International Journal of Forecasting 30 (2014) 415–425

Contents lists available at ScienceDirect

International Journal of Forecasting

journal homepage: www.elsevier.com/locate/ijforecast

Forecasting the US housing market

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ARTICLE INFO

Keywords:
Real estate market
Price forecasting
Smooth transition models
Error correction models
Combining forecasts

ABSTRACT

The recent housing market boom and bust in the United States illustrates that real estate returns are characterized by short-term positive serial correlation and long-term mean reversion to fundamental values. We develop an econometric model that includes these two components, but with weights that vary dynamically through time depending on recent forecasting performances. The smooth transition weighting mechanism can assign more weight to positive serial correlation in boom times, and more weight to reversal to fundamental values during downturns. We estimate the model with US national house price index data. In-sample, the switching mechanism significantly improves the fit of the model. In an out-of-sample forecasting assessment the model performs better than competing benchmark models.

1. Introduction

The bursting of the housing bubble in the US has often been mentioned as the factor triggering the financial crisis in 2007 and 2008. By lending to individuals with poor credit scores, the so called sub-prime market, financial institutions and investors in mortgage-backed securities were effectively speculating on ever-increasing house prices (Gorton, 2009).[1] The housing market may be more vulnerable than other markets to such inefficiencies and occasional crashes due to a lack of effective short selling mechanisms that prevent bearish investors from participating (Hong & Stein, 2003). Clearly, having an econometric model that can help to predict house price returns is of great importance.

The contribution of this paper is that we develop a smooth transition model for housing markets and estimate the model with data from the US national house price index (the Case–Shiller Index). Similar to a standard vector error correction model (VECM) model, the smooth transition model assumes that housing prices revert back to a fundamental value estimate in the long term. The fundamental value estimate is based on rental income. Further, the model has an autoregressive component for capturing the short-term positive serial correlation in real estate prices. The innovative part of the model is that we allow the weights assigned to the fundamental mean reversion and the autoregressive model part to vary dynamically, depending on the recent forecasting performance. This allows the model to give a higher weight to positive return autocorrelation during housing market booms, and to switch back to fundamental value based forecasts during the eventual bust.

We analyze both the in-sample and out-of-sample performances of the model for the US housing market over the period 1960–2012. In-sample, the smooth transition model has a significantly better fit than a static model with constant weights for the fundamental mean reversion and autoregressive model parts. Out-of-sample, we find that the smooth transition model has lower forecast errors than either a vector error correction model (VECM) or an ARIMA model. Additional tests show that the forecasts generated by the smooth transition model are more efficient and

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[1] Alternatively, it could have been based on expected increases in future labor income. For lenders in the sub-prime market, however, this is unlikely.

0169-2070/$ – see front matter
http://dx.doi.org/10.1016/j.ijforecast.2013.12.010

contain more information than several benchmark models. Our findings illustrate that the model can be a useful forecasting tool for both housing market participants and policy makers. In addition to its relevance for understanding and predicting house price index returns, the model may also be of value for pricing futures written on the Case Shiller Index.[2]

Our work is related to several other empirical papers on house price dynamics. Case and Shiller (1989, 1990) provide evidence that the prices of single-family homes do not follow a random walk: year-to-year price changes are positively correlated, while the correlation is negative at higher lags. Case and Shiller (1990) also show that future house price changes can be predicted using rents and other lagged fundamental variables. This confirms the general mean reversion pattern of asset returns found by Cutler, Poterba, and Summers (1991) for stocks, bonds, exchange rates, and precious metals. Rapach and Strauss (2009) focus on the forecastability of house prices across US states, and find that autoregressive models perform relatively well for interior states but less so for coastal states. They interpret this as evidence of a disconnect between prices and fundamentals.

Capozza and Israelsen (2007) develop and estimate a model for the real estate market that captures both the short-term serial correlation and the long-term mean reversion property of housing markets. For a panel of real estate investment trusts (REIT), they estimate how the coefficients of serial correlation and mean reversion depend on REIT properties such as the size and leverage.[3] Our contribution is that we introduce the smooth transition dynamic weighting mechanism and show, both in-sample and out-of-sample, that this feature substantially improves the model's fit and its forecasting ability for the US housing market.

Our paper is also related to the recent literature on bubbles in real estate markets. Coleman, LaCour-Little, and Vandell (2008), Himmelberg, Mayer, and Sinai (2005), Mikhed and Zemčík (2009) and Nneji, Brooks, and Ward (2013a) test whether prices respond to changes in fundamentals and macroeconomic conditions. Nneji, Brooks, and Ward (2013b) and Roche (2001) estimate regime-switching models for the housing market using a bubble state and a crash state. Regime-switching can generate time-variation in the serial correlation and reversion to fundamental value, similar to our model. Nneji et al. (2013b) show that a regime switching model fits the US housing data used in this paper well. One main difference is that our model is not intended to test for bubbles in house prices, but rather to improve out-of-sample forecasts. Furthermore, the transitions between the two components in our model are smooth instead of discrete.

Our paper is also related to and inspired by the literature on heterogeneous agent models (Frankel & Froot, 1991). In recent years, Dieci and Westerhoff (2012), Malpezzi and Wachter (2005) and Sommervoll, Borgersen, and Wennemo (2010) have developed specialized heterogeneous agent models for the housing market. In these models, boundedly rational agents apply different rules for forming expectations about future housing returns. Typically, these rules are 'fundamentalist' and 'chartist', based on mean reversion and past price trends, respectively. Agents can switch between these rules depending on recent forecasting performances, similar to our smooth transition mechanism. However, these heterogeneous agent models have not been calibrated or estimated with housing market data, or used for out of sample forecasting.

2. A smooth transition model for the housing market

In this section we define our econometric model for explaining and predicting the price dynamics of the housing market. Our model exploits two well-known properties of real estate returns: short-term positive autocorrelation and long-term mean-reversion (see Capozza & Israelsen, 2007; and Case & Shiller, 1989, 1990). We assume that the log real house price P_t has a long-term equilibrium relationship with an estimate of the fundamental house value $F_t : P_t = \delta_0 + \delta_1 F_t$, where F_t is based on rental income. We can then explain short-term changes in the house price ($R_{t+1} = P_{t+1} - P_t$) using a standard vector error correction model (VECM):

$$R_{t+1} = c + \alpha(P_t - \delta_0 - \delta_1 F_t) + \sum_{l=1}^{L} \beta_l R_{t-l+1} + \varepsilon_{t+1}, \quad (1)$$

where P_t is the log of the real house price, the return R_{t+1} is defined as the log-price difference $P_{t+1} - P_t$, F_t is the log of the real fundamental value, $\alpha < 0$ is the mean reversion coefficient, and β_l are autoregressive coefficients (for $l = 1, 2, \ldots, L$). In Section 3, we describe in detail how we derive an estimate of the fundamental value based on rents, while in Section 4 we test for cointegration between P_t and F_t.

Inspired by empirical house price behaviors and the heterogeneous agent model literature (see Brock & Hommes, 1997, 1998), we now make several changes to the standard VECM model. Historically, housing markets appear to be prone to prolonged boom periods in which the prices of housing units rise far above fundamental value estimates based on rents, income, or other indicators. In these boom periods, markets appear to be driven mainly by price speculation based on the simple extrapolation rule that "house prices always go up". However, boom periods are inevitably followed by painful corrections, during which real house prices are pulled back down towards the fundamental value.

The boom-bust character of housing markets suggests that the weight of the autoregressive component in the VECM model, as well as the weight of the error correction component, may actually vary through time. A positive

[2] The standard no-arbitrage relationship to price futures does not hold in this case because the underlying house price index cannot be traded easily in the spot market, as it would involve buying and selling housing units in several regions of the US. Expectations of future house price returns therefore become paramount in valuing these futures.

[3] The effect on the model coefficients depends on the difference between a REIT's properties and the overall sample average. Capozza and Israelsen (2007) find that the serial correlation is stronger for larger, more focused and more levered REITs, while mean reversion is faster for more levered and more focused REITs.

return autocorrelation may predict house prices better than normal in boom periods, while the reversion to fundamental value estimates (error correction) matters more during housing market busts. We therefore propose the following smooth transition model:

$$R_{t+1} = c + W_t(Z_t)\alpha(P_t - F_t) + (1 - W_t(Z_t))\beta \times \sum_{l=1}^{L} R_{t-l+1} + \varepsilon_{t+1}, \tag{2}$$

$$W_t(Z_t) = (1 + \exp(\gamma Z_t))^{-1}, \tag{3}$$

where $W_t(Z_t) \in [0, 1]$ is the weight assigned to the error correction component at time t, and $(1 - W_t(Z_t))$ is the weight of the autoregressive term. Eq. (3) is a logistic function that determines the weight $W_t(Z_t)$, conditional on the value of transition variable Z_t. Furthermore, to simplify the dynamic model, we have imposed the following parameter restrictions on the original VECM equation: $\delta_0 = 0$, $\delta_1 = 1$ and $\beta_l = \beta$ for all $l = 1, 2, \ldots, L$.

For the transition variable Z_t, we assume that it is a function of the relative forecasting errors of the fundamental error-correction model component, $\alpha(P_t - F_t)$, versus the autoregressive component, $\beta \sum_{l=1}^{L} R_{t-l+1}$, measured over the previous K periods. This choice is motivated by the literature on heterogeneous agent models (Brock & Hommes, 1997, 1998), where agents in the market switch between different return forecasting models depending on their recent performances:[4]

$$Z_t = \frac{(z_t^f - z_t^a)}{(z_t^f + z_t^a)} \tag{4}$$

$$z_t^f = \sum_{k=1}^{K} |\alpha(P_{t-k} - F_{t-k}) - R_{t-k+1}|, \tag{5}$$

$$z_t^a = \sum_{k=1}^{K} \left| \beta \left(\sum_{l=1}^{L} R_{t-k-l+1} \right) - R_{t-k+1} \right|, \tag{6}$$

where z_t^f and z_t^a are the historical forecast errors of the fundamental mean-reversion part of the model and the autoregressive model component at time t, respectively.

In sum, the equations for the smooth transition model are given in Eqs. (2)–(6). The parameter γ in Eq. (3) controls the sensitivity of the weight $W_t(Z_t)$ to the forecasting performance of the error correction model part during the last K periods, compared to the performance of the autoregressive part. In the heterogeneous agent literature, γ is called the intensity of choice. A positive value of γ implies that weight shifts to the better performing model part. With $\gamma = 0$, the weight is constant at exactly 50% and the model reduces to the standard VECM in Eq. (1), with additional coefficient restrictions $\delta_0 = 0$, $\delta_1 = 1$ and $\beta_l = \beta$ for all $l = 1, 2, \ldots, L$.

The model given by Eqs. (2)–(6) can be combined into a single (non-linear) equation and estimated directly using quasi-maximum likelihood estimation, as it is a non-linear polynomial of R_t, with the fundamental price F_t given as an exogenous variable. The switching mechanism is similar to that in the class of smooth transition autoregressive (STAR) models; see Teräsvirta (1994) and Van Dijk, Teräsvirta, and Franses (2002). Given the non-linear structure of the switching function, the significance of γ cannot be tested using a standard t-test. Instead, we apply a likelihood ratio test. We first estimate the model with constant weights; that is, with $\gamma = 0$ and $W_t = 1/2$. We then estimate the unrestricted model in order to determine the added value of smooth transition weights.

Both the number of autoregressive lags, L, and the number of past forecast errors used for the transition variable, K, are optimized. Specifically, we estimate the model for all 144 combinations of K and L, with K and L being integers between one and twelve, and select the model with the lowest Akaike information criterion (AIC).

The smooth-transition model is also inspired by the literature on heterogeneous agent models, such as the studies by Dieci and Westerhoff (2012) and Frankel and Froot (1991). In these models, market participants apply two return forecasting rules, called fundamentalist and chartist. The fundamentalist rule forecasts mean reversion towards the fundamental value, while the chartist rule is a positive linear function of past returns. Market participants switch between the two rules based on historical forecasting performances in the last K periods. The weights W_t and $(1 - W_t)$ in Eq. (2) can then be interpreted as the percentages of market participants which are following the fundamentalist and chartist forecasting rules, respectively. Finally, the weight W_t can also be thought of as a synchronization device to assist rational arbitrageurs in timing their exit from riding the bubble (chartist strategy), as in the model of Abreu and Brunnermeier (2003).

3. Data and fundamental value estimate

We will estimate the model using quarterly data on prices and rents for the aggregate stock of owner-occupied housing in the United States, as developed by Davis, Lehnert, and Martin (2008) and made available by the Lincoln Institute of Land Policy.[5] The data cover the period 1960Q1 until 2012Q3, a total of 211 quarterly observations. The underlying source for the house price changes is the repeat-sales house price index published by Freddie Mac (CMHPI) until 2000, and the S&P/Case–Shiller US National Home Price Index after 2000. The price data used to construct the house price and rent indices are published with a delay of two months in the relevant out-of-sample prediction period after 2000. Hence, the timing in the model coincides, not with calendar time, but with the time

[4] We have also estimated a model with an alternative transition variable, namely the absolute difference between the price and the fundamental value: $|P_t - F_t|$. We find no significant difference in model fit compared to using relative forecast performance as the transition variable; results are available on request.

[5] The data are located at "Land and Property Values in the US", Lincoln Institute of Land Policy, see http://www.lincolninst.edu/resources/.

of the release of the latest S&P/Case–Shiller US National Home Price Index value.[6]

Our model requires a fundamental value estimate F_t. The estimate does not necessarily have to be equal to the true fundamental value, which is inherently unknown. From an empirical perspective, what matters is that the fundamental value can be calculated using information available at time t, and that the house price index and the fundamental value estimate are cointegrated, with prices correcting back to the fundamental value. We derive our fundamental value estimate from a standard real estate market model by Hott and Monnin (2008) that assumes a no-arbitrage relationship between renting and buying.[7] In this model, the fundamental house price is equal to the present value of all expected future rent payments. Suppose that rents increase at a fixed rate g per period and that the discount rate r is constant; then, the fundamental value is given by

$$F_t = \frac{1+g}{r-g} H_t, \tag{7}$$

where H_t is the rent in period t, and r is the discount rate.

Within the no-arbitrage framework of Hott and Monnin (2008), the discount rate of rents r is equal to the unconditional expected return to housing. The expected return to housing consists of the expected return due to capital gains after depreciation, plus the expected rent yield ($E(H/P)$). Equilibrium implies that the long-run rate of capital gains is equal to the growth rate of rents g. This implies $r = g + E(H/P)$, and our final expression for the fundamental house price reduces to

$$F_t = \frac{1+g}{E(H/P)} H_t, \tag{8}$$

in which $E(H/P)$ is the unconditional expected rent yield. The fundamental house price in Eq. (8) is similar to the estimates used by Nneji et al. (2013b) and Roche (2001) based on the average price-rent ratio. See also Fama and French (2002) for a similar derivation of the fundamental price in an equity market setting.

Davis et al. (2008) construct quarterly rent data for owner occupied housing, which we will use for the calculation of our fundamental price. We estimate g and $E(H/P)$ quarterly as rolling averages of the available historical observations[8] on the yearly growth of rents (H_t/H_{t-4}) and the rental yield (H_t/P_t). Fig. 1 presents our fundamental value estimate, and the actual price for comparison.

Fig. 1 shows that the actual house price tends to fluctuate around the fundamental value estimate. Clearly recognizable is the recent steep run-up and crash in US house prices.[9] The real house price index reached a maximum in the first quarter of 2006, when it was 48% higher than the fundamental value estimate, and the prolonged period of overvaluation ended in the first quarter of 2009, as the price eventually dropped below the fundamental value.

Table 1 presents the descriptive statistics of the data in Panel A and a test for cointegration between the house price and the fundamental value estimate in Panel B. On average, the US national house price index is above its fundamental value ($t = 9.51$), due mainly to the latter part of the sample (1985–2009). Quarterly changes in the house price index display a high level of positive autocorrelation at lags of 1–4 quarters and a significantly negative autocorrelation at lags of 3–5 years, confirming the general autocorrelation pattern found by Cutler et al. (1991) and the pattern for real estate markets found by Case and Shiller (1990). Price changes are twice as volatile as fundamental value changes, confirming the excess volatility puzzle of Shiller (1981) for the housing market.

The correlation between actual price changes and fundamental value changes is 0.308 ($t = 4.66$). The Engle–Granger test in Panel B of Table 1 indicates that house prices and fundamental values are cointegrated (p-value $= 0.014$ for the house return equation).[10] The coefficient estimate of the cointegrating relationship equals $\hat{\delta}_1 = 0.948$, with a standard error of 0.111. Hence, we cannot reject $\delta_1 = 1$, implying that the house price index and the fundamental value estimate tend to move one-on-one in the long term equilibrium relationship.

4. Results

The first column in Table 2 shows the full sample estimation results for the model with constant weights ($\gamma = 0$). The coefficients α and β are significant and have the expected signs: $\alpha < 0$ and $\beta > 0$. The estimate of α is negative, indicating that house prices tend to revert to the fundamental value. However, the speed of reversion to the fundamental value is $2.8/2 = 1.4\%$ per quarter on average, so the reversal is rather slow.[11] The estimate of β is positive, confirming that house price returns are positively correlated. The effect size is that $170/2 = 85\%$ of the last quarter's price change is expected to continue in the next quarter. The optimal number of lags for the autoregressive model component is $L = 1$.

The second column shows the results for the model with dynamic weights for the fundamental mean-reversion and autoregressive model parts. The optimal number of lags for the transition variable Z_t is $K = 6$ and $L = 1$ for the autoregressive lags. The estimate of γ is positive and

6 The S&P/Case–Shiller US National Home Price Index is published quarterly with a two-month lag. New levels are released at 9 am Eastern Standard Time on the last Tuesday of the 2nd month after the end of the quarter. The underlying data for rents are based on 'the rent of primary residence' series, published monthly by the Bureau of Labor Statistics (BLS), which is published within three weeks from the end of the month.

7 As a result, the fundamental value is not conditional on any exogenous information, such as income, apart from rent and price data.

8 Experiments with rolling windows yield very similar results.

9 Clearly, the run-up of the bubble is substantially slower than the crash. This is a common finding for bubbles, and can also be explained by heterogeneous agent models; see e.g. De Grauwe and Grimaldi (2006).

10 The existence of this equilibrium relationship is not driven by the bursting of the housing bubble in the last few years of the sample: we also find a significant cointegration relationship if we repeat the cointegration test in the period 1960–2000.

11 We divide the coefficient by two because of the (constant) weight W of 0.5.

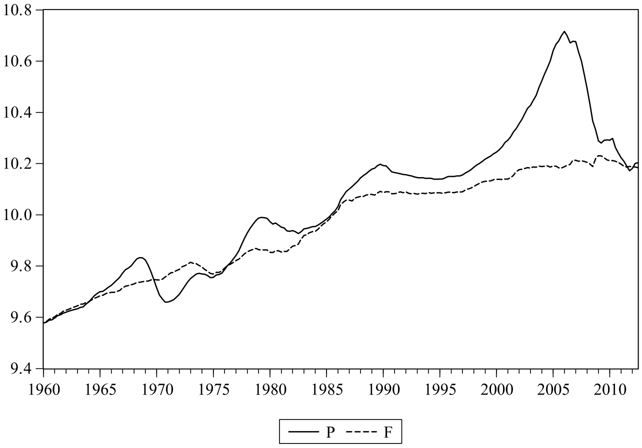

Fig. 1. US house price index and fundamental value estimates. *Notes*: Fig. 1 displays the log-real US house price index P and the log-real fundamental value estimate F based on rents. The data cover the period 1960Q1–2012Q3, a total of 211 quarterly observations. The house price index is the repeat-sales index published by Freddie Mac (CMHPI) until 2000, and the S&P/Case–Shiller US National Home Price Index after 2000.

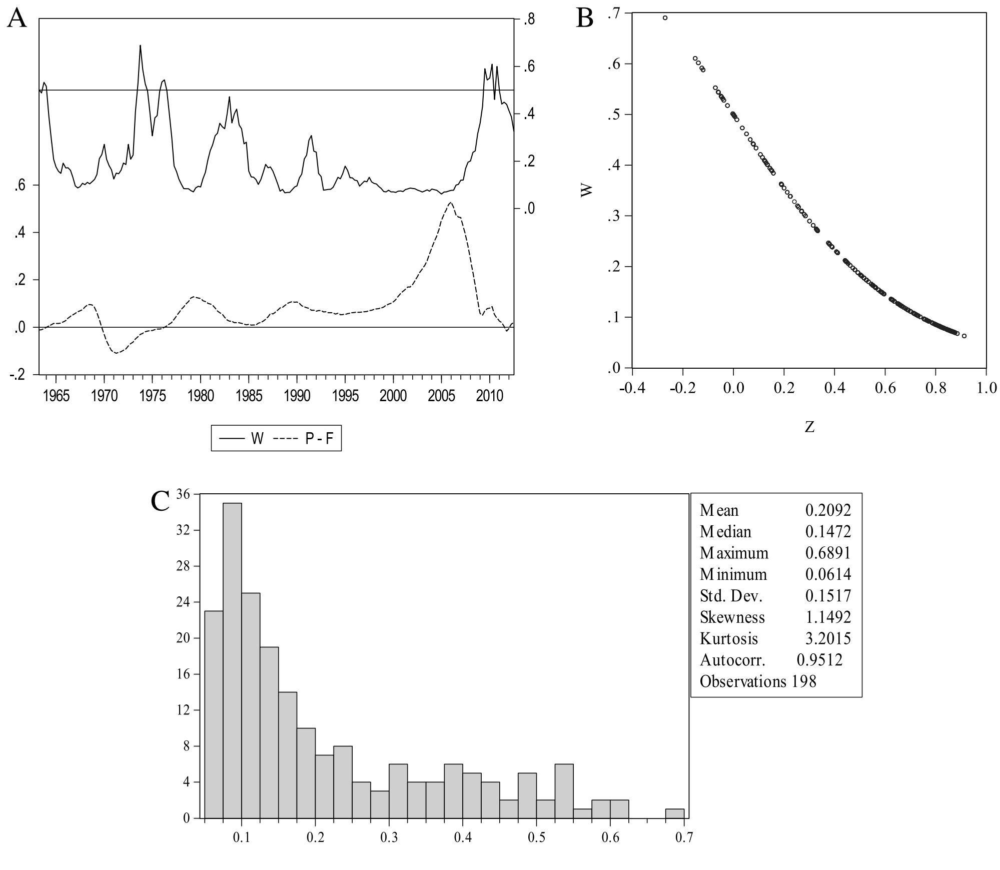

Fig. 2. Weight of the fundamental mean reversion model component. *Notes*: Fig. 2 displays the evolution and characteristics of W_t, the weight assigned to the fundamental mean-reversion model part of the smooth transition model. Panel A shows a time series plot of the weight W_t, with the scale on the right (the straight line denotes the value $W_t = 0.5$). Further, Panel A also shows a time series plot of the difference between the real house price and the fundamental value, $P_t - F_t$, with the scale on the left side (the straight line denotes 0). Panel B shows a scatter plot of the weight W_t versus the transition variable Z_t, where Z_t is the relative forecast error of the fundamental model part relative to the autoregressive model part over the last 6 quarters ($K = 6$). Panel C shows the histogram and descriptive statistics of the weight W_t.

Table 1
Descriptive statistics.

Panel A: Descriptive statistics of the house price index and the fundamental value.

	P	ΔP	F	ΔF	P–F
Mean	10.042	0.003	9.962	0.003	0.082
Median	10.060	0.006	10.045	0.003	0.061
Maximum	10.716	0.041	10.231	0.030	0.528
Minimum	9.578	−0.064	9.582	−0.010	−0.110
Std. dev.	0.287	0.016	0.195	0.006	0.125
Skewness	0.347	−1.652	−0.281	0.645	1.831
Kurtosis	2.438	7.241	1.641	5.538	6.482
Auto-corr. $Q(-1)$	0.999	0.848	1.000	0.445	0.993
Auto-corr. $Q(-4)$	0.980	0.515	0.997	0.188	0.908
Auto-corr. $Q(-8)$	0.935	0.138	0.991	0.011	0.705
Auto-corr. $Q(-12)$	0.882	−0.076	0.985	−0.034	0.472
Auto-corr. $Q(-16)$	0.828	−0.179	0.980	0.036	0.266
Auto-corr. $Q(-20)$	0.786	−0.225	0.973	0.138	0.133
Observations	211	210	210	209	210

Panel B: Cointegration test for the house price index and the fundamental value.

		P	F
Stationarity tests (ADF)			
	ADF for level	−1.458	−2.090
	p-value	(0.553)	(0.249)
	ADF for first difference	−3.878	−5.480
	p-value	(0.003)	(0.000)
Cointegration test (Engle–Granger)			
	z-statistic	−35.443	−37.498
	p-value	(0.014)	(0.001)
Cointegrating coefficient		−0.948	
	p-value	(0.000)	

Notes: Panel A presents descriptive statistics of the US log real house price index P, the change in price ΔP, the log real fundamental value F based on rents, the change in fundamental value ΔF, and the deviation between the log-real price level and the fundamental value (P–F). Rows denoted 'Auto-corr. $Q(-k)$' display the autocorrelation of the series at quarterly lag k. Panel B displays the augmented Dickey–Fuller (ADF) stationarity test for P and F, as well as the Engle–Granger cointegration test. For both tests, we select the optimal number of lags using the AIC (8 lags for the stationarity tests, 1 lag for the cointegration test). The numbers in parentheses are p-values.

significant (p-value <0.01), implying that the weight W_t assigned to the fundamental model part increases when it has relatively low forecast errors (and vice-versa). That is, if the fundamental model part had a more accurate return forecast than the autoregressive model part during periods $t-1$ to $t-6$, it will receive a higher weight W_t at time t. The added value of the smooth transition mechanism is confirmed by the significant increase in the log-likelihood and the decrease in AIC.[12] The coefficient estimates of α and β in the second column remain significant and of the expected sign. The estimate values change somewhat compared to the static model in the first column, due to the low average value of W_t (equal to 0.21 on average) in the transition model with weights.

The last two columns of Table 1 show estimation results for the pre-1995 period. Excluding the recent house price bubble does result in different model coefficient estimates, but all of the signs of the coefficients are still as expected, and the smooth transition mechanism continues to add significant value based on the likelihood ratio test.

Fig. 2 displays several characteristics of the weight W_t assigned to the fundamental mean-reversion component of the model. Panel A of Fig. 2 shows a time series plot of W_t, together with the distance between the actual price and the fundamental price ($P_t - F_t$), for comparison. During the first part of the sample, until 1992, W_t oscillates: several peaks are visible, which are periods during which the fundamental model part receives a higher weight. A break in this regular pattern occurs in the second part of the sample: in the period 1993–2007, the fundamental weight W_t stays relatively low, around 10%, while the autoregressive model part dominates with a weight $(1-W_t)$ of roughly 90%. Eventually, the house price level shoots far above the fundamental value in the period 2000–2006. Soon after the difference between the house price index and the fundamental value estimate reaches its peak in 2006, the fundamental weight W_t shoots back up to almost 60%, while the price level reverts back to its fundamental value. In the last two years, 2011–2012, we observe a decline in W_t.

Panel B of Fig. 2 presents a scatter plot of the fundamental weight W_t versus the transition variable Z_t, where Z_t is the relative forecast error of the fundamental mean-reversion model part compared to the autoregressive model part. Due to the positive value of γ, the line slopes downwards: more accurate forecasts by the fundamental model part result in a higher value of W_t, and vice versa. For example, if the autoregressive model part had

[12] Apart from γ, the dynamic model has one more parameter than the static model: the lag length K. If we increase the degrees of freedom for the chi-square test in Table 2 from one to two to adjust for this, the p-value is 0.00001, still indicating a significantly better fit for the dynamic model. Similarly, the AIC value of the dynamic model still indicates a better fit than the static model after adjusting for this.

forecast errors which were 20% lower than the fundamental model part over the previous six quarters ($K = 6$), this would result in a weight W_t of roughly 0.3.

Finally, Panel C of Fig. 2 shows a histogram and descriptive statistics of W_t. On average, the fundamental mean-reversion component receives a weight of 0.21 in the estimated model, while the autoregressive component has an average weight of 0.79. The autocorrelation of W_t is 0.95, indicating that the weight is fairly stable through time. One factor that may partially explain the low average weight W_t is that our fundamental model in Eq. (8) assumes that rent growth rates are deterministic, and will underestimate prices if the uncertainty about future average rent growth g is high.[13] However, we believe that this uncertainty effect is unlikely to explain the observed gap between prices and fundamental values in the housing market fully, as rent growth has been smooth historically.[14]

4.1. Out-of-sample forecasting

As a final test of the validity of our model for the housing market, we study its forecasting power. We contrast the forecasting accuracy of our smooth transition model with those of five alternative models: VECM, ARIMA, the fundamental mean-reversion model component alone, a static model with equal weights for both components, and a random walk model.

All of the models are initially estimated on the in-sample period 1962Q1–1990Q4, and evaluated on the out-of-sample period 1991Q1–2012Q3.[15] In the in-sample period we select lag parameters, such as K and L, based on the Akaike information criterion (AIC). These parameters are held constant in the out-of-sample period, so there is no look-ahead bias. For the smooth transition model, we use $L = 1$ and $K = 2$; the static model uses $L = 1$. The VECM has one lag, as indicated by the AIC in the in-sample period. The best fitting ARIMA model is ARIMA(1, 0, 0), and is therefore equivalent to the autoregressive component of the smooth transition model. The VECM has five coefficients, the smooth transition model (STM) with $L = 1$ has four coefficients, the ARIMA(1, 0, 0) model has two coefficients, and the random walk has only one.[16] The STM and VECM may have an information advantage over the ARIMA model, not only because of the higher number of coefficients, but also because the fundamental value estimate is taken into account.

Forecasts are created using an expanding estimation window. Each model is first estimated on the sample 1962Q1–1990Q4, after which prices are forecasted from one to four quarters ahead. The model coefficients are then re-estimated on the expanded sample 1962Q1–1991Q1, and a new set of forecasts is generated. This process is repeated, resulting in 83 out-of-sample forecasts. We assess the relative forecasting performance using the ratio of the average forecasting error of the STM to the average forecasting error of the alternative models. A ratio below one implies a better performance for the STM. The forecast error is measured using the mean squared error and mean absolute error. Table 3 presents the forecast performance ratios for horizons of $k = 1, 2, 3$ and 4 quarters. The corresponding Diebold and Mariano (1995) t-statistics are reported below the ratios in parentheses, using a rectangular lag window with $k - 1$ sample autocovariances for the k-step-ahead forecast error.

The results in the first column of Table 3 show that the root mean square error (RMSE) of the smooth transition model (STM) forecasts ranges between 1.1% and 4.7%, and increases with the forecast horizon. Relatively, the STM forecasts are the most accurate among the five models considered: all mean square error (MSE) performance ratios are below one. The performance ratios based on the mean absolute error (MAE) are also below one, except for the ARIMA and STATIC forecasts at a horizon of two quarters ($k = 2$), and the three-period-ahead ARIMA forecast ($k = 3$). The advantage of the smooth transition model versus the benchmark models typically increases at longer forecast horizons. The difference in forecasting performance at each horizon separately is significant compared to the fundamental mean reversion model (FUN) and the random walk model (RW), but insignificant compared to the other models.

We also consider the performances of the models over the four forecast horizons jointly, following an approach similar to that of Banerjee, Marcellino, and Masten (2005). We first calculate the average MSE over all four forecast horizons combined ($k = 1, 2, 3, 4$), for each model separately. We then test for differences in the MSEs of the smooth transition model and the benchmark models, using two-sample t-tests. The p-values of these tests are reported in Table 3, in the row labeled "Joint". We find that the STM significantly outperforms all of the models except ARIMA.

Altogether, we find that models which take advantage of the autocorrelation structure in the returns perform relatively well out-of-sample. The fundamental mean-reversion model part produces the poorest forecasts. The static combination model performs much better than the fundamental model, and does better than the autoregressive model part at the shorter horizons. To shed more light on the issue of which model provides the best predictions, Table 4 shows the results of the bias-efficiency test and the encompassing test, based on estimation results for different versions of the following test equation:

$$\Delta_k P_t = \alpha + \beta_1 E_{t-k}^{\mathrm{STM}}(\Delta_k P_t) + \beta_2 E_{t-k}^{\mathrm{ARMA}}(\Delta_k P_t) + \beta_3 E_{t-k}^{\mathrm{VECM}}(\Delta_k P_t) + \beta_4 E_{t-k}^{\mathrm{STATIC}}(\Delta_k P_t) + \varepsilon_t, \quad (9)$$

where $\Delta_k P_t = P_t - P_{t-k}$. The model with the most informative forecasts will have a significant β coefficient:

[13] Using a similar valuation model, Pástor and Veronesi (2006) show that NASDAQ stock valuations increase substantially if the high level of uncertainty about average future profitability is taken into account. If the uncertainty about future rent growth is high in the housing market as well, and is taken into account, the gap between fundamental and actual prices would drop, reducing the fundamental forecast errors and increasing W_t. We would like to thank an anonymous reviewer for pointing this out.

[14] In our data, the standard deviation of annual rent growth is only 0.6%.

[15] The results are qualitatively insensitive to the exact choice of in-sample period.

[16] Excluding the unknown standard deviation of the error term.

Table 2
Model estimation results.

	1963–2012		1963–1994	
	Static model equal weights	Dynamic model smooth transition	Static model equal weights	Dynamic model smooth transition
c	0.0017*	0.0018**	0.0014**	0.0014**
	(0.0009)	(0.0008)	(0.0006)	(0.0005)
α	−0.0281***	−0.1692***	−0.0526***	−0.0694***
	(0.0061)	(0.0254)	(0.0168)	(0.0196)
β	1.6996***	0.9862***	1.7337***	1.2847***
	(0.0553)	(0.0354)	(0.0747)	(0.0992)
γ	–	2.9768***	–	1.3586***
		(0.2575)		(0.4347)
L lags	1	1	1	1
K lags	–	6	–	2
LL	669.83	681.33	494.96	499.54
$2\Delta LL$	–	23.00***	–	9.16***
AIC	−6.726	−6.832	−7.7317	−7.788
# Obs	198	198	127	127

Notes: The table presents in-sample estimation results of the smooth transition model, specified by Eqs. (2)–(6). Standard errors are reported in parentheses below the estimates. K and L denote the lag parameters of the model (selected based on the AIC). LL is the log-likelihood of the model and AIC denotes the Akaike information criterion. $2\Delta LL$ denotes the difference in two times the log-likelihood compared to the static model with constant equal weights ($\gamma = 0$).
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

Table 3
Comparison of out-of-sample forecast errors.

Horizon	Absolute error	Relative errors				
k	STM	VECM	ARMA	STATIC	FUN	RW
	RMSE	MSE				
1	0.011	0.9568	0.9876	0.9715	0.2680***	0.4845***
		(−0.441)	(−0.108)	(−0.402)	(−3.297)	(−3.592)
2	0.023	0.8917	0.9783	0.9544	0.2967**	0.5517***
		(−0.825)	(−0.148)	(−0.437)	(−2.036)	(−2.117)
3	0.034	0.8150	0.9058	0.9058	0.3013*	0.5912*
		(−1.125)	(−0.839)	(−0.825)	(−1.742)	(−1.825)
4	0.047	0.7593	0.8249	0.8421	0.3156	0.6482*
		(−1.223)	(−1.299)	(−1.361)	(−1.637)	(−1.812)
Joint test		0.0460**	0.2141	0.0963*	0.0000***	0.0000***
	MAE	MAE				
1	0.003	0.9821	0.9989	0.9702	0.4694***	0.5766***
		(−0.349)	(−0.021)	(−0.627)	(−4.904)	(−5.4830)
2	0.008	0.9671	1.0876	1.0107	0.5341***	0.6790***
		(−0.534)	(1.353)	(0.235)	(−3.304)	(−3.057)
3	0.012	0.8833	1.0523	0.9475	0.5354***	0.7002***
		(−1.453)	(0.883)	(−0.816)	(−3.036)	(−2.658)
4	0.018	0.8395	0.9899	0.9030	0.5502***	0.7453***
		(−1.584)	(−0.123)	(−1.258)	(−2.997)	(−2.631)
Joint test		0.0172**	0.3283	0.0936*	0.000***	0.000***

Notes: The table presents the absolute and relative forecast errors of the smooth transition model (STM), compared to five benchmark models. Column 2 shows the root mean squared error (RMSE) and mean absolute error (MAE) of the smooth transition model. Columns 3–7 show relative errors: the ratio of the average forecast error of the smooth transition model (STM) to the average forecast error of the competing vector error correction model (VECM), the ARIMA(1, 0, 0) model (denoted by ARMA), the fundamental error correction component of the smooth transition model considered in isolation (FUN), the static version of the smooth transition model with constant 50/50% weights (STATIC), and the random walk model (RW). Relative forecast errors are measured using two criteria: the mean squared error (MSE) and the mean absolute error (MAE). Numbers less than one (that is, a forecast error ratio <1) imply that the smooth transition model has a better forecasting performance than the model denoted in the column (VECM, ARMA, STATIC, FUN, or RW). Results are shown for four forecast horizons k; that is, forecasts are made $k = 1, 2, 3$ and 4 quarters ahead. Diebold–Mariano t-statistics are reported in parentheses. The row "Joint test" shows the p-value of a two-sample t-test comparing the average forecast error over all four horizons of the STM to the average forecast error of the benchmark model (average over $k = 1, 2, 3$ and 4).
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

Table 4
Forecast efficiency and encompassing test.

	Alpha	STM	VECM	ARMA	STATIC	FUN	Fit
$k = 1$	0.0000	0.9758***					0.7143
	(0.001)	(0.068)					[0.9383]
	−0.0006		0.9419***				0.7140
	(0.001)		(0.066)				[0.5942]
	0.0003			0.9301***			0.7052
	(0.001)			(0.066)			[0.5601]
	0.0002				0.9359***		0.7056
	(0.001)				(0.066)		[0.6164]
	−0.0042					0.6804	0.0175
	(0.003)					(0.432)	[0.0208]
	−0.0007	0.6244**	1.1451	1.2130	−2.0150		0.7169
	(0.001)	(0.312)	(0.989)	(1.307)	(2.051)		
$k = 2$	0.0002	0.9563***					0.6691
	(0.003)	(0.074)					[0.8388]
	−0.0014		0.9181***				0.6672
	(0.003)		(0.071)				[0.4349]
	0.0011			0.8920***			0.6376
	(0.003)			(0.074)			[0.3188]
	0.0008				0.9143***		0.6540
	(0.003)				(0.073)		[0.4747]
	−0.0039					0.3333	−0.0042
	(0.007)					(0.413)	[0.0070]
	−0.0013	0.5922**	−0.0393	0.7355	−0.3340		0.6700
	(0.003)	(0.311)	(0.715)	(1.062)	(1.772)		
$k = 3$	0.0006	0.9675***					0.6471
	(0.004)	(0.079)					[0.9058]
	−0.0022		0.9015***				0.6189
	(0.004)		(0.078)				[0.3720]
	0.0025			0.8702***			0.5814
	(0.004)			(0.081)			[0.2312]
	0.0019				0.9107***		0.6121
	(0.004)				(0.079)		[0.4700]
	0.0003					0.0189	−0.0122
	(0.010)					(0.397)	[0.0014]
	−0.0009	0.7473**	−0.2863	0.3426	0.1652		0.6414
	(0.006)	(0.317)	(0.522)	(0.831)	(1.466)		
$k = 4$	0.0013	0.9736***					0.6116
	(0.005)	(0.085)					[0.9249]
	−0.0030		0.8658***				0.5441
	(0.006)		(0.087)				[0.2512]
	0.0042			0.8385***			0.5109
	(0.006)			(0.090)			[0.1509]
	0.0031				0.8900***		0.5431
	(0.006)				(0.089)		[0.3937]
	0.0083					−0.2818	−0.0055
	(0.013)					(0.381)	[0.0001]
	−0.0005	1.0128***	0.0405	0.2647	−0.3490		0.5998
	(0.008)	(0.334)	(0.453)	(0.713)	(1.313)		

Notes: The table shows the results of the bias-efficiency test and the encompassing tests for the forecasts of the four competing models: the smooth transition model (STM), the vector error correction model (VECM), the ARIMA(1, 0, 0) model (ARMA), and the static model version with constant equal 50/50% weights (STATIC). The following test equation is estimated: $\Delta_k P_t = \alpha + \beta_1 E^{\mathrm{STM}}_{t-k}(\Delta_k P_t) + \beta_2 E^{\mathrm{ARMA}}_{t-k}(\Delta_k P_t) + \beta_3 E^{\mathrm{VECM}}_{t-k}(\Delta_k P_t) + \beta_4 E^{\mathrm{STATIC}}_{t-k}(\Delta_k P_t) + \varepsilon_t$, with $k \in \{1, 2, 3, 4\}$ being the forecast horizon. The column 'Fit' shows the model's adjusted R^2 value, with the Wald-statistic for the test of joint significance of $\alpha = 0$ and $\beta = 1$ in square brackets. Due to overlapping data, Newey–West standard errors are reported (in parentheses).

* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

this is the encompassing test.[17] Furthermore, we estimate Eq. (9) for each single model separately to test the joint hypothesis $\alpha = 0, \beta = 1$, which indicates unbiased forecasts: this is the bias-efficiency test.

The smooth transition model is the only model with a significant beta in the encompassing test results shown in Table 4, for all four forecast horizons. The bias-efficiency tests show that all models make unbiased forecasts, except for the fundamental model (FUN). The STM model has the best model fit and the highest p-value for the null hypothesis $\alpha = 0, \beta = 1$, at all horizons. At shorter forecast horizons ($k = 1, 2$), the differences in

[17] We do not include the fundamental mean reversion model, due to multicollinearity problems. Furthermore, the results from Table 3 indicated that this model performed relatively poorly.

performance among the STM, VECM and ARIMA models are quite small; but at forecast horizons of three and four quarters ($k = 3, 4$), the STM forecasts are clearly more informative, giving higher adjusted R^2 values and beta estimates closer to one than those of the competing models.

5. Conclusions

In this paper we estimate a smooth transition model for the US housing market. The model has two components with time-varying weights: an error correction part, capturing long-term mean reversion to a fundamental value estimate, and an autoregressive component, capturing the autocorrelation in housing market returns. The relative weight assigned to each component varies through time, depending on the recent forecasting performances of the two components, using a smooth transition mechanism. The model specification is motivated by the boom-bust character of the housing market, since the relative importance of fundamental value estimates and price momentum rules seems to vary over time in practice, as well as by the heterogeneous agent model literature.

We derive a fundamental house value estimate based on rents, and demonstrate that house prices are cointegrated with this fundamental value estimate. We then estimate the smooth transition model using quarterly US national house price index data. The model estimation results indicate that the strength of the autocorrelation in housing returns and the long-term mean reversion effect vary significantly over time, depending on recent forecasting performances. The smooth transition model can exploit this time-variation to produce better out-of-sample forecasts of house price index returns than alternative models. Our results also suggest that the US housing market was driven more strongly than usual by positive autocorrelation (momentum) during the period 1992–2005, while house prices rose far above the fundamental value estimate. Eventually, however, the house price index level did revert back completely to the rent-based fundamental value estimate at the end of 2009.

The findings in this paper have several implications for practitioners and policy makers. First, in the housing market both simple price extrapolation rules and long-term reversion to fundamental value can be used to forecast returns. Our interpretation of this evidence, following Case and Shiller (1989, 1990), is that housing markets are not fully efficient. Given that large, and potentially disruptive, house price bubbles may develop through time, we believe it is important that policy makers and practitioners actively try to analyze and forecast house prices. Our research shows that a smooth transition model is especially suited for this task. Tentatively, the time-varying weights of the smooth transition model may help to detect changes in market sentiment, or regime changes. Further development of techniques for predicting key turning points in housing markets is an important avenue for future research.

Acknowledgements

The authors would like to thank Arvi Arunachalam, Stephen Dimmock, Bart Frijns, Tony He, Ryan Israelsen and Diego Salzman for helpful discussions and comments. Furthermore, we would like to thank participants at the 2010 Financial Management Association, NAKE Research Day 2010, the Workshop on Interacting Agents and Nonlinear Dynamics in Macroeconomics, and the 11th Workshop on Optimal Control, Dynamic Games and Nonlinear Dynamics, and participants at seminars at the Tinbergen Institute Rotterdam, Auckland University of Technology and University of Technology Sydney. The usual disclaimer applies.

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