MOODY'S ANALYTICS

ANALYSIS

Prepared by

Andres Carbacho-Burgos
Andres.Carbacho-Burgos@moodys.com
Director

Brent Campbell
Brent.Campbell@moodys.com
Economist

Contact Us

Email
help@economy.com

U.S./Canada
+1.866.275.3266

EMEA
+44.20.7772.5454 (London)
+420.224.222.929 (Prague)

Asia/Pacific
+852.3551.3077

All Others
+1.610.235.5299

Web
www.economy.com
www.moodysanalytics.com

Moody's Analytics Case-Shiller Home Price Index Forecast Methodology

Introduction

Moody's Analytics uses a combined econometric forecast model for the Federal Housing Finance Agency home price indexes and the CoreLogic Case-Shiller Home Price Indexes. The econometric model uses the relationship between the Case-Shiller home price and the FHFA home price indexes in national, state and metropolitan area housing markets. The economic and demographic forces that drive home price determination will mostly impact Case-Shiller prices through the FHFA indexes. The model that Moody's Analytics has developed is a tool for forecasting the Case-Shiller Home Price Index, with the ability to generate alternative forecast scenarios such as the Federal Reserve Bank's Comprehensive Capital Analysis and Review scenarios.

Moody's Analytics Case-Shiller Home Price Index Forecast Methodology

BY ANDRES CARBACHO-BURGOS AND BRENT CAMPBELL

Moody's Analytics uses a combined econometric forecast model for the Federal Housing Finance Agency home price indexes and the CoreLogic Case-Shiller Home Price Indexes. The econometric model uses the relationship between the Case-Shiller home price and the FHFA home price indexes in national, state and metropolitan area housing markets. The economic and demographic forces that drive home price determination will mostly impact Case-Shiller prices through the FHFA indexes. The model that Moody's Analytics has developed is a tool for forecasting the Case-Shiller Home Price Index, with the ability to generate alternative forecast scenarios such as the Federal Reserve Bank's Comprehensive Capital Analysis and Review scenarios.

This study looks at the second half of the process, which is used to forecast the Case-Shiller Home Price Indexes. The econometric model used is designed to forecast the Case-Shiller Home Price Index at the U.S., state and metro area levels, but also includes extensions for tier and condominium indexes as well as to aggregate indexes at the county and ZIP code levels. Data sources for the model are listed in Table 1. The model generates these forecasts in conjunction with the Moody's Analytics U.S. and regional economic and house price forecast models that are specific to each market. This article briefly reviews the theoretical underpinnings of the Moody's Analytics U.S., regional and home price forecast models and discusses the characteristics of the Case-Shiller Home Price Indexes and Case-Shiller home price forecast models. Since the Case-Shiller forecasts take advantage of the cointegration between the two indexes, this article in conjunction with *Moody's Analytics FHFA Home Price Index Forecast Methodology* presents a complete picture of the home price index forecast process. Regression specifications and model validation results are presented for the U.S., states and metro areas for the single-family market index. Regression specifications are also presented for the county, ZIP code, tier and condo indexes.

Moody's Analytics approach to forecasting

As with nearly all Moody's Analytics forecast models, the home price model employs the structural approach which specifies, estimates and then solves equations that mirror the structural workings of U.S. housing markets.[1] Structural macroeconomic models such as the Moody's Analytics U.S. model excel in exploring the economy-wide implications of alternative assumptions about the future, including those used in stress-testing exercises. This approach is also well-suited to extrapolate implications for specific regions.

Home price determination

The approach to model home price determination for the Case-Shiller index is a variant of the structural model, leveraging from the Moody's Analytics model of the FHFA's repeat-purchase home price index. This approach ties the Case-Shiller home price forecasts to their fundamental economic drivers while utilizing the complete state and metropolitan statistical area coverage available in the FHFA index to generate a good relationship between the economic variables and house prices.[2] It also ensures consistency across the suite of home price indexes forecast by Moody's Analytics.

The FHFA home price forecast forms the backbone for home price determination. This fully specified structural model of housing demand and supply allows for serial correlation and mean reversion in regional housing markets. This model can identify the forces driving house prices and assess the degree to which house prices can be explained by fundamental, persistent trends and the de-

1 By comparison, VAR models provide good short-term forecast accuracy but lack causal explanation for such forecasts that can be applied to simulations, while dynamic stochastic general equilibrium models require highly restrictive assumptions about household behavior and about the causal relationship between individual actions and macroeconomic aggregates.

2 For these home price forecast models, Moody's Analytics uses the 2010 Office of Management and Budget metro definitions. Also, metropolitan divisions are treated identically to metropolitan statistical areas; both are referred to as "metro areas". MSAs that are divided into metro divisions are not considered, and their forecasts are simply household-weighted averages of the corresponding metropolitan division forecasts.

Table 1: Variables Tested: Definitions and Sources

Variable	Sources
CoreLogic Case-Shiller® Home Price Index	CoreLogic Inc., Federal Housing Finance Agency
FHFA repeat-sales all-transactions index	Federal Housing Finance Agency
FHFA repeat-sales purchase-only index	Federal Housing Finance Agency
Loan officers tightening mortgage lending, % of total	Federal Reserve Board
Mortgage originations	Mortgage Bankers Association; Home Mortgage Disclosure Act
Average household income	Bureau of Economic Analysis, Census Bureau
Median household income	Census Bureau
Unemployment rate	Bureau of Labor Statistics
User cost of capital	Constructed from FHFA composite mortgage rates, BEA personal income data, ACS property tax data, and BEA core personal consumption expenditure deflator.

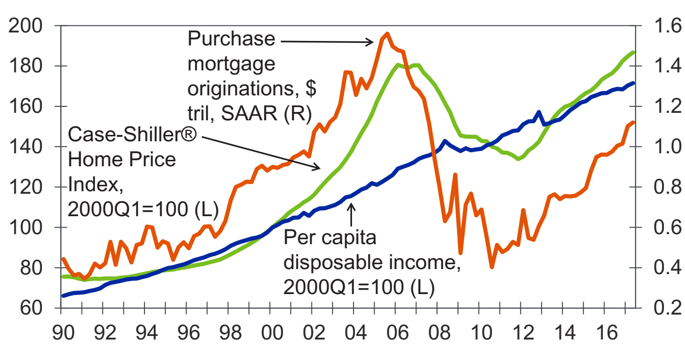
Note: Most of these variables are available at a metropolitan-area level from the source or are constructed by Moody's Analytics

Source: Moody's Analytics

gree to which they are explained by more temporal, business cycle-related trends. Factors such as income growth and household growth govern long-term price trends, while business cycles and construction cycles govern short-term fluctuations in prices. Also, mortgage lending can also generate deviations from long-term price trends such as the house price bubble of the last decade (see Chart 1). These forces include the jobless rate, the user cost of housing, construction costs, and mortgage foreclosure rates. This model also accounts for differences in behavior across regions. Details of the FHFA model can be found in the *Moody's Analytics FHFA Home Price Index Forecast Methodology*.

The Case-Shiller index can be modeled in a similar manner as the FHFA index, but Moody's Analytics elected to model the Case-Shiller index as it relates to the FHFA home price index. Using the FHFA home price index to explain movements in the Case-Shiller index captures the structural relationship between the Case-Shiller index and its fundamental drivers, imposes consistency among the forecasts for different measures of house prices, and leverages the greater geographical coverage of the FHFA indexes. Theoretical and practical considerations drive this approach. Theoretically, because the two indexes measure the same phenomenon, they should track each other well over time. Any deviation of one from the other can be accounted for by differences in the sample of home price data used to construct the indexes or the differences in the algorithms used to calculate the indexes; such differences do not generate any systematic long-term deviations from trend. The correlation between the indexes is close to unity in a large number of regions as is discussed below. This approach essentially assumes a co-integrating relationship between the indexes. This relationship is formally tested as described below; while the housing bubble put this relationship in doubt for a few years, post-2008 data tend to confirm the relationship. This approach is appealing from a practical point of view as well.

Chart 1: Loan Cycle Disrupted Price Trend



Sources: CoreLogic Inc., BEA, MBA, Moody's Analytics

One challenge that regional home price index forecast models face is to maintain the consistency of forecasts across different geography levels. For example, the weighted average of forecast state house price growth rates must not depart too far from the forecasted U.S. growth rate. For this reason, it is important to use a model whose underlying historical data have the widest possible geographical coverage in addition to having long time series, and to have the different forecast models be as similar as possible between the U.S., states and metro areas. Such uniformity will minimize the need for post-forecast calibration to ensure consistency. For this reason, the FHFA home price indexes proved the best starting point.

Data description

To use this forecasting approach, it is important to understand the differences and similarities between the Case-Shiller and FHFA home price indexes. They differ in the way they are calculated and also in the source of data used to calculate the home price indexes. Nevertheless, for the most part, the similarities outweigh the differences. In fact, the indexes are similar enough that CoreLogic substitutes in the FHFA price index in geographies where the sales and home price data are insufficient to construct a robust Case-Shiller index. It is because the

FHFA indexes rely on a single uniform data source, whereas the Case-Shiller indexes use infilling for some geographies, that the FHFA indexes were chosen as the primary forecast drivers for the Case-Shiller indexes.

Case-Shiller Home Price Index

The Case-Shiller Home Price Index is based on price changes in repeat-sales data first calculated using the repeat-sales algorithm developed by Karl Case and Robert Shiller. CoreLogic calculates indexes for different geographies using county public records data. This data source allows CoreLogic to generate Case-Shiller indexes for all states that do not have nondisclosure laws and for most of the metro areas therein. In some cases, especially for small metro areas, the data are not sufficient to generate stable Case-Shiller indexes. For such metro areas, CoreLogic fills in the Case-Shiller indexes with rebased FHFA indexes.

Many states have nondisclosure laws that prevent county offices from releasing sales price data. These states are Alaska, Idaho, Indiana, Kansas, Maine, Mississippi, Missouri, Montana, New Mexico, North Dakota, South Dakota, Texas, Utah, West Virginia and Wyoming. For these states and the metro areas within them, CoreLogic fills in Case-Shiller indexes with rebased FHFA indexes.[3]

All told, CoreLogic covers 223 metro areas, 35 states, and the District of Columbia with CoreLogic indexes generated with its own data; the remaining states and metro areas use rebased FHFA indexes. In the models that follow, Moody's Analytics uses regressions to forecast only these states and metro areas with independent CoreLogic data. The Case-Shiller index forecasts for the remaining 15 nondisclosure states and the remaining 180 metro areas are obtained simply by growing out the rebased historical FHFA indexes with the growth rates of the corresponding FHFA index forecasts.

Federal Housing Finance Agency home price indexes

The Federal Home Finance Agency Home Price Index also uses the repeat sales algorithm created by Case and Shiller; the main difference between the two indexes is thus not in the methodology but in the data sources.[4] The data used to construct the purchase-only and all-transaction FHFA home price indexes are similar to those used to calculate the Case-Shiller HPI, but there are key differences. The FHFA bases its HPI on price data from repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae and Freddie Mac. The HPI is updated monthly for the U.S. and Census divisions and on a quarterly basis for states and metro areas, incorporating additional data as mortgages are purchased or securitized by Fannie and Freddie. These source data are limited to loans that are both conforming and conventional, as described below:

Conforming loan types

- Government-sponsored enterprise (Fannie Mae and Freddie Mac) loans that follow their guidelines
- Federal Housing Administration (FHA) loans that insure first mortgages
- Veteran's Administration (VA) and Rural Housing Service (RHS) loans from banks or other lenders

Conventional loans

- Any loan not under a government-insured program, with FHA and VA loans being the main exclusions.

Because Fannie Mae and Freddie Mac can purchase only mortgages that are conforming and conventional, several types of home purchase transactions are excluded from the FHFA data. These include jumbo mortgages that exceed conforming loan limits, mortgages insured by the FHA, VA and RHS, and of course purchases that are financed with cash or nonmortgage lending. Also, during the height of the housing bubble there was a substantial share of mortgages that were conforming and conventional but were bought up by private-label companies rather than by Fannie Mae and Freddie Mac, and would thus not have been included in the data used to calculate FHFA indexes. Because of this narrower base of data, the FHFA indexes provide a more limited look at house price transactions than do the Case-Shiller indexes, but their larger metro area coverage compensates for this disadvantage.

The FHFA reports two price indexes, a purchase-only index and an all-transaction index.[5] The purchase index includes only house price data from purchase mortgages, while the all-transaction index includes house price data from mortgages for purchase and home value appraisals for refinancing mortgages. Since it represents true market prices better, the purchase-only index is the preferable measure, but data limitations make it available only for the states and larger metro areas. The FHFA publishes purchase-only indexes for the U.S., all 50 states, Washington DC, and 100 metro areas.

Comparing Case-Shiller and FHFA

Because the Case-Shiller index includes information for all arms-length home sales in regions where it is available regardless of the source of financing, it better represents house price trends for the entire housing market.[6] In the long run, the two indexes trend together well, but short-run cyclical differences are evident and are related to the different types of data used to calculate the indexes.

Chart 2 shows the overall trend for the U.S. series. The Case-Shiller and FHFA purchase-only indexes move in lockstep with each other, the only significant exception being the 2003-2007 period when the growth of private label and jumbo loan financing pushed the Case-Shiller index

3 CoreLogic uses FHFA purchase-only indexes to fill in for Case-Shiller if these are available; otherwise, it uses FHFA all-transactions indexes which include refinancing appraisal values in addition to purchase transactions.

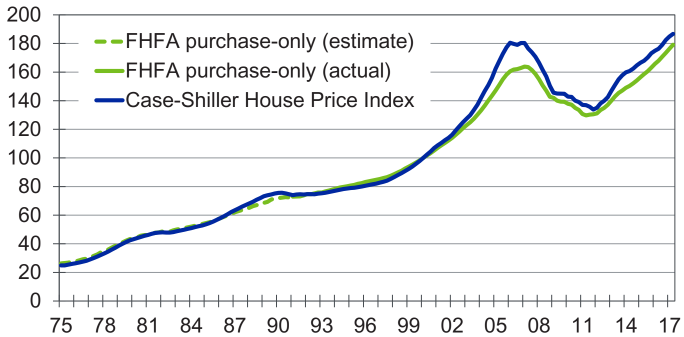
4 The one exception to this methodological similarity is that Case-Shiller indexes calculated with CoreLogic data are value-weighted, whereas FHFA indexes are unit-weighted. In theory, this can lead the Case-Shiller indexes to have larger deviations over time than FHFA indexes calculated with the same data, but the extent of this difference is difficult to measure.

5 There are also expanded data FHFA purchase-only indexes, which include public records data in order to include non-conforming, nonconventional, and cash purchases, but these indexes are not forecast by Moody's Analytics and are therefore not considered.

6 After foreclosure, the sale of real-estate owned properties to third parties is *not* considered arm's length, so sales pairs that are spanned by foreclosure repossessions are not included when calculating the resulting Case-Shiller index. This exclusion reduces the potential volatility of the Case-Shiller index during serious business cycles.

Chart 2: Deviation Varies, Trend Is Similar

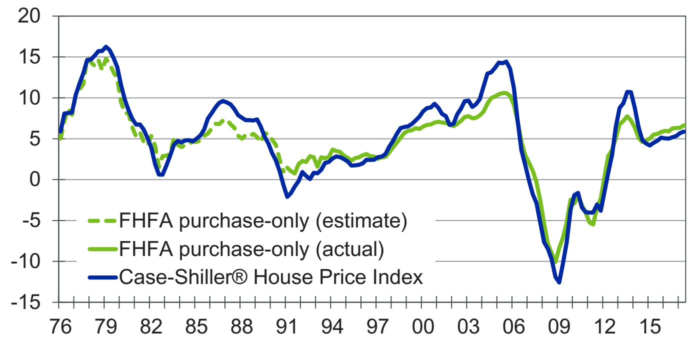
U.S. house price indexes, 2000Q1=100



Sources: CoreLogic Inc., FHFA, Moody's Analytics

Chart 3: HPI Growth Also Converges

U.S. house price indexes, % change yr ago



Sources: CoreLogic Inc., FHFA, Moody's Analytics

Table 2: Case-Shiller Index, Non-Stationarity Tests for U.S., States and Metro Areas

			Augmented Dickey-Fuller Test Results		
	Full sample	**Observations**	**t-statistic**	**Fisher Chi-square Statistic**	**Prob.**
U.S.	1975Q3-2017Q1	167	-1.9999	--	0.2868
State pool*	1991Q1-2017Q1	3,780	--	74.2638	0.4043
Metro area pool**	1990Q1-2017Q1	24,307	--	384.4720	0.9839
	Restricted sample	**Observations**	**t-statistic**	**Fisher Chi-square Statistic**	**Prob.**
U.S.	1975Q3-2001Q4	106	-2.6114	--	0.0939
State pool*	1991Q1-2001Q4	1,584	--	27.0931	1.0000
Metro area pool**	1990Q1-2001Q4	10,704	--	233.8750	1.0000

*36 states

**223 metro areas

The null hypothesis is that the log of the deflated Case-Shiller index has individual unit root processes for the U.S., or for the geographies in each pool.

Source: Moody's Analytics

substantially above the FHFA index.[7] Similarly, in Chart 3, the growth rate of the U.S. Case-Shiller index fluctuates around but never departs in the long term from the growth rate of the FHFA purchase-only index. Most state and metro areas mirror this correlation, though as we will see, this does not necessarily translate into unchallenged evidence of cointegration.

Case-Shiller and FHFA home price indexes: Evidence of co-integration

The first step in the modeling effort is to determine statistically that the Case-Shiller and FHFA indexes are non-stationary series and that the two indexes are cointegrated. That is, that there exists a long-term relationship between the Case-Shiller and FHFA indexes. This relationship provides the statistical validity for using the FHFA forecast to drive the Case-Shiller forecast. The intuition behind the hypothesis that the two price indexes are co-integrated is simple. The indexes represent the relationship between house prices and their fundamental drivers such as per household income and inflation. Therefore, short-run departures can occur because of differences in the way the indexes are calculated, but in the long run, they should trend together.

Tests for non-stationarity of the Case-Shiller indexes (that is, for unit roots in each time series) are shown in Table 2. For states and metro areas, the sample tested is only that which overlaps the regression model, that is, 1990 or 1991 to 2017.[8] For these tests and cointegration tests, a likely objection is that the period of the housing bubble and subsequent correction distort the results and provide evidence only of isolated non-stationarity. To discount the effects of the 2002-2008 housing bubble, the non-stationarity tests were also conducted with a sample restricted to quarters before 2002. With the full sample, the pooled Augmented Dickey-Fuller test for individual unit roots fails to reject the null hypothesis of non-stationarity; the t-statistic for the individual U.S. series fails to reject non-stationarity as well. Tests with the restricted pre-2002 sample also fail to reject the null hypothesis of non-stationarity,

7 For 1975-1990, the U.S. FHFA purchase-only index is estimated based on its 1991-2014 correlation with the all-transactions index, which goes back to 1975.

8 For the U.S. test, the test period was 1975-2014, using an estimate of the FHFA purchase-only index for 1975-1990, as the 1991-2017 sample period has too few observations.

Table 3: FHFA Indexes, Non-Stationarity Tests for U.S., States and Metro Areas

			Augmented Dickey-Fuller Test Results		
	Full sample	Observations	t-statistic	Fisher Chi-square Statistic	Prob.
U.S. purchase-only index	1976Q1-2017Q1	165	-1.6939	--	0.4325
State pool*	1991Q1-2017Q1	3,624	--	48.8047	0.9836
Metro area pool**	1990Q1-2017Q1	24,068	--	434.5780	0.6418
	Restricted sample	**Observations**	**t-statistic**	**Fisher Chi-square Statistic**	**Prob.**
U.S.	1976Q1-2001Q4	104	-1.0504	--	0.7328
State pool*	1991Q1-2001Q4	1,499	--	57.8211	0.8874
Metro area pool**	1990Q1-2001Q4	10,476	--	263.8040	1.0000

*36 states, FHFA purchase-only index

**223 metro areas, FHFA all-transactions index

The null hypothesis is that the log of the deflated FHFA index has individual unit root processes for the U.S., or for the geographies in each pool.

Source: Moody's Analytics

Table 4: Cointegration Tests For U.S., States and Metro Areas

			Engle-Granger Test Results		
	Full sample	Observations	z-statistic	Group ADF Statistic †	Prob.
U.S.	1975Q1-2017Q1	169	-10.0604	--	0.3494
State pool*	1991Q1-2017Q1	3,780	--	-4.4189	0.0000
Metro area pool**	1990Q1-2017Q1	24,307	--	-17.9150	0.0000
	Restricted sample	**Observations**	**z-statistic**	**Group ADF Statistic †**	**Prob.**
U.S.	1975Q1-2001Q4	108	-48.7013	--	0.0000
State pool*	1991Q1-2001Q4	1,584	--	-3.1693	0.0008
Metro area pool**	1990Q1-2001Q4	10,656	--	-8.8571	0.0000

*36 states

**223 metro areas

†Corrected for degrees of freedom. Alternative hypothesis is that cross-sections have individual AR coefficients

The null hypothesis is that the log of the Case-Shiller index and the log of the FHFA purchase-only index (states) or FHFA all-transactions index (metro areas) are not cointegrated.

Source: Moody's Analytics

even when considering the case of the single U.S. time series where the lack of a pre-2002 house price bubble would make stationarity a more plausible assumption. Table 3 gives similar results for the FHFA purchase-only index (U.S., states), and the FHFA all-transactions index (metro areas).

Table 4 shows the results of Engle-Granger tests for cointegration between the Case-Shiller index and either the FHFA purchase-only index (U.S., states) or the FHFA all-transactions index (metro areas). For states and metro areas, there were enough observations for both samples that the tests rejected the null hypothesis of no cointegration even with the distorting effects of the housing bubble. The results of the U.S. index cointegration test are more ambiguous. The full sample test fails to reject the null hypothesis of no cointegration. However, this result is influenced by the 2012-2017 quarters, when the two indexes started to diverge. When the test is restricted to pre-2002 data, or even to 1975-2011 data (not shown), the test rejects the null hypothesis of no cointegration at the 1% confidence level. We can therefore conclude that the housing bubble notwithstanding, the Case-Shiller and FHFA indexes are non-stationary and are cointegrated, so that each can be modeled based on an error-correction process with respect to the other.

Case-Shiller HPI models: U.S. and states

Once the Case-Shiller and FHFA home price indexes are determined to be co-integrated, Moody's Analytics turns to the models that best explain variations in the Case-Shiller index relative to the FHFA index and other drivers that would explain the short-run variations between the indexes.[9] The models tested are error correction models that allow for near-term differences between the Case-Shiller and FHFA indexes while ensuring that long-term trends are

9 Both indexes are seasonally adjusted and are updated quarterly for FHFA indexes and monthly for the Case-Shiller indexes, though the regression model is quarterly.

similar. The models drive convergence of the Case-Shiller index to the FHFA index through a mean reversion term, where the mean is effectively the FHFA index forecast. These models can be expressed as follows. First, an equilibrium trend for the relevant Case-Shiller index is obtained from the fitted value of the regression equation

$$\log(CSI_t) = \alpha_0 + \alpha_j + \alpha_1 \log(FHFA_t) + \varepsilon_t$$

where:

- CSI = Case-Shiller index for region
- FHFA = FHFA purchase-only index for U.S. and states, or all-transactions index for metro areas
- ε_t is the random error term
- Subscript t indicates the current quarter
- Subscript j indicates the particular cross-section (state or metro area).

and the parameters α_0, α_j and α_1 are estimated using the existing historical data. The actual forecast for the relevant Case-Shiller index is then obtained from the first-difference regression

$$\Delta\log(CSI_t) = \beta_1 \Delta\log(CSI_{t-1}) + \beta_2 \Delta\log(CSI\_EQ_t) + \beta_3(\log(CSI_{t-1}) - \log(CSI\_EQ_{t-1})) + \beta_4 X + \mu_t$$

where

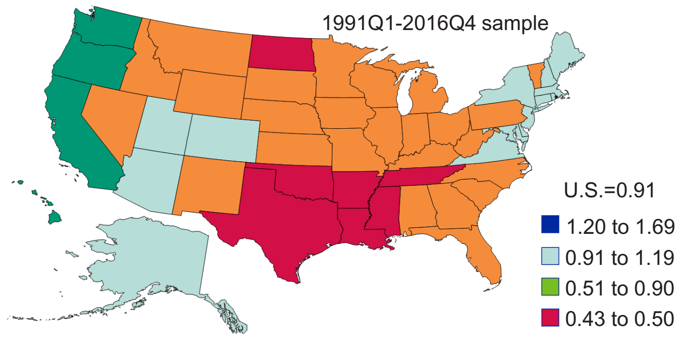
- CSI_EQ = equilibrium Case-Shiller index obtained from the first equation
- X = variables that can explain short-term differences between behavior of the CSI and FHFA indexes
- μ is the random error term
- Subscript t indicates the current quarter and t-1 the previous quarter.

And the parameters β_1, β_2, β_3 and β_4 are estimated using the existing historical data.

The error correction term $\log(CSI_{t-1})$-$\log(CSI\_EQ_{t-1})$ drives the Case-Shiller index to appreciate more quickly (slowly) when the Case-Shiller index has been appreciating more slowly (quickly) than the FHFA index.[10]

Chart 4: Income Effect Strongest in Coasts

Elasticity, FHFA purchase-only index relative to per capita income



Sources: FHFA, BEA, Moody's Analytics

Through its equilibrium value, the Case-Shiller index is also driven by how quickly the FHFA index appreciates; hence this equation includes the contemporaneous FHFA index. Note that this term captures concurrent economic and demographic drivers of home prices. The faster the FHFA index appreciates, the faster the Case-Shiller index appreciates.

This indirect effect is crucial, as there is substantial period and regional variation in FHFA index growth that is consequently captured in the Case-Shiller forecast. For example, different regions of the U.S. have varying sensitivity to per capita income growth. Sensitivity is especially pronounced for the Pacific coast states and most of the Northeast states, where urban land amenable to zoning is scarce and the housing supply is consequently constrained. By contrast, the Midwest and most southern states have more available land and consequently much less house price sensitivity to per capita income (see Chart 4). By attaching the Case-Shiller indexes to the FHFA indexes in an error correction model, Moody's Analytics eliminates the need to create fully specified regional driver models for both indexes.

The lagged dependent variable is also included in the regression model. This variable captures the tendency for appreciation to be persistent—past behavior of house prices helps to predict future behavior—and prevents the Case-Shiller index from reverting too quickly to the level of the FHFA index.

Finally, several variables that can explain short-term differences between behavior of the Case-Shiller and FHFA indexes were tested in the regression analysis. In the end only two were chosen due to the shortage of extensive regional data, especially at the metro level.

Tables 5A, 5B, 6A, and 6B present the results of the model for the U.S. and the 36 states with independent CoreLogic data. The coefficients are as expected, and of the right signs. The coefficient on the mean reversion term for the U.S. index is approximately -0.042, which indicates that other things being equal, the U.S. Case-Shiller index tends to converge with the FHFA index-determined trend over a period of between three and four years, which corresponds with historical experience as seen in Chart 2. The main driver of the forecast is the log change in the Case-Shiller equilibrium series, which is itself driven by changes in the U.S. FHFA purchase-only index.

Case-Shiller HPI models: Metro areas

The metro area models are fashioned in a similar manner to the state models, with two main differences. First, the FHFA does not report a purchase-only index for all metro areas, so the all-transaction index was used.[11] Second, some way of compensating for the refinancing inertia present in the all-transactions index has to be used. Inertia refers to the fact that the FHFA all-transactions index includes home values obtained from refinancing appraisals, and these values are based on purchases of similar nearby homes that can lag by several months, and conse-

10 It should also be noted that the second equation includes neither a constant term nor fixed effects, mainly because one or both could interfere with the mean reversion properties of the model, possibly preventing the Case-Shiller forecast from reverting to the trend of the FHFA index forecast.

11 It is also possible to have two separate metro area regressions, splitting pools into those metro areas where FHFA purchase-only indexes are available and those metro areas with only an all-transactions index. However, this procedure increases the number of steps in the forecast process as well as the steps needed to calibrate consistency between metro areas and states, so it was avoided in favor or a single regression pool with a single FHFA index driver.

Table 5A: U.S. CoreLogic Case-Shiller® Home Price Index Equilibrium Equation

Dependent Variable: LOG(CoreLogic® Case-Shiller® House Price Index)
Method: Least Squares
Sample (adjusted): 1975Q1 2017Q1
Included observations: 169 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.4622	0.0216	-21.3714	0.0000
LOG(FHFA purchase-only index)	1.0412	0.0045	228.8656	0.0000

R-squared	0.9968	Mean dependent var	4.4565
Adjusted R-squared	0.9968	S.D. dependent var	0.5550
S.E. of regression	0.0314	Akaike info criterion	-4.0734
Sum squared resid	0.1645	Schwarz criterion	-4.0364
Log likelihood	346.2017	Hannan-Quinn criter.	-4.0584
F-statistic	52379.4574	Durbin-Watson stat	0.0485
Prob(F-statistic)	0.0000		

Source: Moody's Analytics

Table 5B: U.S. CoreLogic Case-Shiller® Home Price Index Adjustment Equation

Dependent Variable: DLOG(CoreLogic Case-Shiller® House Price Index)
Method: Least Squares
Sample (adjusted): 1991Q2 2017Q1
Included observations: 104 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(CoreLogic Case-Shiller® House Price Index lagged one quarter)	0.4950	0.0694	7.1349	0.0000
DLOG(Equilibrium CoreLogic Case-Shiller® House Price Index)	0.5259	0.0798	6.5899	0.0000
LOG(CoreLogic Case-Shiller® House Price Index lagged one quarter) - LOG(Equilibrium CoreLogic Case-Shiller® House Price Index lagged one quarter)	-0.0416	0.0185	-2.2507	0.0266

R-squared	0.8512	Mean dependent var	0.0087
Adjusted R-squared	0.8483	S.D. dependent var	0.0155
S.E. of regression	0.0060	Akaike info criterion	-7.3498
Sum squared resid	0.0037	Schwarz criterion	-7.2740
Log likelihood	388.87	Hannan-Quinn criter.	-7.3191
Durbin-Watson stat	1.9748		

Source: Moody's Analytics

quently do not provide an up-to-date measure of house prices.

To compensate for refinancing inertia, the metro area forecast model introduces two drivers. For metro areas with FHFA purchase-only indexes, the difference between the log differences of the metro area FHFA purchase-only index and the FHFA all-transactions index was used as an additional driver. For metro areas without an FHFA purchase-only index, the extra driver is the difference between the state FHFA purchase-only index log difference and the state FHFA all-transactions index log difference, with this difference being multiplied by the metro area's share of refinancing transactions. For either type of metro area, the extra driver is intended to reduce the inertia inherent in the included lagged house prices. For example, if FHFA-measured house price growth from the previous two quarters was strong and the current refinancing share of originations is significantly above zero, then the Case-Shiller index should grow at a significantly faster rate than the contemporaneous FHFA all-transactions index, given that the latter contains lagged, and presumably smaller, house price values. Similarly, a significant decline in house prices from the previous two quarters, combined with a significant share of refinancing originations, should lead the Case-Shiller index to decline at a faster rate than the contemporaneous FHFA all-transactions index.

The results for the pooled metro area equilibrium and adjustment equation regressions are shown in Table 7A and 7B. The results for the first three drivers of the adjustment equation are similar to the regression for the states. The coefficient on the second refinancing lag driver looks rather strong, but it should be noted that the refinancing share of mortgage originations seldom exceeds 0.6, so that in effect the coefficient on lagged FHFA house price growth is closer to 0.25. Because of this, the two additional drivers do a good job of showing the greater variability of the Case-Shiller index and the

Table 6A: CoreLogic Case-Shiller® Home Price Index, Equilibrium Forecast Equation for States

Dependent Variable: LOG(CoreLogic Case-Shiller® House Price Index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1991Q1 2017Q1
Included observations: 105 after adjustments
Cross-sections included: 36
Total pool (balanced) observations: 3780
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.2349	0.0057	-41.0323	0.0000
LOG(FHFA Purchase-Only Index)	0.9875	0.0011	878.3101	0.0000

	Weighted Statistics		
R-squared	0.9956	Mean dependent var	6.1721
Adjusted R-squared	0.9956	S.D. dependent var	2.1102
S.E. of regression	0.0277	Sum squared resid	2.8805
F-statistic	23,704.7300	Durbin-Watson stat	0.2442
Prob(F-statistic)	0.0000		

	Unweighted Statistics		
R-squared	0.9930	Mean dependent var	4.7847
Sum squared resid	2.8818	Durbin-Watson stat	0.1881

Note: Fixed effects coefficients available on request. States whose Case-Shiller® Indexes were infilled with FHFA indexes are not included in the pooled regression
Source: Moody's Analytics

Table 6B: CoreLogic Case-Shiller® Home Price Index, Adjustment Forecast Equation for States

Dependent Variable: DLOG(CoreLogic Case-Shiller® House Price Index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1991Q2 2017Q1
Included observations: 104 after adjustments
Cross-sections included: 36
Total pool (balanced) observations: 3744
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(CoreLogic Case-Shiller® House Price Index, lagged one quarter)	0.4179	0.0120	34.9437	0.0000
DLOG(Equilibrium Case-Shiller Index Forecast)	0.5003	0.0113	44.1432	0.0000
LOG(CoreLogic Case-Shiller® House Price Index lagged one quarter) - LOG(Equilibrium CoreLogic Case-Shiller® House Price Index lagged one quarter)	-0.0663	0.0053	-12.5218	0.0000

	Weighted Statistics		
R-squared	0.7346	Mean dependent var	0.0103
Adjusted R-squared	0.7344	S.D. dependent var	0.0188
S.E. of regression	0.0096	Sum squared resid	0.3423
Durbin-Watson stat	2.4750		

	Unweighted Statistics		
R-squared	0.6805	Mean dependent var	0.0083
Sum squared resid	0.3450	Durbin-Watson stat	2.6349

Note: States whose Case-Shiller® Indexes were infilled with FHFA indexes were not included in the pooled regression

Source: Moody's Analytics

Table 7A: CoreLogic Case-Shiller® Home Price Index, Equilibrium Forecast Equation for Metro Areas

Dependent Variable: LOG CoreLogic Case-Shiller® House Price Index
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1975Q2 2017Q1
Included observations: 168 after adjustments
Cross-sections included: 223
Total pool (unbalanced) observations: 31831
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.1131	0.0020	-56.9932	0.0000
LOG(FHFA All-Transactions Index)	0.9840	0.0004	2372.8950	0.0000

	Weighted Statistics		
R-squared	0.9949	Mean dependent var	5.8207
Adjusted R-squared	0.9949	S.D. dependent var	2.4881
S.E. of regression	0.0424	Sum squared resid	56.9409
F-statistic	27,665.8700	Durbin-Watson stat	0.3030
Prob(F-statistic)	0		

	Unweighted Statistics		
R-squared	0.9918	Mean dependent var	4.5786
Sum squared resid	56.9479	Durbin-Watson stat	0.2134

Note: Fixed effects coefficients available on request. Metro areas whose Case-Shiller® Indexes were infilled with FHFA indexes are not included in the pooled regression

Source: Moody's Analytics

Table 7B: CoreLogic Case-Shiller® Home Price Index, Adjustment Forecast Equation for Metro Areas

Dependent Variable: DLOG(Case-Shiller® House Price Index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1991Q2 2017Q1
Included observations: 104 after adjustments
Cross-sections included: 223
Total pool (unbalanced) observations: 23048
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(CoreLogic Case-Shiller® House Price Index, lagged one quarter)	0.3583	0.0059	61.0927	0.0000
DLOG(Equilibrium Case-Shiller® index forecast)	0.5216	0.0059	88.1443	0.0000
LOG(CoreLogic Case-Shiller® House Price Index lagged one quarter) - LOG(CoreLogic Case-Shiller® House Price Index Equilibrium Trend lagged one quarter)	-0.0491	0.0023	-21.6528	0.0000
DLOG(FHFA Purchase-Only Index) - DLOG(FHFA All-Transactions Index)*	0.3245	0.0073	44.6841	0.0000
Refinance share of mortgage originations * DLOG(State FHFA Purchase-Only Index) - DLOG(State FHFA All-Transactions Index)^0.5297				0.0196
27.0149	0.0000			

	Weighted Statistics		
R-squared	0.5777	Mean dependent var	0.0094
Adjusted R-squared	0.5776	S.D. dependent var	0.0219
S.E. of regression	0.0141	Sum squared resid	4.5862
Durbin-Watson stat	2.5148		

	Unweighted Statistics		
R-squared	0.5505	Mean dependent var	0.0079
Sum squared resid	4.6046	Durbin-Watson stat	2.5419

Note: Metro areas whose Case-Shiller® Indexes were infilled with FHFA indexes were not included in the pooled regression

*For metro areas with an FHFA purchase-only index. Set to zero for metro areas without this index.
^Only for metro areas without a FHFA purchase-only index; uses state FHFA indexes. Set to zero for metro areas with a purchase-only index.

Source: Moody's Analytics

FHFA purchase-only index relative to the all-transactions index.

Alternative specifications

Being a model in which economic and demographic drivers flow through the FHFA index, the basic model for the Case-Shiller indexes has less room for experimentation than the fully specified structural model for the FHFA indexes. In particular, adding alternative drivers makes sense only if these would affect transactions whose data are collected by CoreLogic, not by the FHFA. Foreclosures and distress sales are an obvious candidate, but the shortage of regional data prevents a sound specification using these variables. For example, distress sales data suffer from numerous gaps at the metro area level and from an uneven collection process that creates latency in the historical data, making forecasts difficult. Foreclosure filings data do not suffer from this problem, but the connection between filings and subsequent distress sales that affect prices is tenuous at best and did not generate results that were robust to validation.

Similarly, possible attempts to model the boom in speculative mortgage lending that fed more into Case-Shiller index growth than FHFA index growth also suffer from a paucity of data at the regional level. In particular, regional data on subprime lending are available thanks to the Home Mortgage Disclosure Act, but are only annual in frequency and have too short a time series to be of use in a forecast model.

In addition to the above problems, most of these proposed drivers suffer from significant collinearity with the mean reversion term. That is, series that would tend to capture the effects of unconventional mortgage lending or of distress sales would tend to coincide with a mean reversion term showing a large degree of overvaluation, while series that would tend to capture a large share of cash purchases, a large share of institutional investor purchases, or a small number of nondistress listings would tend to coincide with a mean reversion driver that indicates a large degree of undervaluation.

To give one example of this latter problem, one additional driver that could be included in the U.S. equation to account for short-term differences is the share of loan officers reporting that they are tightening lending conditions, as reported in the quarterly Federal Reserve Board bank loan officers' survey. The rationale for this inclusion is straightforward: As lending standards become tighter, as was the case during the 2008 financial panic, a greater share of home purchases is financed by FHA, VA or RHS mortgages or by cash transactions. Both types of transactions are excluded in the FHFA data but appear in public records data that can be picked up by CoreLogic in states permitting disclosure. Furthermore, when loan officers tighten mortgage lending standards, houses purchased with cash or other unconventional financing are more likely to be foreclosed homes selling at a discount. Conversely, when loan officers loosen lending restrictions, the share of discounted, unconventionally financed home purchases decreases, putting upward pressure on house prices.

However, the result of including loan tightening as a driver of the U.S. Case-Shiller index is that even through its resulting coefficient was economically and statistically significant, it reduced both the magnitude and t-statistic for the mean reversion driver, and also worsened the diagnostic for multicollinearity. Adding in drivers for the foreclosure share at the state level created the same problem. As a result, it was felt that other than correcting for refinancing inertia, a pure error correction model without external drivers was the most efficient way to model Case-Shiller index fluctuations around the contemporaneous FHFA index.

Validation

To test the accuracy of the forecast model for the Case-Shiller aggregate index, Moody's Analytics selected 13 quarters of historical observations in the three-year period from the first quarter of 2014 to the first quarter of 2017. The tests were made more rigorous in two ways. First, the tested variable was the level of the Case-Shiller index, *not* the one-period change in its logarithm. By choosing the level of the forecast rather than its rate of change, Moody's Analytics allows any systematic forecast errors to accumulate the farther out one goes from the fourth quarter of 2013. Second, three types of forecasts are tested. The simplest test is an in-sample test where the 2014Q1-2017Q1 observations are included in the Tables 5-7 regressions and help to determine their coefficients. By contrast, *ex-post* out-of-sample tests rerun the regressions but exclude the 2014Q1-2017Q1 observations. Lastly, an *ex-ante* out of sample tests not only excludes the 2014Q1-2017Q1 observations in the regressions, but also uses the forecast rather than actual values of the FHFA indexes in order to generate the Case-Shiller index forecasts. One would thus expect the ex-ante out-of-sample tests to generate the largest forecast errors, given that they are tests of the combined FHFA and Case-Shiller forecast model, rather than just of the Case-Shiller forecast equations.

Tables 8-10 show the validation tests results for the U.S., states and metro areas. Since the root mean squared error can vary not just with the error in the forecast but also with the size of a given geography's index values, the root mean squared errors were also normalized by dividing through by the average of the Case-Shiller actual values in 2014Q1-2017Q1. Table 8 shows that the national model does quite well, with the normalized root mean squared error being less than 0.034 or 3.4% regardless of which test was used.

Table 9 presents the results for the states and also uses 2010 decennial census households for each state in order to obtain an overall weighted average for the states. Two quick observations are in order. First geographies with small samples tend to have more volatile historical indexes and would thus be expected to have larger forecast errors. Second, individual geographic characteristics are not always fully captured using the interacting dummy variables of the FHFA index forecast model. For example, the significant zoning restrictions and the property tax penalty for sales inherent in Proposition 13 resulted in California house prices increasing faster than expected in the model and thus having a larger NRMSE value.

Because the Case-Shiller model involves mean reversion toward an FHFA home price-

Table 8: Validation Results for U.S. Case-Shiller® Home Price Index Forecast

Forecast period: 2014Q1 to 2017Q1
Observations: 13

	Root Mean Squared Error	Normalized Root Mean Squared Error
In-sample*	4.5907	2.63%
Out-of-sample, ex post*	5.6001	3.01%
Out-of-sample, ex ante**	5.8551	3.35%

*Uses actual historical values for the FHFA purchase-only index regressor.
**Uses forecasted values for the FHFA purchase-only index regressor.

Root mean squared error = Square root of [sum of (forecast values - actual values) squared, divided by number of observations]
Normalized root mean squared error = Root mean squared error divided by mean of actual values

Source: Moody's Analytics

determined Case-Shiller trend value, it tends to offset forecast errors for the FHFA indexes, so that the *ex ante* model validation results are very close to the *ex post* model validation results as shown in Tables 9 and 10. Nonetheless, there were still significant large errors for several geographies. In particular, Washington DC had a NRMSE of approximately 14%, which was much higher than the household-weighted NMRSE of 3% for all U.S. states. The forecast error for DC was high even though the capital has its own regional interaction term in the FHFA model to account for its very tight zoning restrictions. This suggest that other measures may be required to minimize error including squeezing the DC forecast to its corresponding metro area forecast rather than to the U.S. as a whole.

Table 10 shows similar results for the 223 U.S. metro areas with CoreLogic-derived Case-Shiller indexes. Here also, the largest individual NRMSEs are either for small metro areas with a relatively sparse sample of repeat sales in 2014-2017 (e.g. Binghamton NY and Kahului HI) or for metro areas where inflows of financial wealth drove up house prices in upper-tier markets much higher than would be indicated by simply looking at that metro area's economic fundamentals—San Francisco and urban Honolulu being the main examples. Even so, the weighted average NRMSE of the toughest test—the *ex ante* out-of-sample test—is below 6%, indicating that the combined FHFA and Case-Shiller forecast model does relatively well. Another observation is that for a large sample of metro areas, a weighted average NRMSE tends to be better than a simple average, as larger metro areas tend to have less volatile Case-Shiller indexes and therefore tend to have smaller forecast errors.

Calibration

The full structural model that generates the FHFA index forecasts is subsequently calibrated so that the weighted average of state index growth rates and the weighted average of metro index growth rates approximate the U.S. index forecast growth rate. Therefore, there should be much less need to calibrate the Case-Shiller index forecasts, particularly since the U.S., state and metro regressions are very similar. Nevertheless, Moody's Analytics carefully examines both the weighted average of state and metro growth rates, and the distribution of state and metro index forecasts, around the U.S. index growth rates and adjusts the regional forecasts as needed, setting the weighted average of state CSI growth rates equal to the growth rate of the U.S. CSI forecast and setting the weighted average of metro area CSI growth rates equal to the CSI growth rate for their corresponding states. Because calibration has already taken place for the FHFA index forecast drivers, these adjustments to the CSI forecasts are usually minor.

Expanding the scope of the model

Moody's Analytics uses the metro area model obtained after extensive validation and calibration checks to expand the scope of the house price forecasting process to include different levels of geography (states, counties and ZIP codes) and other price measures (condo price indexes and single-family home prices by tier). This section describes the forecast process for these additional price measures.

Census divisions, MSAs with divisions

For larger geographies, the Case-Shiller forecast is obtained through an aggregation process. For Census division Case-Shiller indexes, the forecast is obtained by taking a household-weighted average of the CSI growth rates for each state in the Census division, and then applying that average growth rate to the Census division's CSI history.[12]

Similarly, for metropolitan statistical areas with metro divisions, the CSI forecast is obtained by growing out the index history with a household weighted average growth rate of the CSI forecasts for each metro division within the MSA.

County model

The county Case-Shiller forecast model is a share-down model, based on the long-run relationship between the county price index and the price index for the metro area within which the county resides. If the county is part of a MSA, the share-down is based on the corresponding metro area. However, some counties are not part of any metro area; in this case, the forecast is then based on a share-down from the state forecast.

The forecast equation assumes that there is a close relationship between the county house price and the corresponding state or metro area price. The regression is a pooled cross-section regression with fixed effects:

12 Moody's Analytics has also tried weighted averages based on the single-family housing stock, but these have never given significantly different results. Weighted averages based on single-family home sales have the disadvantage of uneven historical data and a resulting unreliability of forecasts. e.g., National Association of Realtors data on state home sales was discontinued and ends in 2011. CoreLogic data on home sales are more extensive, but there are several smaller metro areas that do not have home sales time series.

Table 9: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, States

Forecast period: 2012Q3 to 2016Q4
States: 36†
Observations: 432

		Normalized Root Mean Squared Errors		
	Household weight, 2010 census	**In-sample***	**Out-of-sample, ex post***	**Out-of-sample, ex ante****
Alabama	0.0197	1.91%	3.59%	3.20%
Arkansas	0.0120	1.28%	2.24%	2.05%
Arizona	0.0249	2.54%	3.70%	3.34%
California	0.1315	5.99%	6.66%	6.78%
Colorado	0.0206	2.11%	4.46%	4.38%
Connecticut	0.0143	2.00%	2.64%	3.07%
District of Columbia	0.0028	7.90%	14.33%	13.07%
Delaware	0.0036	2.54%	2.79%	2.40%
Florida	0.0776	1.93%	3.24%	3.38%
Georgia	0.0375	1.25%	2.26%	2.09%
Hawaii	0.0048	5.89%	5.10%	4.96%
Iowa	0.0128	0.53%	0.23%	0.39%
Illinois	0.0506	1.86%	1.40%	1.53%
Kentucky	0.0180	1.56%	1.55%	1.51%
Louisiana	0.0181	1.50%	2.33%	2.03%
Massachusetts	0.0266	2.86%	2.78%	2.94%
Maryland	0.0226	1.12%	2.77%	2.68%
Michigan	0.0405	4.07%	4.27%	4.45%
Minnesota	0.0218	0.73%	0.68%	0.72%
North Carolina	0.0392	1.76%	3.36%	3.12%
Nebraska	0.0075	0.38%	0.75%	0.58%
New Hampshire	0.0054	2.01%	1.27%	1.39%
New Jersey	0.0336	1.48%	0.73%	0.83%
Nevada	0.0105	3.60%	3.49%	3.47%
New York	0.0765	2.92%	2.85%	3.12%
Ohio	0.0481	1.55%	1.62%	1.80%
Oklahoma	0.0153	2.49%	3.63%	3.46%
Oregon	0.0159	0.87%	1.68%	1.37%
Pennsylvania	0.0525	0.58%	1.09%	1.07%
Rhode Island	0.0043	2.98%	2.42%	2.69%
South Carolina	0.0188	1.55%	1.57%	1.87%
Tennessee	0.0261	0.76%	1.52%	1.37%
Virginia	0.0320	1.80%	2.00%	2.21%
Vermont	0.0027	3.01%	2.10%	2.35%
Washington	0.0274	2.88%	2.10%	2.41%
Wisconsin	0.0238	2.15%	2.89%	3.07%
	Simple avg	**2.29%**	**2.83%**	**2.81%**
	Household-weighted avg	**2.48%**	**2.99%**	**3.04%**

*Uses actual historical values for the FHFA purchase-only index regressor.
**Uses forecasted values for the FHFA purchase-only index regressor.
†States whose Case-Shiller Indexes are infilled with FHFA indexes are not included in validation testing.

Root mean squared error = Square root of [sum of (forecast values - actual values) squared, divided by number of observations]
Normalized root mean squared error = Root mean squared error divided by mean of actual values

Source: Moody's Analytics

Table 10: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, Metro Areas

Forecast period: 2012Q3 to 2016Q4
Metro areas: 216†
Observations: 2,592

	Household weight, 2010 census	Normalized Root Mean Squared Errors In-sample*	Out-of-sample, ex post*	Out-of-sample, ex ante**
Akron OH	0.0038	2.32%	2.92%	3.60%
Albany OR	0.0006	5.29%	5.77%	7.50%
Albany-Schenectady-Troy NY	0.0047	2.85%	4.36%	5.44%
Allentown-Bethlehem-Easton PA-NJ	0.0042	1.94%	0.87%	0.94%
Altoona PA	0.0007	2.28%	2.46%	2.53%
Anaheim-Santa Ana-Irvine CA	0.0131	8.58%	9.94%	11.19%
Ann Arbor MI	0.0018	7.51%	12.04%	14.49%
Asheville NC	0.0024	4.64%	4.88%	5.56%
Athens-Clarke County GA	0.0010	1.78%	1.54%	1.48%
Atlanta-Sandy Springs-Roswell GA	0.0256	3.93%	4.26%	4.59%
Atlantic City-Hammonton NJ	0.0014	4.89%	5.55%	6.01%
Augusta-Richmond County GA-SC	0.0028	2.56%	4.13%	4.26%
Bakersfield CA	0.0034	5.89%	6.21%	7.11%
Baltimore-Columbia-Towson MD	0.0137	1.47%	1.43%	1.39%
Barnstable Town MA	0.0013	3.93%	6.69%	8.20%
Bellingham WA	0.0011	3.62%	4.22%	5.90%
Bend-Redmond OR	0.0008	3.13%	2.01%	2.36%
Binghamton NY	0.0013	13.91%	17.64%	19.45%
Boston MA	0.0096	6.68%	9.36%	11.25%
Boulder CO	0.0016	5.55%	6.64%	8.06%
Bremerton-Silverdale WA	0.0013	5.99%	7.62%	9.37%
Bridgeport-Stamford-Norwalk CT	0.0044	6.95%	12.15%	13.89%
Brunswick GA	0.0006	5.13%	8.67%	10.50%
Buffalo-Cheektowaga-Niagara Falls NY	0.0062	4.27%	5.65%	6.84%
Burlington-South Burlington VT	0.0011	5.69%	6.93%	7.79%
California-Lexington Park MD	0.0005	1.44%	1.85%	2.42%
Cambridge-Newton-Framingham MA	0.0114	5.47%	7.66%	9.11%
Camden NJ	0.0061	2.72%	2.00%	2.26%
Canton-Massillon OH	0.0021	2.25%	3.21%	3.93%
Cape Coral-Fort Myers FL	0.0034	6.69%	7.98%	9.19%
Carbondale-Marion IL	0.0007	3.06%	3.15%	3.32%
Cedar Rapids IA	0.0014	2.34%	5.08%	6.28%
Champaign-Urbana IL	0.0012	1.97%	1.86%	1.81%
Charleston-North Charleston SC	0.0034	1.72%	1.63%	1.98%
Charlotte-Concord-Gastonia NC-SC	0.0112	1.82%	1.50%	2.02%
Charlottesville VA	0.0011	3.44%	5.02%	6.34%
Chattanooga TN-GA	0.0028	0.75%	0.91%	1.21%
Chicago-Naperville-Arlington Heights IL	0.0355	3.83%	3.63%	4.01%
Chico CA	0.0012	3.56%	4.07%	5.40%
Cincinnati OH-KY-IN	0.0109	2.68%	2.29%	2.58%
Clarksville TN-KY	0.0013	1.15%	2.59%	3.18%
Cleveland-Elyria OH	0.0113	2.91%	3.73%	4.32%
Colorado Springs CO	0.0032	0.89%	0.93%	1.07%
Columbia SC	0.0039	1.62%	2.70%	3.28%
Columbus OH	0.0099	3.31%	2.89%	3.38%
Corvallis OR	0.0005	4.02%	5.02%	6.21%
Crestview-Fort Walton Beach-Destin FL	0.0012	8.96%	9.92%	11.24%
Dalton GA	0.0006	3.88%	3.94%	4.56%
Danville IL	0.0004	4.86%	3.49%	3.69%
Davenport-Moline-Rock Island IA-IL	0.0020	2.88%	5.05%	5.93%

Table 10: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, Metro Areas (Cont.)

	Household weight, 2010 census	Normalized Root Mean Squared Errors: In-sample*	Out-of-sample, ex post*	Out-of-sample, ex ante**
Dayton OH	0.0043	1.83%	2.73%	3.51%
Deltona-Daytona Beach-Ormond Beach FL	0.0033	5.18%	3.03%	3.29%
Denver-Aurora-Lakewood CO	0.0132	2.94%	2.58%	2.88%
Des Moines-West Des Moines IA	0.0029	2.93%	3.41%	4.23%
Detroit-Dearborn-Livonia MI	0.0093	11.29%	11.84%	13.86%
Dover DE	0.0008	3.67%	3.99%	4.69%
Duluth MN-WI	0.0015	7.02%	10.00%	11.67%
Durham-Chapel Hill NC	0.0027	2.27%	2.84%	2.76%
Dutchess County-Putnam County NY	0.0019	1.96%	1.76%	2.58%
Eau Claire WI	0.0008	1.91%	1.50%	1.70%
El Centro CA	0.0006	3.70%	3.44%	3.85%
Elgin IL	0.0028	3.44%	2.90%	3.67%
Elmira NY	0.0005	2.04%	4.37%	5.48%
Erie PA	0.0015	1.34%	2.23%	2.43%
Eugene OR	0.0019	3.98%	4.14%	5.43%
Fayetteville NC	0.0018	4.29%	4.79%	5.31%
Fayetteville-Springdale-Rogers AR-MO	0.0023	0.90%	0.84%	0.81%
Flagstaff AZ	0.0006	3.30%	3.48%	4.08%
Florence SC	0.0010	1.33%	1.20%	1.16%
Fort Collins CO	0.0016	3.36%	4.42%	5.58%
Fort Lauderdale-Pompano Beach-Deerfield Beach FL	0.0090	6.92%	6.91%	7.55%
Fort Smith AR-OK	0.0014	1.51%	1.08%	1.11%
Fresno CA	0.0038	8.29%	9.31%	10.67%
Gainesville FL	0.0014	7.19%	6.66%	7.94%
Gainesville GA	0.0008	6.64%	7.71%	9.10%
Glens Falls NY	0.0007	5.51%	7.26%	8.34%
Grand Junction CO	0.0008	2.02%	3.18%	4.14%
Greeley CO	0.0012	7.88%	10.57%	12.22%
Green Bay WI	0.0016	3.08%	3.55%	4.42%
Greensboro-High Point NC	0.0038	0.67%	1.47%	1.67%
Greenville-Anderson-Mauldin SC	0.0042	1.14%	3.05%	3.68%
Hanford-Corcoran CA	0.0005	3.13%	3.67%	4.73%
Harrisburg-Carlisle PA	0.0029	1.26%	1.25%	1.28%
Hartford-West Hartford-East Hartford CT	0.0062	0.83%	0.91%	1.09%
Hilton Head Island-Bluffton-Beaufort SC	0.0010	5.52%	6.22%	8.28%
Homosassa Springs FL	0.0008	6.31%	6.19%	6.91%
Hot Springs AR	0.0005	2.82%	5.24%	5.37%
Ithaca NY	0.0005	5.07%	7.88%	9.11%
Jackson TN	0.0007	1.41%	1.01%	1.28%
Jacksonville FL	0.0069	2.43%	1.97%	2.63%
Johnson City TN	0.0011	1.99%	2.86%	3.23%
Kahului-Wailuku-Lahaina HI	0.0007	12.92%	17.36%	19.54%
Kennewick-Richland WA	0.0012	2.55%	5.67%	7.33%
Kingsport-Bristol-Bristol TN-VA	0.0017	0.92%	0.94%	1.28%
Kingston NY	0.0009	8.10%	8.69%	10.07%
Knoxville TN	0.0045	0.75%	0.77%	1.25%
Lake County-Kenosha County IL-WI	0.0040	3.78%	3.64%	3.79%
Lake Havasu City-Kingman AZ	0.0011	3.67%	5.67%	6.93%
Lakeland-Winter Haven FL	0.0030	4.13%	2.76%	3.32%
Lancaster PA	0.0025	2.82%	2.52%	2.81%
Lansing-East Lansing MI	0.0024	9.11%	14.52%	17.06%
Las Vegas-Henderson-Paradise NV	0.0094	8.94%	9.35%	10.28%
Lawton OK	0.0006	2.94%	2.32%	2.08%

Table 10: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, Metro Areas (Cont.)

	Household weight, 2010 census	Normalized Root Mean Squared Errors In-sample*	Out-of-sample, ex post*	Out-of-sample, ex ante**
Lima OH	0.0005	2.13%	2.21%	3.51%
Little Rock-North Little Rock-Conway AR	0.0037	0.92%	2.68%	3.25%
Longview WA	0.0005	4.89%	6.71%	8.92%
Los Angeles-Long Beach-Glendale CA	0.0427	11.48%	14.56%	16.93%
Louisville/Jefferson County KY-IN	0.0065	4.54%	5.57%	6.64%
Macon GA	0.0012	3.29%	3.47%	4.13%
Madera CA	0.0006	4.26%	3.45%	4.63%
Madison WI	0.0033	3.41%	5.74%	7.10%
Manchester-Nashua NH	0.0020	4.19%	5.70%	7.00%
Mankato-North Mankato MN	0.0005	2.15%	3.69%	4.80%
Mansfield OH	0.0006	5.97%	7.06%	8.56%
Medford OR	0.0011	4.41%	4.89%	6.18%
Memphis TN-MS-AR	0.0065	0.74%	0.82%	0.75%
Merced CA	0.0010	9.80%	9.42%	10.63%
Miami-Miami Beach-Kendall FL	0.0114	10.93%	10.99%	12.20%
Milwaukee-Waukesha-West Allis WI	0.0082	2.20%	1.58%	2.09%
Minneapolis-St. Paul-Bloomington MN-WI	0.0171	1.91%	1.52%	1.76%
Modesto CA	0.0022	12.42%	12.79%	14.92%
Monroe MI	0.0008	3.53%	5.89%	7.24%
Montgomery County-Bucks County-Chester County PA	0.0095	2.20%	1.71%	1.93%
Mount Vernon-Anacortes WA	0.0006	6.82%	7.19%	9.01%
Myrtle Beach-Conway-North Myrtle Beach SC-NC	0.0021	4.12%	2.28%	2.51%
Napa CA	0.0006	10.34%	11.42%	13.24%
Naples-Immokalee-Marco Island FL	0.0018	5.35%	8.32%	9.38%
Nashville-Davidson--Murfreesboro--Franklin TN	0.0085	1.16%	0.82%	0.93%
Nassau County-Suffolk County NY	0.0125	6.30%	7.74%	9.11%
New Bern NC	0.0007	1.91%	1.66%	1.29%
New Haven-Milford CT	0.0044	3.59%	4.30%	5.14%
New Orleans-Metairie LA	0.0061	1.44%	4.91%	6.00%
New York-Jersey City-White Plains NY-NJ	0.0680	3.16%	2.64%	3.25%
Newark NJ-PA	0.0118	3.29%	3.72%	4.53%
North Port-Sarasota-Bradenton FL	0.0041	2.81%	2.17%	2.72%
Norwich-New London CT	0.0014	5.39%	6.70%	7.85%
Oakland-Hayward-Berkeley CA	0.0121	8.67%	9.62%	11.14%
Ocala FL	0.0018	9.22%	8.73%	8.88%
Ocean City NJ	0.0005	6.83%	10.83%	13.70%
Oklahoma City OK	0.0064	1.39%	2.63%	3.65%
Olympia-Tumwater WA	0.0013	5.21%	4.47%	5.17%
Omaha-Council Bluffs NE-IA	0.0044	2.25%	3.03%	3.87%
Orlando-Kissimmee-Sanford FL	0.0105	3.55%	2.24%	2.58%
Oxnard-Thousand Oaks-Ventura CA	0.0035	7.16%	8.06%	9.20%
Palm Bay-Melbourne-Titusville FL	0.0030	6.22%	6.39%	7.32%
Panama City FL	0.0010	5.35%	5.08%	6.09%
Pensacola-Ferry Pass-Brent FL	0.0023	4.62%	4.09%	4.67%
Peoria IL	0.0020	1.05%	1.73%	1.79%
Philadelphia PA	0.0106	2.11%	1.84%	1.90%
Phoenix-Mesa-Scottsdale AZ	0.0202	2.68%	2.39%	2.22%
Pittsburgh PA	0.0132	2.10%	1.88%	2.09%
Pittsfield MA	0.0007	7.09%	8.07%	8.71%
Port St. Lucie FL	0.0023	1.49%	2.57%	3.34%
Portland-Vancouver-Hillsboro OR-WA	0.0114	4.30%	2.40%	3.00%
Prescott AZ	0.0012	4.38%	5.28%	6.22%
Providence-Warwick RI-MA	0.0082	3.34%	3.54%	4.49%

Table 10: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, Metro Areas (Cont.)

	Household weight, 2010 census	Normalized Root Mean Squared Errors In-sample*	Out-of-sample, ex post*	Out-of-sample, ex ante**
Pueblo CO	0.0008	5.16%	7.63%	9.50%
Punta Gorda FL	0.0010	3.58%	3.58%	4.63%
Raleigh NC	0.0057	0.99%	3.26%	4.26%
Reading PA	0.0020	3.50%	4.84%	5.98%
Redding CA	0.0009	4.44%	6.02%	7.46%
Reno NV	0.0022	8.82%	9.88%	11.09%
Richmond VA	0.0062	0.82%	1.07%	1.21%
Riverside-San Bernardino-Ontario CA	0.0171	8.76%	8.91%	9.84%
Roanoke VA	0.0017	3.13%	3.00%	3.35%
Rochester MN	0.0011	2.49%	2.62%	3.10%
Rochester NY	0.0057	2.35%	2.91%	3.63%
Rockford IL	0.0018	5.64%	6.48%	7.64%
Rockingham County-Strafford County NH	0.0021	4.84%	4.43%	5.16%
Rome GA	0.0005	1.94%	2.67%	3.34%
Sacramento--Roseville--Arden-Arcade CA	0.0104	8.71%	9.01%	10.41%
Salem OR	0.0019	4.93%	4.42%	6.30%
Salinas CA	0.0017	8.73%	12.19%	14.67%
Salisbury MD-DE	0.0019	1.72%	1.28%	1.49%
San Diego-Carlsbad CA	0.0143	9.06%	10.49%	12.01%
San Francisco-Redwood City-South San Francisco CA	0.0079	11.57%	15.95%	18.38%
San Jose-Sunnyvale-Santa Clara CA	0.0082	10.77%	13.94%	16.33%
San Luis Obispo-Paso Robles-Arroyo Grande CA	0.0013	9.34%	11.32%	13.23%
San Rafael CA	0.0014	10.25%	13.77%	16.10%
Santa Cruz-Watsonville CA	0.0012	10.03%	12.66%	14.57%
Santa Maria-Santa Barbara CA	0.0019	11.24%	15.46%	18.31%
Santa Rosa CA	0.0024	9.70%	10.16%	11.94%
Savannah GA	0.0017	1.05%	1.33%	1.63%
Seattle-Bellevue-Everett WA	0.0139	6.33%	7.26%	8.88%
Sebastian-Vero Beach FL	0.0008	4.46%	5.26%	6.20%
Sebring FL	0.0006	7.49%	6.99%	7.82%
Shreveport-Bossier City LA	0.0023	1.01%	1.71%	1.86%
Sierra Vista-Douglas AZ	0.0007	3.44%	4.02%	5.07%
Silver Spring-Frederick-Rockville MD	0.0058	2.18%	2.41%	2.65%
Spokane-Spokane Valley WA	0.0028	5.05%	6.26%	7.53%
Springfield IL	0.0012	1.81%	3.25%	3.97%
Springfield MA	0.0031	2.94%	4.09%	5.32%
Springfield OH	0.0007	3.51%	5.60%	6.83%
St. Cloud MN	0.0009	4.57%	7.11%	8.83%
St. Louis MO-IL	0.0146	3.65%	3.73%	4.25%
Stockton-Lodi CA	0.0028	12.69%	12.76%	14.62%
Syracuse NY	0.0034	2.36%	3.68%	4.62%
Tacoma-Lakewood WA	0.0039	7.85%	7.54%	8.45%
Tallahassee FL	0.0019	6.25%	7.10%	8.04%
Tampa-St. Petersburg-Clearwater FL	0.0152	2.55%	2.78%	3.94%
The Villages FL	0.0005	5.28%	6.92%	8.60%
Toledo OH	0.0032	2.86%	3.82%	4.33%
Trenton NJ	0.0018	4.31%	7.16%	8.65%
Tucson AZ	0.0051	3.82%	3.23%	3.38%
Tulsa OK	0.0048	1.61%	1.46%	1.43%
Urban Honolulu HI	0.0041	7.14%	10.14%	12.30%
Utica-Rome NY	0.0016	2.46%	4.72%	5.51%
Valdosta GA	0.0007	3.63%	4.05%	4.11%
Vallejo-Fairfield CA	0.0019	11.73%	11.60%	12.30%

Table 10: Validation Results for Case-Shiller® Home Price Index Forecast Adjustment Equation, Metro Areas (Cont.)

		Normalized Root Mean Squared Errors		
	Household weight, 2010 census	In-sample*	Out-of-sample, ex post*	Out-of-sample, ex ante**
Vineland-Bridgeton NJ	0.0007	2.53%	2.64%	2.74%
Visalia-Porterville CA	0.0017	8.73%	9.71%	11.48%
Warner Robins GA	0.0009	1.26%	2.06%	2.83%
Warren-Troy-Farmington Hills MI	0.0129	5.04%	6.79%	8.09%
Washington-Arlington-Alexandria DC-VA-MD-WV	0.0217	1.38%	1.47%	1.57%
West Palm Beach-Boca Raton-Delray Beach FL	0.0072	2.16%	2.76%	3.76%
Wilmington DE-MD-NJ	0.0035	1.22%	1.31%	1.42%
Wilmington NC	0.0014	3.35%	3.23%	3.51%
Winston-Salem NC	0.0034	2.03%	2.34%	2.20%
Worcester MA-CT	0.0046	4.93%	5.22%	6.12%
York-Hanover PA	0.0022	3.50%	3.59%	4.42%
Youngstown-Warren-Boardman OH-PA	0.0030	1.31%	1.56%	1.85%
Yuba City CA	0.0007	12.19%	12.09%	13.89%
Yuma AZ	0.0009	5.53%	7.43%	8.51%
Simple avg		4.44%	5.24%	6.16%
Household-weighted avg		4.56%	5.14%	5.98%

*Uses actual historical values for the FHFA all-transactions index regressor.
**Uses forecasted values for the FHFA all-transactions index regressor.
†Metro areas whose Case-Shiller Indexes are infilled with FHFA indexes are not included in validation testing

Root mean squared error = Square root of [sum of (forecast values - actual values) squared, divided by number of observations]
Normalized root mean squared error = Root mean squared error divided by mean of actual values

Source: Moody's Analytics

$$\Delta \log(CSI_{ct}) = \beta_0 + \beta_{ct} + \beta_1 \Delta \log(CSI_{msa}) + \beta_2\left(\log(CSI_{ct,t-4}) - \log(CSI_{msa,t-4})\right) + \beta_3 \Delta \log(Y_{rat})$$

where CSI_{ct} is the county house price index and CSI_{msa} is the CSI house price forecast of the corresponding metro area; β_{ct} is a coefficient that varies by county, β_0 is a constant term, and β_1, β_2, and β_3 are regression coefficients. Finally, Y_{rat} is the ratio of county to metro area median household income.

The most important explanatory variable in the house price equation is the county share-down of the corresponding state or metro area CSI. On average, a 1% increase in the metro area (or state) house price leads to a proportional increase in county house prices (see Table 11).[13]

To keep county CSI forecasts in line with their larger state or metro area CSI forecasts, a variable is added to reduce county price growth in excess of the metro area. Theoretically, if housing is much more expensive in one county than another in the same metro area, new homebuyers will favor the cheaper county, all else being equal. Therefore, in the long run, prices among counties within a metro area should converge. A variable has been added that will help support this convergence; on average, counties where prices are 1% above the metro area in the previous year will see prices fall around 0.1 percentage point in their CSI forecast.

The model also includes the county to metro area median household income ratio. Specifically, the model incorporates median household income in excess of the metro area. On average, for every 1% increase in income growth relative to the metro area, house prices will rise 0.01 percentage point. Median household income seems to be the only wedge driver between metro area and county house price indexes that has any perceptible effect; the much more dispersed data for per capita disposable income, when used in the regression, had a coefficient that was also close to zero and was much less statistically significant.

ZIP code model

Analogous to the county model, the ZIP code house price model forecast is based on the long-run relationship between the price index for the ZIP code and the price index for the county within which it resides. Because of a dearth of reliable, accurate and timely data at the ZIP code level, only one independent variable is used in these equations: the house price index in the county in which the ZIP code lies. In the situation where historical ZIP code house price data exist but the county's do not, the

13 The regression sample is limited to 427 counties with independent Case-Shiller data. There are a further 77 counties that use infilled FHFA indexes and are not included in the pooled regression.

Table 11: Case-Shiller® Home Price Index, Forecast Equation for Counties

Dependent Variable: DLOG(Case-Shiller® Home Price Index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1971Q1 2015Q4
Included observations: 185 after adjustments
Cross-sections included: 427
Total pool (unbalanced) observations: 69535
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.0001	0.0000	-14.2623	0.0000
DLOG(Case-Shiller metro area index)	0.9986	0.0003	3314.3510	0.0000
LOG(Case-Shiller county index lagged 4 qtr) - LOG(Case-Shiller metro area index lagged 4 qtr)	-0.0108	0.0007	-14.6283	0.0000
DLOG ratio of county to metro area median income, 4-qtr MA	0.0066	0.0030	2.1888	0.0286
	Weighted Statistics			
R-squared	0.9941	Mean dependent var		0.0365
Adjusted R-squared	0.9940	S.D. dependent var		0.1189
S.E. of regression	0.0086	Sum squared resid		4.9388
F-statistic	26129.76	Durbin-Watson stat		2.2709
Prob(F-statistic)	0.0000			
	Unweighted Statistics			
R-squared	0.8126	Mean dependent var		0.0106
Sum squared resid	6.5186	Durbin-Watson stat		1.9619

Fixed effects coefficients available on request.

Source: Moody's Analytics

metro area forecast is used. If the ZIP code in question is outside of a metro area, the state CSI forecast is used.

The ZIP code forecast model is a two-stage model. In the first step, an equilibrium equation is established. The equilibrium equation assumes there is a close relationship between the ZIP code house price and county price levels over the long term. The regression is a pooled regression with fixed effects:

$$\log(CSI_{zip}) = \beta_0 + \beta_{zip} + \beta_1 \log(CSI_{ct})$$

where CSI_{zip} is the ZIP code house price index and CSI_{ct} is the Case-Shiller house price forecast of the corresponding county; β_0 is a constant term that varies by broad geographical region as described below, β_{zip} is a coefficient that varies by ZIP code, and β_1 is a regression coefficient.

In the second stage, an adjustment equation is established. The basis for the adjustment equation is that growth rates in the ZIP code will mimic that in the corresponding county. Like the equilibrium equation, the regression is a pool cross-sectional regression with fixed effects:

$$\Delta\log(CSI_{zip}) = \beta_0 + \beta_{zip} + \beta_1 \Delta\log(CSI_{ct}) + \beta_2(\log(CSI_{ct,t-4}) - \log(CSI_{zip,t-4}))$$

with similar notation, and the addition of β_2 as the coefficient of the mean reversion term, which is also lagged four quarters. In the final step, the forecast from the adjustment equation reverts to the forecast from the equilibrium equation through a mean reversion process.[14]

Fourteen pools have been constructed across the 6,202 ZIP code areas included in the estimation. The pools are based on geography, with separate pools for each Census division. The East North Central division is further broken down into eastern (Ohio, Indiana and parts of Michigan) and western (Illinois, Wisconsin, and most of Michigan) pools. Further, there are separate pools for Florida, New York and California, which is also broken down into northern and southern halves. The classification of the regions is based on the idea that these areas share long-run trends of demographics and economic composition. The pooling creates a large number of observations to allow for greater localization of the variables included in the estimation, although the pools vary by size. The large number of observations also improves the accuracy of the model estimation. Tables 12A and 12B show the regression results for all 14 pools. The results in Table 12A are singularly uniform: the higher the county house price, the higher the ZIP code house price, with the coefficient varying between 0.99 and 1.04. Also, the large number of observations and the use of fixed effects almost guarantee that the fit of each pooled regression will be close to one. This relative uniformity occurs despite the uneven distribution of ZIP codes in the historical data, with the Great Plains states in particular being underrepresented because of nondisclosure laws.

14 This reversion has to be programmed in manually to affect all ZIP codes, as otherwise it is almost unavoidable that a few ZIP codes will have second equation fitted values that diverge from the fitted values of the first equation, especially for the West South Central division pool, where the estimated reversion coefficient is negative.

Table 12A: Case-Shiller® Home Price Index, Equilibrium Equation for ZIP Codes

Dependent variable: LOG(ZIP code Case-Shiller index) Pool	Regressor	Coefficient	Std. error	t-statistic	Prob.	Adj. R squared	Cross-Sections†
New England Census division	LOG(county Case-Shiller index)	1.0031	0.0002	5993.0060	0.0000	0.9974	555
New York state	LOG(county Case-Shiller index)	1.0069	0.0002	6627.0590	0.0000	0.9983	437
New Jersey, Pennsylvania	LOG(county Case-Shiller index)	1.0130	0.0002	5542.5350	0.0000	0.9959	762
South Atlantic Census division, except Florida	LOG(county Case-Shiller index)	1.0158	0.0002	5789.8340	0.0000	0.9961	804
Florida	LOG(county Case-Shiller index)	1.0197	0.0003	3219.9780	0.0000	0.9894	669
East North Central Census division, eastern half	LOG(county Case-Shiller index)	1.0246	0.0003	3011.5860	0.0000	0.9927	401
East North Central Census division, western half	LOG(county Case-Shiller index)	0.9992	0.0002	4194.7670	0.0000	0.9963	402
East South Central Census division	LOG(county Case-Shiller index)	1.0320	0.0005	2230.7730	0.0000	0.9958	126
West North Central Census division	LOG(county Case-Shiller index)	1.0214	0.0004	2716.5350	0.0000	0.9961	170
West South Central Census division	LOG(county Case-Shiller index)	1.0430	0.0006	1861.7540	0.0000	0.9926	156
Mountain Census division	LOG(county Case-Shiller index)	1.0175	0.0003	3794.2930	0.0000	0.9952	423
Southern California	LOG(county Case-Shiller index)	1.0108	0.0003	3361.0700	0.0000	0.9933	454
Northern California	LOG(county Case-Shiller index)	1.0086	0.0002	4444.5480	0.0000	0.9962	454
Pacific Census division, except California	LOG(county Case-Shiller index)	1.0163	0.0002	4313.5000	0.0000	0.9965	389
						Total ZIP codes	**6,202**

Constant terms and fixed effects coefficient are available on request.
†Each ZIP code has 169 observations between 1975Q1 and 2017Q1

Source: Moody's Analytics

Table 12B shows the result of the adjustment equation regressions. The faster the county house price has been rising relative to the ZIP code house price, the faster the ZIP code house price will appreciate. This is confirmed with the results, with all pools having coefficients for the county index driver of between 0.77 and 0.93. In addition, the error-correction term is positive in all but one of the regressions and points to gradual reversion of the ZIP code to the county indexes of between 0.5% and 3% per quarter, depending on the region.

Condo and price tier models

Separate models are also developed for forecasting house prices of condominiums and tiers. The forecast equation assumes that condo and single-family tier prices within a metro area would move in sync with the broader housing market of the metro area.[15] Since these price indices represent specific segments of a metro area's housing market, and the metro area aggregate single-family house price is a good indicator of the larger market, the metro area aggregate price index is a main driver of the condo and tier forecast models. Other variables are also included to explain deviations in the index's growth path relative to the aggregate index.

The condo regression is a pooled cross-section regression with fixed effects:

$$\log(CSI_{co}) = \beta_0 + \beta_{co} + \beta_1 \log(CSI_{msa}) + \beta_2 \Delta\log(UC_{msa})$$

where CSIco is the condo house price index and CSImsa is the aggregate Case-Shiller house price for the corresponding metro area; βco is a coefficient that varies by county, β0 is a constant term, β1 and β2 are the other regression coefficients. UCmsa is the after-tax user cost of owning a home in a metro area, calculated as a tax-adjusted effective composite mortgage rate minus the rate of core inflation. The rationale for including user costs is that condo prices are usually lower than single-family home prices and are therefore more in demand by younger households with fewer members; as a result, changes in the user cost of capital might make more of a difference in the decision to purchase a condo than in the decision to purchase a single-family home.

Tables 13 and 14 present the regression results for state and metro area condo indexes.[16] The most important explanatory variable in the condo house price equation is the metro area's Case-Shiller house price index. On average, a 1% increase in the metro forecast leads to an approximately 0.88-percentage point increase in condo house prices. The user cost of owning a home—which takes into account institutional variables such as property taxes, mortgage rates, and maintenance and obsolescence—is of the right sign and is economically significant, being retained in the model even though it did not make statistical significance at the 5% confidence level.

In forecasting the house price tier indices, Moody's Analytics assumes that tiers prices within a metro area would move in sync with the broader housing market of the

15 With new data available from CoreLogic, the Case-Shiller indexes have recently expanded condo index coverage to states, and tier index coverage to states, Census divisions, and counties. Regardless of geographical coverage, the same pooled regression specifications are used. For simplicity, the following discussion assumes that only metro area indexes are being considered.

16 The metro area pool of condo indexes includes metro divisions and a few metro areas with divisions, as a result of the incomplete metro division coverage for condo indexes. Some metro areas with divisions have full condo index coverage, but a few like Detroit have condo indexes for only one or two of their metro divisions

Table 12B: Case-Shiller® Home Price Index, Adjustment Equation for ZIP Codes

Dependent variable: DLOG ZIP code Case-Shiller index Pool	Regressor	Coefficient	Std. error	t-statistic	Prob.	Adj. R squared	Cross-Sections†
	DLOG(county Case-Shiller index)	0.8845	0.0015	597.8592	0.0000		
New England Census division	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0118	0.0007	17.1390	0.0000	0.7980	555
	DLOG(county Case-Shiller index)	0.8416	0.0019	451.1230	0.0000		
New York state	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0145	0.0009	15.5917	0.0000	0.7449	437
	DLOG(county Case-Shiller index)	0.7981	0.0016	487.9899	0.0000		
New Jersey, Pennsylvania	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0204	0.0006	35.8251	0.0000	0.6630	762
	DLOG(county Case-Shiller index)	0.8408	0.0014	585.9599	0.0000		
South Atlantic Census division, except Florida	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0101	0.0004	24.3192	0.0000	0.7263	804
	DLOG(county Case-Shiller index)	0.8493	0.0017	513.9865	0.0000		
Florida	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0135	0.0005	27.8035	0.0000	0.7087	669
	DLOG(county Case-Shiller index)	0.7674	0.0025	311.7041	0.0000		
East North Central Census division, eastern half	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0055	0.0006	9.7358	0.0000	0.5990	401
	DLOG(county Case-Shiller index)	0.9015	0.0018	505.0293	0.0000		
East North Central Census division, western half	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0078	0.0007	11.2024	0.0000	0.7944	402
	DLOG(county Case-Shiller index)	0.8310	0.0038	217.7766	0.0000		
East South Central Census division	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0018	0.0009	2.0541	0.0400	0.6986	126
	DLOG(county Case-Shiller index)	0.8066	0.0033	247.3611	0.0000		
West North Central Census division	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0064	0.0009	6.9247	0.0000	0.6886	170
	DLOG(county Case-Shiller index)	0.9317	0.0026	358.9852	0.0000		
West South Central Census division	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	-0.0012	0.0008	-1.4625	0.1436	0.8343	156
	DLOG(county Case-Shiller index)	0.9064	0.0016	574.9015	0.0000		
Mountain Census division	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0126	0.0006	20.8612	0.0000	0.8276	423
	DLOG(county Case-Shiller index)	0.9172	0.0017	537.2333	0.0000		
Southern California	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0283	0.0006	45.9582	0.0000	0.7992	454
	DLOG(county Case-Shiller index)	0.8764	0.0015	567.3284	0.0000		
Northern California	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0257	0.0007	37.0692	0.0000	0.8149	454
	DLOG(county Case-Shiller index)	0.9032	0.0017	534.7627	0.0000		
Pacific Census division, except California	LOG(county Case-Shiller index, lagged four qtr) - LOG(ZIP code Case-Shiller index, lagged four qtr)	0.0083	0.0005	15.5830	0.0000	0.8192	389
						Total ZIP codes	**6,202**

Constant terms and fixed effects coefficient are available on request

†Each ZIP code has 165 observations between 1976Q1 and 2017Q1

Source: Moody's Analytics

Table 13: Case-Shiller® Condo Price Index Forecast Equation for States

Dependent Variable: DLOG(Case-Shiller Condo Index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1973Q1 2017Q1
Included observations: 177 after adjustments
Cross-sections included: 26*
Total pool (unbalanced) observations: 3606
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.0004	0.0009	0.4628	0.6435
DLOG(Case-Shiller single-family home price index)	0.9634	0.0127	75.6150	0.0000
LOG(Case-Shiller condo index, lagged 1 qtr) - LOG(Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0116	0.0023	-4.9704	0.0000
LOG(User cost of capital)	-0.0144	0.0130	-1.1059	0.2688

*States without condo indexes are not included in the regression.

	Weighted Statistics		
R-squared	0.6142	Mean dependent var	0.0107
Adjusted R-squared	0.6138	S.D. dependent var	0.0277
S.E. of regression	0.0172	Sum squared resid	1.0650
F-statistic	1911.1840	Durbin-Watson stat	1.9949
Prob(F-statistic)	0.00		

	Unweighted Statistics		
R-squared	0.4355	Mean dependent var	0.0090
Sum squared resid	1.1832	Durbin-Watson stat	1.9566

Source: Moody's Analytics

Table 14: Case-Shiller® Condo Price Index Forecast Equation for Metro Areas

Dependent Variable: DLOG(Case-Shiller condo index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1973Q1 2017Q1
Included observations: 177 after adjustments
Cross-sections included: 83*
Total pool (unbalanced) observations: 12,201
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.00101	0.000609	1.657696	0.0974
DLOG(Case-Shiller single-family home price index)	0.8821	0.0072	122.6917	0.0000
LOG(Case-Shiller condo index, lagged 1 qtr) - LOG(Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0097	0.0014	-6.8905	0.0000
User cost of capital	-0.0139	0.0084	-1.6421	0.1006

*Metro areas without condo indexes are not included in the regression.

	Weighted Statistics		
R-squared	0.5533	Mean dependent var	0.0103
Adjusted R-squared	0.5532	S.D. dependent var	0.0289
S.E. of regression	0.0193	Sum squared resid	4.5557
F-statistic	5035.31	Durbin-Watson stat	1.9877
Prob(F-statistic)	0		

	Unweighted Statistics		
R-squared	0.4817	Mean dependent var	0.0093
Sum squared resid	4.6579	Durbin-Watson stat	2.0056

Source: Moody's Analytics

metro area, with modifiers included that can explain any deviations from the market average. Therefore, the tier indices are forecast using the following pooled cross-section regression with fixed effects:

$$\Delta\log(CSI_{low}) = \beta_0 + \beta_1\Delta\log(CSI_{msa}) + \beta_2(\log(CSI_{low}) - \log(CSI_{msa})) + \beta_3\Delta(U_{msa})$$

$$\Delta\log(CSI_{med}) = \beta_0 + \beta_1\Delta\log(CSI_{msa}) + \beta_2(\log(CSI_{med}) - \log(CSI_{msa}))$$

$$\Delta\log(CSI_{high}) = \beta_0 + \beta_1\Delta\log(CSI_{msa}) + \beta_2\left(\log(CSI_{high}) - \log(CSI_{msa})\right) + \beta_3\Delta\log\left(\frac{SP_{t-1}}{SP}\right) + \beta_4\Delta\log(Y_{dis})$$

CSI_{msa} is the aggregate price in a metro area and CSI_{low}, CSI_{med} and CSI_{high} refer to indices for the low tier, medium tier and high tier, respectively; β_0 is a constant term, β_1, β_2 and β_3 are regression coefficients. SP is the Standard and Poor's 500 stock market index and U_{msa} is the difference between the current unemployment rate and its 12-month moving average for the metro area, and Y_{dis} is the ratio of average to median household income, used to proxy income distribution in the metro area. Tables 15A, 15B and 15C present the regression results for metro area indexes.

The main explanatory variable is the metro area house price. To keep metro area forecasts in line with their constituent county forecasts, a mean reversion variable is added to reduce price growth in a certain tier in excess of the overall price growth in a metro area. Thus, for example, if housing is much more expensive in the high tier in the same metro area, new homebuyers will favor the medium tier, all else being equal. Therefore, in the long run, tier price indexes among tiers within a metro area should converge (though the underlying dollar prices will not converge). A variable has been added that will help support this convergence. When a low tier or high tier price index is 1% above the metro area aggregate index, the tier index will fall by between 0.04 and 0.16 percentage point. The coefficient on the convergence term is higher for the mid-tier index; a 1% excess above the aggregate index will cause house prices to fall by about 0.19 percentage points. The higher sensitivity of the mid-tier price index to the aggregate index reflects the fact that the mid-tier index tracks the aggregate index more closely than the low and high tiers.

The model for low tiers includes an additional explanatory variable, the current unemployment rate minus its 12-month moving average. The unemployment rate is relevant since the buyers of lower-cost homes tend to have lower incomes and are thus more sensitive to the local business cycle and job prospects than higher-income households.

By contrast, a better explanatory variable in the high-tier index regression equation is the ratio of average household income to median household income. The higher this ratio, the greater the concentration of income among high-earning households and the greater the demand for more expensive homes. A 1% increase in this share will cause the high-tier house price index to increase by about 0.14 of a percentage point. Wealth, as proxied by the S&P 500 stock market index, has a smaller but still perceptible effect on the price of high-tier homes.

Table 15A: Case-Shiller Low-Tier Index, Forecast Equation for Metro Areas

Dependent Variable: DLOG(Case-Shiller low tier index)
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1979Q4 2017Q1
Included observations: 150 after adjustments
Cross-sections included: 100
Total pool (unbalanced) observations: 9,456
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.0014	0.0002	6.5252	0.0000
DLOG(Case-Shiller aggregate index)	1.1373	0.0088	129.8101	0.0000
LOG(Case-Shiller low tier index, lagged 1 qtr) - LOG(Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0157	0.0021	-7.4841	0.0000
LOG(current unemployment rate, 8-qtr MA) - LOG(unemployment rate, lagged 8 qtrs, 8-qtr MA)	-0.0069	0.0006	-10.9714	0.0000
	Weighted Statistics			
R-squared	0.6823	Mean dependent var		0.0129
Adjusted R-squared	0.6822	S.D. dependent var		0.0357
S.E. of regression	0.0200	Sum squared resid		3.7768
F-statistic	6767.40	Durbin-Watson stat		2.1542
Prob(F-statistic)	0			
	Unweighted Statistics			
R-squared	0.6587	Mean dependent var		0.0113
Sum squared resid	3.7849	Durbin-Watson stat		2.1347

Source: Moody's Analytics

Table 15B: Case-Shiller Middle-Tier Index, Forecast Equation for Metro Areas

Dependent Variable: DLOG Case-Shiller middle tier index
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1971Q1 2017Q1
Included observations: 185 after adjustments
Cross-sections included: 100
Total pool (unbalanced) observations: 17,496
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.0003	0.0001	4.5990	0.0000
DLOG Case-Shiller aggregate index	0.9854	0.0026	380.6161	0.0000
(LOG Case-Shiller middle tier index, lagged 1 qtr - LOG Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0192	0.0018	-10.7028	0.0000

	Weighted Statistics		
R-squared	0.8924	Mean dependent var	0.0145
Adjusted R-squared	0.8923	S.D. dependent var	0.0283
S.E. of regression	0.0092	Sum squared resid	1.4772
F-statistic	72507.09	Durbin-Watson stat	2.5569
Prob(F-statistic)	0		

	Unweighted Statistics		
R-squared	0.8623	Mean dependent var	0.0125
Sum squared resid	1.4810	Durbin-Watson stat	2.6073

Source: Moody's Analytics

Table 15C: Case-Shiller High-Tier Index, Forecast Equation for Metro Areas

Dependent Variable: DLOG Case-Shiller high-tier index
Method: Pooled EGLS (Cross-section weights)
Sample (adjusted): 1971Q1 2017Q1
Included observations: 185 after adjustments
Cross-sections included: 100
Total pool (unbalanced) observations: 16,902
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.0003	0.0001	-5.2014	0.0000
DLOG Case-Shiller aggregate index	0.9622	0.0021	462.8236	0.0000
(LOG Case-Shiller high tier index, lagged 1 qtr - LOG Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA			-0.0037	0.0012
-3.0826	0.0021			
LOG S&P 500 index, lagged 1 qtr - LOG S&P 500 index, lagged 5 qtrs	0.0023	0.0003	8.3399	0.0000
DLOG ratio of average to median household income	0.0143	0.0036	3.9948	0.0001

	Weighted Statistics		
R-squared	0.9290	Mean dependent var	0.0129
Adjusted R-squared	0.9290	S.D. dependent var	0.0262
S.E. of regression	0.0070	Sum squared resid	0.8236
F-statistic	55281.21	Durbin-Watson stat	2.2653
Prob(F-statistic)	0		

	Unweighted Statistics		
R-squared	0.9130	Mean dependent var	0.0114
Sum squared resid	0.8241	Durbin-Watson stat	2.3346

Source: Moody's Analytics

About the Author

Andres Carbacho-Burgos is an economist at the West Chester office of Moody's Analytics. He covers the U.S. housing market, residential construction, and U.S. regional economies. Before joining Moody's Analytics, he taught economics at Texas State University, where he also researched open-economy macroeconomics and income inequality. Born in Chile, he obtained his PhD and master's in economics from the University of Massachusetts at Amherst and his BA in economics from Carleton College.

Brent Campbell is an economist at Moody's Analytics. He is responsible for monitoring the Ohio economy and those of its major metropolitan areas as well as the economies of Latvia and Kuwait. In addition, Brent works closely with the regional and global house price forecasting systems and covers several housing market indicators. Brent holds a bachelor's degree in economics and international relations from the University of Pennsylvania and is a CFA® charterholder.

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