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Exploring House Price Momentum in the U.S. after the Subprime Mortgage Crisis*

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Abstract This paper examines the relationship between house prices, rents, and user costs of housing in the United States from January 2009 to March 2022. We first use the time-varying coefficient cointegration model to explain the long-run relationship and adopt an error correction model with endogenous regime switching, which turns out to fit the data better than existing models. Our results show that, following the sub-prime mortgage crisis, the U.S. housing market has switched between a strong or a weak house price momentum state. In the strong momentum regime, house price returns have been more persistent and error correction has been slower. The degree of house price momentum is estimated to be very high and explosive in the strong regime while it is moderate in the weak regime. It is estimated that 74% of the data remains in the strong momentum regime. The extracted latent factor determines the regime of the housing market, and we run the adaptive lasso on the FRED-MD to identify the link between house price momentum and the macroeconomic and financial variables.

Keywords House prices, house price momentum, time-varying coefficient cointegration, endogenous regime switching.

JEL Classification R30, G10, C50.

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1. INTRODUCTION

The great recession following the housing-related global financial crisis sparked substantial interest in what drives house price growth and how the housing market affects macroeconomic and financial stability. To that end, there has been substantial research highlighting the economic role of house price growth, and one cannot emphasize enough the importance of understanding house price dynamics. Unlike typical financial asset return series such as stock returns, house price returns are positively autocorrelated and quite persistent; this phenomenon is known as house price momentum. Case and Shiller (1989) and Capozza *et al.* (2004) showed the persistence of house price momentum and argued that house price momentum could not be empirically explained by existing models. Recent studies have attempted to provide theoretic explanations for house price momentum. For example, Glaeser and Nathanson (2017) used the extrapolative expectation of home buyers to account for house price momentum. Guren (2018) introduced an amplification mechanism to elucidate house price momentum. Ma (2020) found that households' subjective house-price expectations capture the momentum but not the reversion to fundamentals.

The empirical literature on house price modeling includes the house price-rent approach, which is based on the present-value model of asset prices by Campbell and Shiller (1988). Shiller (2015) and Bourassa *et al.* (2019) proposed that a house rent-price ratio measure is a useful and reliable benchmark for assessing whether the housing market is under or overvalued. This approach assumes that absent frictions and credit restriction-arbitrage between owner-occupied and rental housing implies that the house rent-price ratio is a function of the user cost of housing, which is defined as the after-tax mortgage interest rate adjusted for expected house price appreciation. This approach has been extensively used in house prices analysis. Under the conditions of perfect arbitrage and no credit constraint, the house rent-price ratio and the user cost of housing should be cointegrated. However, the previous empirical literature has hardly shown the existence of such a linear cointegration. Although Gallin (2008) adopted the standard error-correction model based on the linear cointegration between the rent-price ratio and the use cost of housing, he did not provide a cointegration test result for them. Meanwhile, Mikhed and Zemčík (2009) showed that house prices and rents in the U.S. housing market are not cointegrated and argued that an error-correction model is not appropriate.

The user cost of housing should consider the risk premium associated with housing and expected capital gains; we provide more details for this in the next section. The risk premium and expected capital gains associated with housing depend on the economic situation and are inevitably time-varying. However, since the risk premium and expected capital gains are unobservable, the user cost of housing that has been considered in existing empirical studies has excluded them. As long as the time-varying risk premium and expected capital gains are missing from the data of the user cost of housing, it would be more appropriate to expect the long-run relationship between the rent-price ratio and the user cost of housing to be time-varying.

One of the main motivations of this paper is to explore this aspect and find an econometric model that fits the house price data better than existing models. Therefore, this paper examines the relationship between house prices, rents, and user costs of housing after the global financial crisis. We consider monthly data from January 2009 to March 2022. As in Gallin (2008), we consider an error correction model of the rent-price ratio. However, we adopt two different econometric models for the long-run and short-run dynamics of house prices. For the long-run relationship, instead of the typical linear cointegration, we adopt the time-varying coefficient cointegration approach proposed by Park and Hahn (1999). Next, we use an error correction model (ECM) with regime switching. Specifically, we employ the endogenous regime switching model introduced by Chang *et al.* (2017). One of the advantages of the model proposed by Chang *et al.* (2017) is that we can extract the latent factor that decides regimes. Finally, we use the adaptive LASSO method introduced by Zou (2006) to find links between the house price momentum and macroeconomic fundamentals.

The main findings of this work are as follows. First, the linear cointegration between the rent-price ratio and the user cost of housing does not exist for the sample period and, as expected, the time-varying coefficient cointegration is found to be suitable for their long-run relationship. Second, the ECM with endogenous regime switching fits the data better than the ECM with the conventional Markov regime switching or a linear ECM. Third, our model exhibits two regimes in the housing market: a strong momentum regime and a weak momentum regime. In the strong momentum regime, house price returns are very persistent and error correction is slower. The degree of house price momentum is estimated to be 1.104, which is similar to the maximum value of house price momentum for bubble Metropolitan Statistical Areas (MSAs) presented in Lai and Van Order (2017). By contrast, in the weak momentum regime, house price returns are less persistent and error correction is faster. The degree of house price momentum is estimated to be 0.339, which is similar to the average value of momentum for non-bubble MSAs in Lai and Van Order (2017). The estimation results show that, for the sample period, 74% (26%) of the data remain in the strong (weak) momentum regime.

Fourth, we run the adaptive least absolute shrinkage and selection operator (LASSO) of the latent factor from our model on the FRED-MD dataset, which shows the link between the house price momentum and macroeconomic and financial variables. Among a total of 125 variables, eight variables are selected. New private housing permits in the Midwest area and housing starts in the South area are selected. It is not surprising that these house demand-/supply- related variables are related to house price momentum. The six-month treasury bill minus federal fund rates and Moody's Aaa corporate bond minus federal fund rates are also selected, which shows that the house price momentum is affected by monetary policy. The change rate (log difference) of the S&P price-earnings ratio (S&P PE Ratio) is selected as well, which suggests a link between the stock market and the housing market.

The rest of this paper is organized as follows. In section 2, we explain the basic model of house prices, the user cost of housing, and the econometric methods. In Section 3, we explain the data and provide the estimation results for the long-run and short-run dynamics of house prices. Based on the adaptive LASSO method, we also link the economic fundamentals with the house price momentum.

2. ECONOMETRIC METHODS

In this section, we explain the basic model of rent, house price, and user cost of housing and econometric methods we adopt in our empirical analyses. Gallin (2008) analyzed the long-run and short-run dynamics of house prices by using the standard error-correction model based on the linear cointegration. We basically follow his approach and focus on an error-correction model. However, we consider two different econometric methods: First, instead of the linear cointegration, we explore the time-varying coefficient (TVC) cointegration, which can account for the nonlinear and time-varying long-run relationship between variables. Second, we allow for regime switching in the error-correction model so that one regime represents the state of weak house price momentum whereas the other regime characterizes the state of strong house price momentum. We employ either the conventional Markov regime switching or the endogenous regime switching introduced by Chang *et al.* (2017) in the error correction model.

2.1. BASIC MODEL AND USER COST OF HOUSING

In equilibrium, the cost of renting a house should be equal to the annual "flow" cost of owning one. As is the case in Himmelberg *et al.* (2005) Gallin (2008), Chen *et al.* (2022), Gilbukh *et al.* (2023) and Lee *et al.* (2023), under the frictionless and credit arbitrage assumptions in the housing market, the basic model of rent, house price, and user cost of housing can be expressed as ,

$$R_t = P_t \times C_t, \tag{1}$$

where R_t denotes rents, P_t is house prices, and C_t is the user cost of housing. From this, the rent-price ratio can be expressed as the user cost of housing as,

$$\frac{R_t}{P_t} = C_t. \tag{2}$$

It should be noted that the user cost of housing C_t in (1) includes the risk premium associated with housing and expected capital gains, which depend on the economic situation and are inevitably time-varying. However, since the risk premium and expected capital gains are unobservable, Gallin (2008) defined $\widetilde{C}_t$ as the user cost of housing excluding the risk premium and expected capital gains[1], which is given by

$$\widetilde{C}_t = \left(i_t + \tau_t^p\right)(1 - \tau_t^y) + \delta_t, \tag{3}$$

where i_t denotes the nominal interest rate, τ_t^p is the marginal property tax rate, τ_t^y is the marginal income tax rate, δ_t is the depreciation rate of housing. He used $\widetilde{C}_t$ instead of C_t in his empirical analyses. Based on (2), he applied the linear cointegration between the rent-price ratio R_t / P_t and the user cost of housing $\widetilde{C}_t$. We consider such a linear cointegration model to be unsuitable because the user cost included in his model excludes time-varying risk premium and expected capital gains. As long as the time-varying risk premium and expected capital gains are missing in the data of the user cost of housing, it would be more appropriate to expect the long-run relationship between the rent-price ratio and the user cost of housing $\widetilde{C}_t$ to be time-varying. We explore this aspect by adopting the cointegrating regression with time-varying coefficients for R_t / P_t and $\widetilde{C}_t$, which we will explain in the next subsection.

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[1]Gallin (2008) let

$$C_t = \widetilde{C}_t + \Lambda_t - E_t G_{t+1},$$

where Λ_t is the risk premium associated with housing and $E_t G_{t+1}$ is expected capital gains.

Instead of using $\widetilde{C}_t$ defined by Gallin (2008), we adopt recent modifications of the user cost of housing that have been provided in the related literature. The nominal interest rate in (3) represents the cost of capital and, following Gilbukh *et al.* (2023) and Lee *et al.* (2023), it can be rewritten as

$$i_t = (1-\mu_t)r_t^d + \mu_t r_t^m,$$

where μ_t denotes loan-to-value ratio, r_t^d is deposit interest rate, and r_t^m is mortgage rate. This means that the cost of capital consists of two parts: the cost of down payment and the cost of mortgage. We can also include the transaction cost ϖ, as was done in Gilbukh *et al.* (2023) and Lee *et al.* (2023). Following Gallin (2008), we also use inflation expectation to calculate the user cost of housing in real terms. Consequently, the real user cost of housing $\widetilde{\mathbf{C}}_t$ is defined as

$$\widetilde{\mathbf{C}}_t = \left[(1-\mu_t)r_t^d + \mu_t r_t^m + \tau_t^p\right](1-\tau_t^y) + \delta_t + \varpi - \pi^e, \tag{4}$$

where π^e is inflation expectation, which we use in our empirical analyses. It should be noted that $\widetilde{\mathbf{C}}_t$ in (4) still does not include risk premium and expected capital gains. A detailed data description of this is provided in Section 3.1.

2.2. COINTEGRATING REGRESSION WITH TIME-VARYING COEFFICIENTS

We let p_t denote the logarithm of the real house price. r_t is the logarithm of real rent and c_t is the logarithm of the real user cost of housing. The log-transformed version of (2) corresponds to

$$y_t = \tau + \alpha c_t + \varepsilon_t, \tag{5}$$

where $y_t = r_t - p_t$ is the logarithm of rent-price ratio. From (2) and (5), one can see that, given rent R_t, house price P_t increases if user cost C_t decreases. For example, (2) implies that a decrease of interest rate is associated with an increase of house price (or decrease of rent-price ratio). This relationship corresponds to a positive value of α in (5). It should be noted that the user cost C_t or c_t includes positive risk premium and negative expected capital gains as explained in footnote 1. Even if risk premium and expected capital gains are time-varying, their movements are reflected in c_t and, consequently, the coefficient α in (5) can remain positive.

However, risk premium and expected capital gains are unobservable and, therefore, instead of (5), one estimates

$$y_t = \tau + \alpha\widetilde{\mathbf{c}}_t + \varepsilon_t, \tag{6}$$

where $\widetilde{\mathbf{c}}_t$ is the logarithm of the real user cost of housing $\widetilde{\mathbf{C}_t}$ in (4). This is the standard linear cointegration mode that was estimated in previous studies as in Gallin (2008), and it can be also called the fixed coefficient (FC) cointegration model. If risk premium and expected capital gains are constant, a decrease of interest rate will be associated with an increase of house price and, consequently, the value of α in (6) will be positive. However, if risk premium or expected capital gains largely fluctuate over time, such a relationship may not hold.

As an example, let us consider a period when expected capital gains are largely negative (in other words when house price is expected to rapidly decrease). A decrease of the user cost data $\widetilde{\mathbf{C}_t}$ (such as a decrease of interest rate) could be associated with a decrease of house price for the period. This could lead to a negative value of the coefficient α in (6) for the period. Next, let us consider a period when expected capital gains are largely positive (in other words when house price is expected to rapidly increase). A decrease of interest rate would be associated with a large increase of house price for the period. This would lead to a large positive value of α in (6) for the period.

These examples show that the fixed coefficient model cannot accommodate such a relationship between hous price and expected capital gains or risk premium, and they advocate a time-varying coefficient model as an alternative model.[2] We can consider the possibility of a time-varying coefficient of the user cost $\widetilde{\mathbf{c}}_t$, which is given as

$$y_t = \tau + \alpha_t \widetilde{\mathbf{c}}_t + \varepsilon_t. \tag{7}$$

During the period when expected capital gains are largely negative or risk premium is large, the value of α_t in (7) could be largely negative. During the period when expected capital gains are largely positive or risk premium is small, the value of α_t would be positive. The estimated time-varying coefficient α_t in (7) may provide information on expected capital gains or risk premium.

We apply the TVC cointegrating approach introduced by Park and Hahn (1999) for (7). We let $\alpha_t = \alpha(t/T)$ for $t = 1, 2, \cdots, T$, where $\alpha(\cdot)$ is a function defined over the unit interval and admits a Fourier flexible form (FFF). Specifi-

[2] Many studies use the time-varying approach to investigate the relationship between house prices and economic fundamentals. Gelain and Lansing (2014) allow for time-varying fundamentals in a house price-rent ratio model. Christou *et al.* (2019) use a time-varying approach-a quantile analysis-to show the existence of cointegration in the real estate market. Albuquerque *et al.* (2020) employ a time-varying parameter vector autoregression (VAR) to analyze the dynamic interaction between house price and monetary policy since the global financial crisis. Plakandaras *et al.* (2020) use a time-varying VAR to emphasize the time-varying role of macroeconomic shock on house price. The time-varying cointegration or error correction approach has been also applied to exchange rate models as in Borger and Kempa (2024) and Park and Park (2013).

cally, we use

$$\alpha_{pq}(r) = \lambda_0 + \sum_{j=1}^{p} \lambda_j r^j + \sum_{j=1}^{q} (\lambda_{p+2j-1}, \lambda_{p+2j}) \phi_j(r), \tag{8}$$

where $\phi_j(r) \equiv (\cos 2\pi jr, \sin 2\pi jr)'$ for $r \in [0,1]$, which approximates FFF as p and q increase. By defining $\lambda_{pq} \equiv (\lambda_0, \cdots, \lambda_{p+2q})'$ and $\phi_{pq}(r) \equiv (1, r, \cdots, r^p, \phi_1^{'}(r), \cdots, \phi_q^{'}(r))'$, we may write $\alpha_{pq}(t/T)\widetilde{\mathbf{c}}_t$ as $\lambda_{pq}^{'}\phi_{pq}(t/T)\widetilde{\mathbf{c}}_t$ or further as $\lambda_{pq}^{'}\widetilde{\mathbf{c}}_{pqt}$ with $\widetilde{\mathbf{c}}_{pqt} \equiv \phi_{pq}(t/T)\widetilde{\mathbf{c}}_t$. In other words, the nonlinear function may be approximated by a linear function of a new regressor vector $\widetilde{\mathbf{c}}_{pqt}$. Using this specification, the TVC model can be written as

$$y_t = \tau + \lambda_{pq}^{'}\widetilde{\mathbf{c}}_{pqt} + \varepsilon_{pqt},$$

where $\varepsilon_{pqt} \equiv \varepsilon_t + (\alpha(t/T) - \alpha_{pq}(t/T))\widetilde{\mathbf{c}}_t$. ε_{pqt} includes both the original disequilibrium error and the approximation error from fixing p and q. As suggested by Park and Hahn (1999), we adopt the canonical cointegrating regression (CCR) introduced by Park (1992) to estimate the model.

2.3. COINTEGRATING REGRESSION WITH TIME-VARYING COEFFICIENTS

Regime switching is widely used in time series analysis. Many studies exploring house price dynamics have used the Markov regime switching model introduced by Hamilton (1989) to identify the state-dependent house price growth. For example, Lai and Van Order (2010) applied regime switching models to find evidence of house price momentum in the United State. Nneji *et al.* (2013) exploited a regime-switching model to test the bubbles in the U.S housing market. Hall *et al.* (1997) and Kim and Chung (2014) adopted error correction models with the Markov regime switching to investigate the UK and US house prices, respectively. Regimes are typically defined as the housing boom and bust regime, housing bubble builder and bubble burster, and bear and bull market in the financial market.

In the conventional Markov regime switching model, the Markov chain determining regimes is independent of all other parts of the model. This implies that future transition between states is solely determined by the current state, not by realization of an underlying time series. The endogenous regime switching model proposed by Chang *et al.* (2017) has the advantage of future transitions being dependent on the realization of underlying time series as well as the current and potential past states. An endogenous regime switching ECM can be written as

$$\Delta y_t = \beta_0(s_t) + \beta_1(s_t)\widehat{\varepsilon}_{t-1} + \sum_{i=1}^{l} \beta_{i+1}(s_t)\Delta y_{t-i} + \sum_{i=1}^{m} \gamma_i(s_t)\Delta \mathbf{c}_{t+1-i} + u_t,$$

where $u_t \sim N(0, \sigma^2(s_t))$. The state process (s_t) represents the low or high state, depending on whether it takes a value of zero or one, and it is given by

$$s_t = 1\{\omega_t \geq \tau\},$$

where τ is the threshold level and $1\{\cdot\}$ is the indicator function. The latent factor ω_t follows a first-order autoregressive process and is given by

$$\omega_t = \eta\,\omega_{t-1} + \upsilon_t, \tag{9}$$

for $\eta \in (-1, 1]$ and i.i.d. standard normal error (υ_t). Taking into account the realized value of the latent factor ω_t and the threshold level τ, we describe the two events $\{\omega_t < \tau\}$ and $\{\omega_t \geq \tau\}$ as two regimes that are switched between. The transition probabilities of the state process (s_t) from the low state to the low state and from the high state to the high state is denoted by

$$\begin{aligned} a(\alpha,\tau) &= P\{s_t = 0 | s_{t-1} = 0\} \\ b(\alpha,\tau) &= P\{s_t = 1 | s_{t-1} = 0\}. \end{aligned} \tag{10}$$

Note that

$$\begin{aligned} P\{s_t &= 0|\omega_{t-1}\} = P\{\omega_t < \tau|\omega_{t-1}\} \\ P\{s_t &= 1|\omega_{t-1}\} = P\{\omega_t \geq \tau|\omega_{t-1}\}. \end{aligned}$$

Specifically, u_t and υ_t are jointly i.i.d and distributed as

$$\begin{pmatrix} u_t \\ \upsilon_{t+1} \end{pmatrix} =_d N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right). \tag{11}$$

For $\rho \neq 0$, as the observed time series Δy_t is correlated with the future latent factor ω_{t+1}, the future transition between states is endogenously affected by underlying time series Δy_t. However, when $\rho = 0$, there is no correlation between u_t and υ_{t+1} and the future transition between states now does not depend on Δy_t. In this situation, the model reduces to the conventional Markov switching model. Readers are encouraged to refer to Section 2.2 in Chang *et al.* (2017)for further detail. We estimate the endogenous regime switching ECM by the maximum likelihood (ML) method using the filter given by Chang *et al.* (2017).

3. EMPIRICAL ANALYSES

In this section, we first explain the data and report the unit root test results. The main results of this paper consist of three parts: The first part is about the long-run relationship based on the time-varying coefficient cointegration. Meanwhile, the second part provides the estimation results of the error correction model with endogenous regime switching. Lastly, the third part links the house price momentum with economic fundamentals, using the adaptive LASSO method.

3.1. THE DATA AND UNIT ROOT TESTS

We consider monthly U.S. national level house prices and rents from January 2009 to March 2022. The data are available from the Federal Reserve Economics Data (FRED-MD). As was done in Gallin (2008), we use the S&P/Case-Shiller U.S. national home price index to describe house prices nationwide. The index adopts the repeat sales method to estimate the aggregate value of single-family housing stock, which is the most reliable way to measure house price movements. We adopt the owners' equivalent rent of residents in U.S. city average as rents. This measures the change in the rental value of owner-occupied housing and uses the change in 'pure rent' that excludes the cost of any utilities included in the rental contract. Owners' equivalent rent is preferred as a metric over others like tenants' rent because it is a measure of the rents that homeowners would earn from renting in a competitive market. In other words, it is closer to the concept of housing 'dividend' for owners, thus making it more in line with the present value models in asset pricing theory.[3] House prices and rents are transformed into real terms using personal consumption expenditures (PCE) excluding food and energy.

The data used to calculate the user cost of housing is sourced from the FRB/US model packages at the Federal Reserve Board. We use the 10-year treasury rate as the deposit interest rate and the monthly reported 30-year fixed-rate mortgage rate as the mortgage interest rate. The loan-to-value ratio can be obtained from the Federal Housing Finance Agency. We also use marginal state and local tax rate on personal property as the marginal property tax rate, marginal federal personal income tax rate-which is twice median family income-as marginal income tax rate and depreciation rate of housing as depreciation. As

[3] Gallin (2008) could not use this as rents in his paper because of data availability. He instead used tenants' rent from the consumer price index, because it begins well before 1970Q1. By contrast, owners' equivalent rent is only available from 1983.

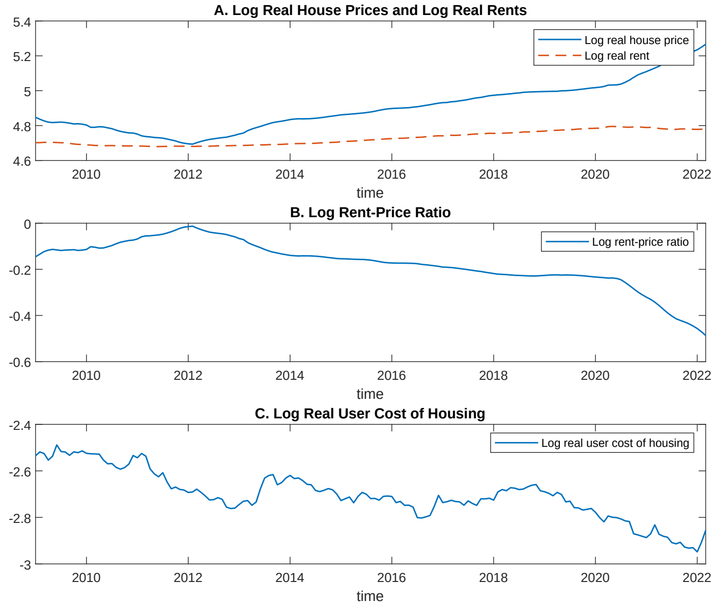

Figure 1: ORIGINAL DATA PATH. Log real house prices p_t, log real rents r_t, log rent-price ratio y_t and log user cost of housing x_t.

was done in Lee *et al.* (2023), we fix the transaction cost as $\delta = 2.5\%$. As the inflation expectation, we use the one-year ahead inflation forecasts from the survey of professional forecasters, which is available from the Federal Reserve Bank of Philadelphia.

Figure 1 presents the log transformed variables, where it can be seen that all three variables are quite persistent. Figure 1(A) shows that, after the subprime mortgage crisis, house prices decreased to the lowest point from 2009 to early 2012. With a stabilizing situation, house prices recovered from 2012 to 2019. After the outbreak of COVID-19, house prices increased more rapidly. Meanwhile, rents steadily increased until mid-2020. Starting from late 2020, there was a slight decline in rent due to the COVID-19 pandemic. Figure 1(B) provides the the logarithm of the rent-price ratio and its movement is mainly affected by the fluctuation of house prices because rents are more stable over the period. Figure 1(C) shows that the user cost in general kept decreasing except that it exhibited fluctuation from 2013 to 2019.

Table 1 provides the results of the augmented Dickey-Fuller (ADF) and GLS-detrended Dickey-Fuller (DF-GLS) unit root tests and Kwiatkowski-Phillips-

	With intercept			With intercept and trend		
	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
y_t	2.008	1.647	6.323^{***}	0.325	-0.098	0.861^{***}
$\widetilde{\mathbf{c}}_t$	-1.599	-0.153	5.471^{***}	-2.599	-2.564	0.528^{***}

Table 1: UNIT ROOT TEST RESULTS. The ADF and DF-GLS have the null hypothesis of a unit root, while the KPSS has the null hypothesis of stationary. The 10%, 5% and 1% critical values for ADF test are -2.57, -2.87 and -3.44 with intercept, and -3.13, -3.42 and -3.98 with intercept and trend. The 1% critical value for KPSS is 0.739 with intercept and 0.216 with intercept and trend. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

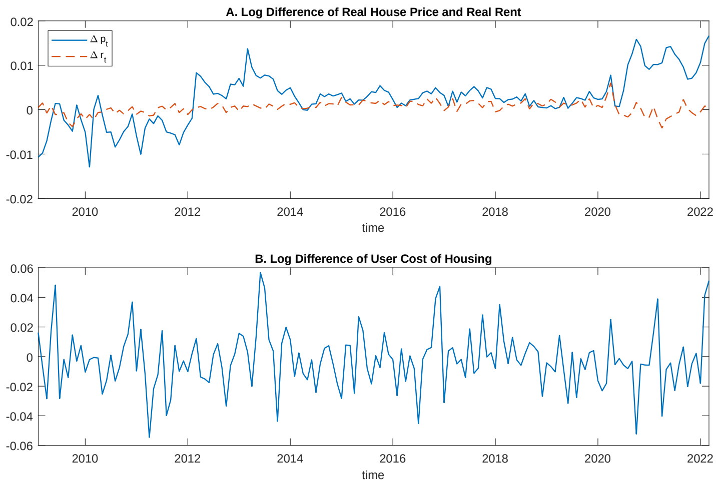

Figure 2: DIFFERENCED DATA PATH. Log difference of real house prices Δp_t, log difference of real rents Δr_t, and log difference of user cost of housing Δx_t.

Schmidt-Shin (KPSS) stationarity tests with lag lengths chosen by the Schwarz-/Bayesian information criterion (BIC) for a maximum of 8. We present test results both with intercept as well as with intercept and linear trend. The test statistics clearly show that all three variables, p_t, r_t, and $\widetilde{\mathbf{c}}_t$, can be modeled as unit root processes rather than stationary processes. There is no series or specification for which both unit root tests reject the unit root null hypothesis. Moreover, the KPSS test firmly rejects the stationarity null hypothesis against a unit root alternative for all series and specifications. Since the data are non-stationary, it is necessary to test for cointegration and apply estimation methods that are suitable for non-stationary data. Figure 2 presents the log difference of each variable. In particular, Figure2(A) exhibits the house price momentum. The log difference of real house price is still persistent and its autoregressive coefficient is estimated to be 0.875 for the sample period.

3.2. ESTIMATION RESULTS OF COINTEGRATION MODELS

First, we estimate the usual fixed coefficient cointegration model given in (5). Table 2 shows the estimation result of the model, for which we adopt the canonical cointegrating regression (CCR) method. The coefficient of user cost α is estimated to be 0.931. Table 3 presents the Phillips-Ouliaris cointegration test result for the model. The null hypothesis is that there is no cointegrating relationship in the FC model, and we cannot reject this null hypothesis. Figure 3(A) provides the residual of the FC model, which exhibits a stochastic trend and does not seem to be stationary. These results indicate that the FC model is not suitable for the data, which is consistent with what our initial expectations. As we mention in Section 2.1, the data of the user cost of housing is missing the time-varying risk premium and expected capital gains and, consequently, and the linear relationship between the rent–price ratio and the user cost of housing is not suitable for the data.

	est.	s.e
τ	2.345^{***}	0.501
α	0.931^{***}	0.185
Long-run variance of CCR errors		
σ^2	0.066	

Table 2: FIXED COEFFICIENT MODEL ESTIMATES. The estimation results of the fixed coefficient model are reported. Standard errors are reported after their corresponding estimates. The FC model is the TVC model when $p = q = 0$. *, ** and *** i indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Value	P-value
Phillips-Ouliaris τ-statistic	-0.638	0.951
Phillips-Ouliaris z-statistic	-2.189	0.923

Table 3: COINTEGRATION TEST FOR FIXED COEFFICIENT MODEL. The null hypothesis is that two series are not cointegrated.

Duca *et al.* (2021) points out that the risk premium for housing is inherently time-varying, and expected capital gains would depend on the economic situation and are inevitably time-varying. To account for this, we apply the TVC model in (7), which allows the coefficient of the user cost $\widetilde{\mathbf{c}}_t$ to vary over time. Based on BIC and cross-validation, $p = 2$ and $q = 3$ are selected for (8). Table 4 lists the estimation results of the TVC model.

	est	s.e
τ	-0.270^{***}	0.049
Time-varying parameter α		
α_0	-0.067^{***}	0.019
$\alpha_1: \frac{t}{T}$	-0.092^{***}	0.027
$\alpha_2: (\frac{t}{T})^2$	0.230^{***}	0.027
$\alpha_3: \cos(2\pi\frac{t}{T})$	-0.012^{***}	0.003
$\alpha_4: \sin(2\pi\frac{t}{T})$	0.007^{***}	6.148×0.1^4
$\alpha_5: \cos(4\pi\frac{t}{T})$	0.011^{***}	7.138×0.1^4
$\alpha_6: \sin(4\pi\frac{t}{T})$	0.006^{***}	3.239×0.1^4
$\alpha_7: \cos(6\pi\frac{t}{T})$	0.007^{***}	3.777×0.1^4
$\alpha_8: \sin(6\pi\frac{t}{T})$	0.008^{***}	4.260×0.1^4
Long-run variance of CCR errors		
σ^2	3.125×0.1^5	

Table 4: TIME-VARYING COEFFICIENT MODEL ESTIMATES. The estimation results of the time-varying coefficient model are reported. Standard errors are reported after their corresponding estimates. The cross-validation is used to select the orders p and q of the FFF approximation. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 3(B) provides the estimate of α_t, which decreased from 2009 to 2011 before continually increasing from 2012. The estimate of α_t used to be negative before 2020, but it turned to be positive from 2020 from which point it kept increasing more rapidly. Initially the estimate α_t is negative and decreases until the end of year 2011. After the subprime mortgage crisis, although the user cost decreased, people would not prefer buying a home. Consequently, with a negative expectation of capital gains and high risk premium, the demand for owning a house declined, which is reflected in the estimate of α_t. From early 2020, the estimate of α_t turns to be positive and rapidly increased. After the outbreak of COVID-19, liquidity in the financial market dramatically increased due to the financial and fiscal policies in the U.S. This might have led to high

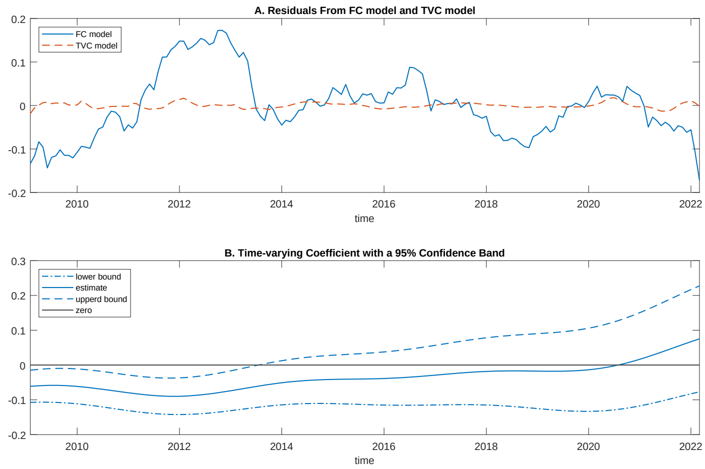

Figure 3: RESIDUALS FROM FC MODEL AND TVC MODEL AND TIME-VARYING COEFFICIENT ESTIMATE $\hat{\alpha}_t$. In the top panel, the blue solid line represents the residual from the fixed coefficient model, while the red dashed line represents the residual from the time-varying coefficient model. In the bottom panel, the solid line represents the estimate of the time-varying coefficient, while the dotted line represents the lower bound of 95% confidence interval, and the dashed line represents the upper bound of 95% confidence interval.

expected capital gains and low risk premium associated with housing and to a rapid increase of the estimate of α_t.

Table 5 provides several test results showing that the TVC model is suitable for the data. The first column in Table 5 provides the test result of the null hypothesis that the FC model is valid ($\lambda_1 = \lambda_2 = \cdots = \lambda_{p+2q} = 0$ in (8)) against the alternative hypothesis that the TVC model is suitable. We reject the null hypothesis, thus implying that the TVC is suitable for the data. The second column in Table 5 presents the test result of the null hypothesis that the TVC model is cointegrated against the alternative, which is spurious. We cannot reject the null hypothesis in this case, which means that the TVC is considered to be cointegrated. The third column shows the test result of the null hypothesis that the FC is cointegrated against the alternative, which is spurious. We reject the null hypothesis, which indicates that the FC is not suitable. Figure 3(A) shows the residuals of the TVC model, which are much smaller than those of the FC model. More importantly, the residuals of the TVC model look stationary.

Comparison		VAT: TVC		VAT: FC	
Test Stat.	5%CV	Test Stat.	5%CV	Test Stat.	5%CV
27063.46	15.51	5.34	9.49	10304.47	9.49

Table 5: TEST RESULTS OF COMPARISON AND COINTEGRATION. The test results of the model comparison between the FC model and the TVC model and cointegration tests are reported. Following Park and Hahn (1999), we add fourth-order polynomial trends to the models. The first column shows test of the null hypothesis that the FC model is valid against the alternative that the TVC model is suitable. The second column shows the test of the null hypothesis that the TVC model is cointegrated against the alternative that it is spurious. The third column shows the test of the null hypothesis that the FC is cointegrated against the alternative that it is spurious.

3.3. ESTIMATION RESULTS OF ECMS

By using the residual of the TVC model $\widehat{\varepsilon}_t$ in (7), we estimate three error correction models (the linear ECM, the ECM with the Markov regime switching, and the ECM with the endogenous regime switching) and examine which ECM model fits the data best. First, we estimate the linear ECM given as

$$\Delta y_t = \beta_0 + \beta_1 \widehat{\varepsilon}_{t-1} + \sum_{i=1}^{l} \beta_{i+1} \Delta y_{t-i} + \sum_{i=1}^{m} \gamma_i \Delta \widetilde{\mathbf{c}}_{t+1-i} + u_t,$$

where $u_t \sim \mathbb{N}(0, \sigma^2)$. The AIC and BIC selection criteria suggest the ECM model with lag order $l = 1$ and $m = 1$, which can be written as

$$\Delta y_t = \beta_0 + \beta_1 \widehat{\varepsilon}_{t-1} + \beta_2 \Delta y_{t-1} + \gamma \Delta \widetilde{\mathbf{c}}_t + u_t. \tag{12}$$

Table 6 shows the estimation results for the linear ECM model. The error correction coefficient β_1 shows the adjustment speed toward the long-run equilibrium, which is estimated to be -0.170 and is statistically significant at the 1% significance level. This supports the existence of an error correction mechanism. The autoregressive coefficient β_2 is estimated to be 0.891, and it is found to be statistically significant at the 1% level. This implies the existence of house price momentum, because we can consider β_2 as the autoregressive coefficient for house price changes. Since $\Delta y_t = \Delta r_t - \Delta p_t$, (12) can be written as

$$\Delta p_t = -\beta_0 - \beta_1 \widehat{\varepsilon}_{t-1} + \beta_2 \Delta p_{t-1} - \gamma \Delta \widetilde{\mathbf{c}}_t + \Delta r_t - \beta_2 \Delta r_{t-1} - u_t.^4 \tag{13}$$

This equation shows that β_2 represents the degree of house price momentum.

[4] In this equation, $(-\widehat{\varepsilon}_{t-1})$ can be considered as the disequilibrium error for the long-run model of house prices because $-\widehat{\varepsilon}_{t-1} = p_{t-1} - r_{t-1} + \widehat{\tau} + \widehat{\alpha}_t x_{t-1}$ from (7).

	est	s.e
β_0	-0.000^{**}	0.000
β_1	-0.170^{***}	0.032
β_2	0.891^{***}	0.027
γ	-0.015	0.011
σ	0.002^{***}	0.000
Log-likelihood	737.90	
AIC	-1465.8	
BIC	-1450.52	

Table 6: LINEAR ERROR CORRECTION MODEL ESTIMATES. The estimation results of linear error correction model are reported. Standard errors are reported after their corresponding estimates. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.3.1. Error correction models with regime switching

Based on the above linear ECM, the regime switching ECM can be written as

$$\Delta y_t = \beta_0 + \beta_1(s_t)\widehat{\varepsilon}_{t-1} + \beta_2(s_t)\Delta y_{t-1} + \gamma\Delta\widetilde{\mathbf{c}}_t + u_t, \tag{14}$$

where $u_t \sim \mathbb{N}(0, \sigma^2)$.[5] Table 7 reports the estimation results of the endogenous regime switching error correction model (ERS-ECM) and the Markov switching error correction model (MS-ECM). The ECMs with regime switching exhibit higher log-likelihood value and lower information criteria than the linear ECM, indicating that the ECMs with regime switching fit the data better than the linear ECM.

When we consider only the coefficients appearing in (14), the estimates of the ERS-ECM are quite similar to those of the MS-ECM. Therefore, in terms of the estimates of $\beta_1(s_t)$ and $\beta_2(s_t)$, we have qualitatively similar interpretations for both ERS-ECM and MS-ECM. The error correction coefficient $\beta_1(s_t)$ is negative in both low regime $(s_t = 0)$ and high regime $(s_t = 1)$, which supports the existence of an error correction mechanism. For the ERS-ECM, $\beta_1(s_t = 0)$ and $\beta_1(s_t = 1)$ are estimated to be -0.465 and -0.143, respectively, and they are both found to be statistically significant at the 1% significance level. These results imply that the low regime is associated with the fast disequilibrium adjustment

[5]Initially we let all the parameters, including β_0, γ, and σ be regime switching. However, the estimation result shows that there is no substantial difference between $\beta_0(s_t = 0)$ and $\beta_0(s_t = 1)$, which is similar for $\gamma(s_t)$ and $\sigma(s_t)$. Hence, we do not allow for regime switching for β_0, γ and σ.

	ERS-ECM		MS-ECM	
	est	s.e	est	s.e
β_0	0.000	0.000	0.000	0.000
β_1^w	-0.465^{***}	0.004	-0.450^{***}	0.003
β_1^s	-0.143^{***}	0.003	-0.134^{***}	0.003
β_2^w	0.339^{***}	0.002	0.369^{***}	0.010
β_2^s	1.014^{***}	0.003	1.013^{***}	0.002
γ	-0.009^{***}	0.003	-0.011^{***}	0.003
σ	0.002^{***}	0.000	0.002^{***}	0.000
η	0.990^{***}	0.002		
τ	-0.465^{***}	0.003		
ρ	-0.888^{***}	0.002		
$P\{s_t = 1 \mid s_t = 1\}$	Time-varying		0.946	
$P\{s_t = 0 \mid s_t = 0\}$	Time-varying		0.748	
Log-likelihood	755.99		751.353	
AIC	-1496		-1488.7	
BIC	-1471.5		-1467.3	
LR test	9.274^{***}			

Table 7: REGIME SWITCHING MODEL ESTIMATES. The estimation results of error correction models with regime switching are reported. The first two columns show the estimation results of endogenous regime-switching ECM, while the last two columns show the estimation results of Markov regime-switching ECM. The LR test is the likelihood ratio test for the existence of endogeneity. The null hypothesis is the there is no existence endogeneity, that is, $\rho = 0$. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

whereas the high regime is associated with the slow adjustment. The autoregressive coefficient $\beta_2(s_t)$ represents the degree of house price momentum in a similar manner as in (13). For the ERS-ECM, $\beta_2(s_t = 0)$ and $\beta_2(s_t = 1)$ are estimated to be 0.339 and 1.104, respectively, and they are both found to be statistically significant at the 1% significance level. In the low regime, house price changes are less persistent, which indicates weak house price momentum. Meanwhile, in the high regime, house price changes are very persistent, which implies strong house price momentum. Based on the estimates of $\beta_1(s_t)$ and $\beta_2(s_t)$, we may call the low regime the *weak momentum regime* and the high regime the *strong momentum regime*.

It is interesting to compare our estimates of $\beta_1(s_t = 0)$ and $\beta_1(s_t = 1)$ with the findings of Lai and Van Order (2017). They analyzed U.S. house prices across

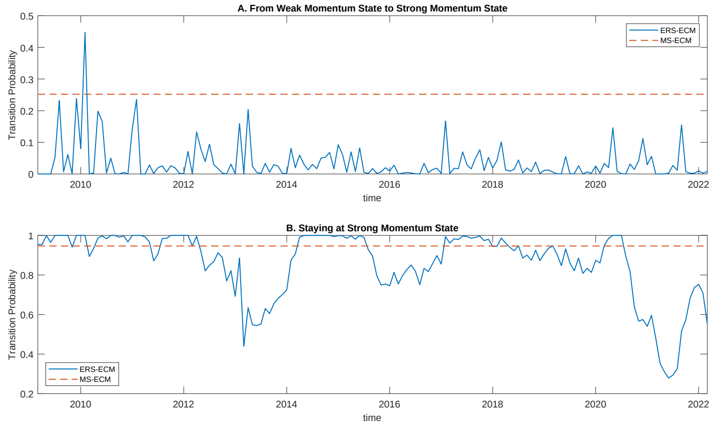

Figure 4: ESTIMATED TRANSITION PROBABILITY FROM THE MODEL. The top graph shows the transition probability from weak to strong momentum state: the blue solid line is from the endogenous regime switching model, while the black dashed line is from the conventional Markov switching model. Similarly, the bottom graph shows the transition probabilities of staying at strong momentum state.

45 MSAs-instead of national level house prices-from 1980 to 2012 by adopting panel models. They showed that the average value of momentum for non-bubble MSAs is 0.3495, which is consistent with our estimate of $\beta_1(s_t = 0)$. They also showed that the maximum value of momentum for bubble MSAs is 1.088, which corresponds to our estimate of $\beta_1(s_t = 1)$. Our result that the estimate of $\beta_1(s_t = 1)$ is even larger than unity may suggest that the strong momentum regime corresponds to housing bubble periods.

It should be noted that the ERS-ECM fits the data better than the MS-ECM. The ERS-ECM exhibits a higher log-likelihood value and lower information criteria than the counterparts of the MS-ECM. Moreover, the likelihood ratio (LR) test shows that the ERS-ECM is significantly better than the MS-ECM. We conduct the LR test for $H_0 : \rho = 0$ and $H_1 : \rho \neq 0$ in (11). In both (9) and (11), the correlation coefficient ρ measures the degree of endogeneity of regime changes.[6] The LR test rejects the null hypothesis of no endogeneity at the 1% significance level, which supports the endogenous regime switching model. The correlation coefficient ρ represents the correlation between the economic shock (u_t) in (14) and the disturbance (v_{t+1}) of the latent factor ω_t. The estimate of ρ is -0.888 and it is found to be statistically significant at the 1% level. This implies that a

[6]As shown in Chang *et al.* (2017), if $\rho = 0$ and $|\eta| < 1$, the endogenous regime switching model reduces to the conventional Markov switching model.

negative (or positive) economic shock (u_t) at time t increases (or decreases) the latent factor at time $t+1$ and enhances the likelihood of a regime to be defined as a strong (or weak) momentum regime.

Figure 4 plots the transition probabilities estimated by the ERS-ECM (solid line) and the MS-ECM (dashed line). The transition probability estimated by the ERS-ECM varies over time as the probability depends upon the previous state (s_{t-1}) as well as the realized value of the lagged dependent variable Δy_{t-1}. On the other hand, the transition probability estimated by the MS-ECM is constant over the entire sample period as the future transition between states is completely determined by the current state and fully independent of the realization of the underlying time series.

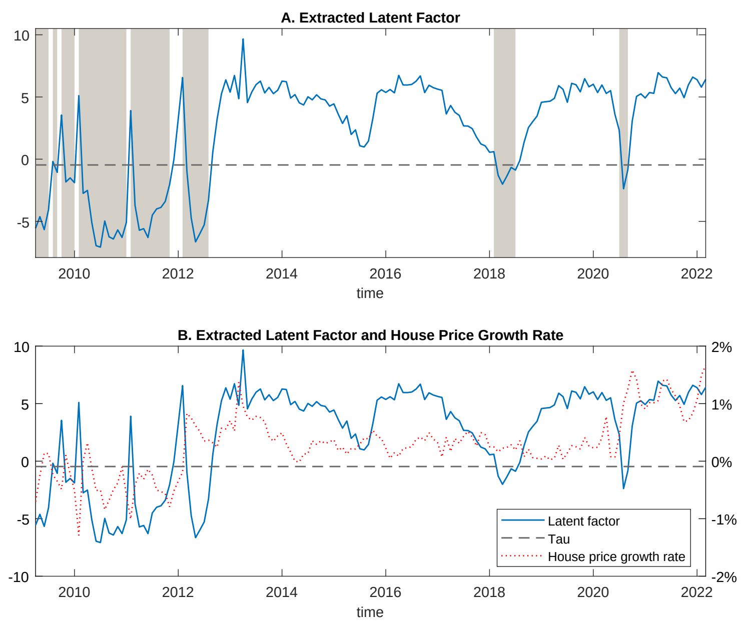

Figure 5: EXTRACTED LATENT FACTOR. The blue solid line presents the latent factor extracted from the error correction model with endogenous regime switching, while the dashed line presents the estimated threshold value. In the top panel, shaded areas indicate periods that belong to the weak momentum regime. In the bottom panel, the red dotted line presents the house price growth rate.

3.3.2. Extracted latent factor and revealed regimes in the ERS-ECM

In the endogenous regime switching model, two events-namely, $\{\omega_t < \tau\}$ and $\{\omega_t \geq \tau\}$- that are regarded as two regimes are switched by the realized value of the latent factor ω_t and the threshold level τ. The autoregressive coefficient η of the latent factor is estimated to be 0.990, indicating that the latent factor is very persistent. After estimating the model, we can extract the latent factor, which represents unobserved economic fundamentals determining weak or strong momentum regime. Figure 5(A) plots the extracted latent factor. If the value exceeds the estimated threshold level ($\widehat{\tau} = -0.466$), the period is identified as the strong momentum regime. Figure 5(B) shows that the house price growth rate is higher in strong momentum regimes. Based on the revealed regimes, Table 8 shows the features of the two regimes. It shows that 74% of the data remain in the strong momentum regime, while 26% of the data belong to the weak momentum regime. Moreover, the average house price growth and the average rent growth in the strong momentum regime are positive, whereas those in the weak momentum regime are negative. Figure 6 provides the inferred probability that we were in the weak momentum regime. It is relatively high until 2012, but it is in general low for the rest period.

	Weak momentum regime	Strong momentum regime
Percentage over the sample period	26%	74%
Degree of house price momentum	0.339	1.014
Speed of error correction	-0.465	-0.143
Average house price growth (Δp_t)	-0.060%	0.404%
Average rent growth (Δr_t)	-0.024%	0.074%

Table 8: REGIME FEATURES. The table reports the state-dependent regime features. The weak momentum state and strong momentum state exhibit different characteristics.

3.4. VARIABLE SELECTION FOR HOUSE PRICE MOMENTUM

The latent factor extracted from the ERS-ECM represents unobserved economic fundamentals determining weak or strong momentum regime in the housing market. We adopt the adaptive LASSO method proposed by Zou (2006) and select macroeconomic or financial variables that are related to the latent factor. We may consider the selected variables to be related to house price momentum. The adaptive LASSO method generalizes the LASSO method introduced by Tibshirani (1996). We use the adaptive LASSO for variable selection be-

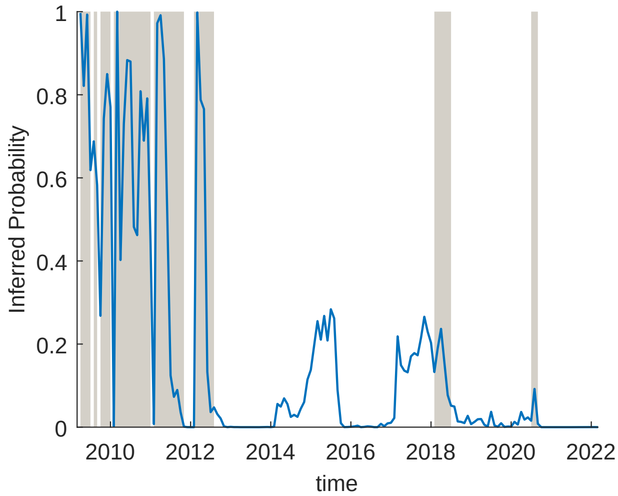

Figure 6: INFERRED PROBABILITY OF THE WEAK MOMENTUM REGIME. The blue line presents the inferred probability that we were in the weak momentum state, and the shaded areas present periods belongings to the weak momentum regime.

cause it satisfies the oracle properties; the failure to do so was a limitation of the original LASSO.

The estimator of the adaptive LASSO with weighted L_1 penalty is defined as

$$\widehat{\beta}_{L_1}(\lambda) = \operatorname{argmin}_{\beta}(Y - X\beta)'(Y - X\beta) + \lambda \sum_{i=1}^{N} w_i|\beta_i|,$$

where Y is the vector of the latent factor extracted from the ERS-ECM and X is the matrix including all explanatory variables. As explanator variables, we use a large body of macroeconomic and financial variables provided by the FRED-MD database. The dataset is updated in real time based on the Federal Reserve Bank of St. Louis database.[7] We use the vintage as of January 2023 and use only variables with all observations in the sample period (total 125 variables). N is the dimension of X, λ is a non-negative regularization parameter, and w_i is the adaptive weight. In our model, the weight is generated as $w_i = 1 \Big/ |\widehat{\beta}_{lasso,i} + N^{-1/2}|$, where $\widehat{\beta}_{lasso,i}$ is the estimate from the original LASSO. The tuning parameter λ is chosen using the cross-validation method.

[7] Available from https://research.stlouisfed.org/econ/mccracken/fred-databases/. All variables are transformed to be stationary by following the transformation code given in the FRED-MD. The detailed data construction and transformation information can be found in McCracken and Ng (2016).

Order	Name	Est.	Description	Tcode
1	PERMITMW	0.53	New Private Housing Permits, Midwest (SAAR)	$\log(x_t)$
2	HOUSTS	0.27	Housing Starts, South	$\log(x_t)$
3	TB6SMFFM	-0.18	6-Month Treasury C Minus FEDFUNDS	x_t
4	UEMP5TO14	0.14	Civilians Unemployed for 5-14 Weeks	$\Delta\log(x_t)$
5	EXJPUSx	0.11	Japan / U.S. Foreign Exchange Rate	$\Delta\log(x_t)$
6	AAAFFM	0.10	Moody's Aaa Corporate Bond Minus FEDFUNDS	x_t
7	S&P PE Ratio	0.02	S&P's Composite Common Stock: Price-Earnings Ratio	$\Delta\log(x_t)$
8	TOTRESNS	0.01	Total Reserves of Depository Institutions	$\Delta^2\log(x_t)$

Table 9: ADAPTIVE LASSO SELECTION WITH EXTRACTED LATENT FACTOR. The table presents the variables selected for the extracted latent factor by the adaptive LASSO with a penalty of $\lambda = 0.0619$, which was selected via cross-validation. The second column shows the estimates obtained from the adaptive LASSO. Tcode denotes the data transformation provided by the FRED-MD.

Table 9 shows that eight variables are selected by the adaptive LASSO method. We sort these variables by the magnitude of its estimates. The two variables with the largest coefficients are new private housing permits in the Midwest area (PERMITMW) and housing starts in the South area (HOUSTS), at 0.53 and 0.27, respectively. It is not surprising that these house demand-/supply-related variables are positively related to the house price momentum.[8]

Interestingly, Figure 7(A) shows that the new private housing permits and housing starts exhibit predictability for the latent factor. Moreover, six-month treasury bill minus federal fund rates (TB6SFFM) has a coefficient of -0.18. Figure 7(B) suggests that this short-term interest rate spread has a negative relationship with the latent factor, particularly due to the movement of two variables during 2018-2019. The FED maintained its zero interest rate policy from December 2008 through December 2015, for which the short-term interest rate spread was close to zero. The Fed increased the interest rate from January 2016 to February 2019. In particular, in 2018, the six-month treasury bill rate moved a bit faster and was higher than the federal fund rate, which made TB6SFFM positive. In August 2019, the FED started lowering the interest rate due to concerns about the economic outlook and the risk of a potential recession; due to the outbreak of the COVID-19 pandemic, it lowered the interest rate close to zero

[8]The Midwest area in the U.S is known as the Corn Belt states, and Sant'Anna and Katchova (2020) showed that land values in the Corn Belt states experienced larger changes over time than average U.S land value. Such volatile land values could be a reason why new private housing permits in the Midwest area is selected for house price momentum. Moreover, Glaeser (2020) found that some productive Sun Belt cities have significant amounts of new private housing starts. This could be related to the selection of housing starts in the South area.

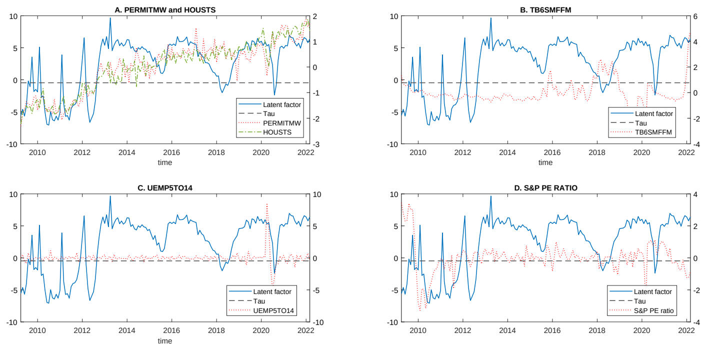

Figure 7: EXTRACTED LATENT FACTOR AND SELECTED VARIABLES USING ADAPTIVE LASSO. The blue solid line presents the latent factor extracted from the error correction model with endogenous regime switching, while the black horizontal dashed line presents the estimated threshold value. The red dotted line and green dash-dotted line represents the selected macroeconomic variables. The macroeconomic variables were first transformed into stationary series using the FRED-MD tcode and then standardized.

again in April 2020. The six-month treasury bill rate started decreasing in January 2019, which made TB6SFFM negative from April 2019 to March 2020. It seems that the movement of TB6SFFM for the period of 2018-2019 particularly contributed to the negative relationship between TB6SFFM and the latent factor.

The remaining fundamentals, including civilians unemployed for 5-14 weeks (UEM5TO14), Japan/US foreign exchange rate (EXJPUSx), Moody's Aaa corporate bond minus federal fund rates (AAAFFM), S&P composite common stock price-earnings ratios (S&P PE Ratio) and total reserves of depository institutions (TOTRESNS), all have smaller coefficients, indicating a weaker relationship with the latent factor. The change rate (log difference) in the number of unemployed people, i.e., civilians unemployed for 5-14 weeks (UEMP5TO14), is estimated to be positively related to the latent factor. Figure 7(C) shows the change rate of UEMP5TO14, which suggests that its large increase in April 2020 and its large decrease in July 2020 were the main contributors to the positive relationship between the change rate of UEMP5TO14 and the latent factor. The change rate (log difference) of the S&P price-earnings ratio (S&P PE Ratio) is estimated to be positively related to the latent factor. Figure 7(D) shows that the change rate of the price-earnings ratio seems to have predictability for the house price momentum.

4. CONCLUSION

In this paper, we investigate the long-run and short-run relationship between house prices, rents, and user costs of housing after the 2008 global financial crisis. As shown in Figure 1(A), the U.S. housing market experienced a rapid decline until the end of 2011 and a bounce back from 2012. It should be noted that the FED maintained the zero interest rate policy from December 2008 through December 2015. The FED lowered the interest rate close to zero again in April 2020 because of the outbreak of the COVID-19 pandemic and the enormous liquidity supply seems to be related to the more rapid increase of house prices in recent years.

The existing empirical models cannot properly explain the fluctuations in house prices after the global financial crisis. In the present work we have attempted to find an empirical model to fit the data better and adopt two distinct econometric models. First, we use the time-varying coefficient cointegration model to examine the long-run house price dynamics. Second, we combine the endogenous regime switching model in the error correction model. The estimation results show that our model fit the data better, and we find that house price changes can be classified into two regimes: a strong momentum regime and a weak momentum regime. Finally, we use the adaptive LASSO method to select the related macroeconomic variables that affect the house price momentum. We show that eight variables related to house demand/supply, monetary policy, and the stock market are related to house price momentum in the U.S housing market.

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