968	-10.1478	96.7783	21.5241	-82.3900	-99.1620

Note: (a) Panel A reports values of RMSFE for the multivariate model system of the FCVAR and CVAR. (b) Panel B reports comparisons of RMSFE values between the FCVAR and CVAR. (c) Negative values favour the FCVAR model.