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

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Abstract

Moody's Analytics has developed a combined econometric model for the Federal Housing Finance Agency house price indexes and the CoreLogic Case-Shiller home price indexes. The econometric model uses the relationship between the Case-Shiller house price and the FHFA house price indexes in national, state and metropolitan area housing markets. The economic and demographic forces that drive house 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 CELIA CHEN

Moody's Analytics has developed a combined econometric model for the Federal Housing Finance Agency house price indexes and the CoreLogic Case-Shiller home price indexes. The econometric model uses the relationship between the Case-Shiller house price and the FHFA house price indexes in national, state and metropolitan area housing markets. The economic and demographic forces that drive house 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.

The econometric model used in this study 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 house price forecast models and discusses the characteristics of the Case-Shiller indexes and Case-Shiller house price forecast models. Since the Case-Shiller forecasts take advantage of the co-integration between the two indexes, this article, in conjunction with *Moody's Analytics FHFA Home Price Index Forecast Methodology,* presents a complete picture of the house 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.

Table 1: Variables Tested: Definitions and Sources

Variable	Sources
Case-Shiller® Home Price Index	CoreLogic, FHFA
FHFA repeat-sales all-transactions index	FHFA
FHFA repeat-sales purchase-only index	FHFA
Mortgage originations	Mortgage Bankers Association, Home Mortgage Disclosure Act
Avg household income	BEA, Census Bureau
Median household income	Census Bureau
S&P 500 index	S&P
Unemployment rate	BLS
User cost of capital	Constructed from FHFA composite mortgage rates, BEA personal income data, National Association of Home Builders property tax data, and BEA core personal consumption expenditure deflator.

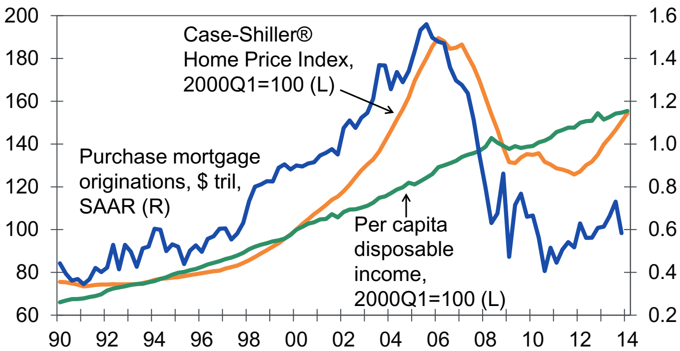
Note: Most of these variables are available at a metropolitan area level from the source or are constructed by Moody's Analytics.

The Moody's Analytics approach

As with nearly all Moody's Analytics forecast models, the house 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

1 By comparison, VAR models provide good short-term forecast accuracy but lack any 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.

Chart 1: Loan Cycle Disrupted the Price Trend



Sources: CoreLogic, BEA, Mortgage Bankers Association, Moody's Analytics

about the future, including those used in stress-testing exercises. This approach is also well-suited to extrapolating implications for specific regions.

House price determination

The approach to model house 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 house price index. This approach ties the Case-Shiller house price forecasts to their fundamental economic drivers while utilizing the complete state and metro 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 house price indexes forecast by Moody's Analytics.

The FHFA house price forecast forms the backbone for house 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 degree 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 generate deviations from long-term price trends such as the house price bubble of the last decade, whose effects are still being felt in most housing markets (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 house price index. Using the FHFA house 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 phenomena, 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 house 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 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.

One challenge that regional house price index forecast models face is maintaining 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 forecast 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 house 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 house price indexes. They differ in the way they are calculated and in the source of data used to calculate the house price indexes. Nevertheless, for the most part, the similarities outweigh the differences. The indexes are similar enough that CoreLogic substitutes in the FHFA price index in geographies where the sales and house 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, 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' county public records data. This data source allows CoreLogic to

2 For these house price forecast models, Moody's Analytics uses the 2000 OMB metro definitions, as some key data sources such as the Bureau of Labor Statistics have not yet switched to the 2010 OMB 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.

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 Alabama, Alaska, Idaho, Indiana, Kansas, Louisiana, Maine, Mississippi, Missouri, Montana, New Mexico, North Dakota, Texas, Utah and Wyoming. For these states and the metro areas within them, CoreLogic also fills in Case-Shiller indexes with rebased FHFA indexes.[3]

All told, CoreLogic covers 216 metro areas and 36 states with CoreLogic indexes generated with its own data, while 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 168 metro areas are obtained simply by growing out the rebased historical FHFA indexes with the growth rates of the corresponding FHFA index forecasts.

FHFA house price indexes

The Federal Housing Finance Agency Home Price Index also uses the repeat-sales algorithm created by Case-Shiller; the main difference between the two indexes is thus not on the methodology but in the data sources.[4] The data used to construct the purchase-only and all-transaction FHFA house price indexes are similar to those used to calculate the Case-Shiller HPI, but there are some 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
- Veterans Affairs (VA) and Rural Housing Service (RHS) insured loans from banks or other lenders

Conventional loans

- Any loan not under a government-insured program

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, agency mortgages from 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 a substantial share of mortgages 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. 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 arm's-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. There is one important exception: the Case-Shiller indexes exclude sales pairs that span bank repossessions (which are considered non-arm's length transactions), in effect excluding most real estate-owned sales. By comparison, the FHFA indexes can include REO sales, but this greater inclusivity is offset by their lack of cash, jumbo mortgage, and private label transactions; as a result, the difference in the cyclical swings for the two indexes is not large. 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 substantially above the FHFA index.[5] 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 co-integration.

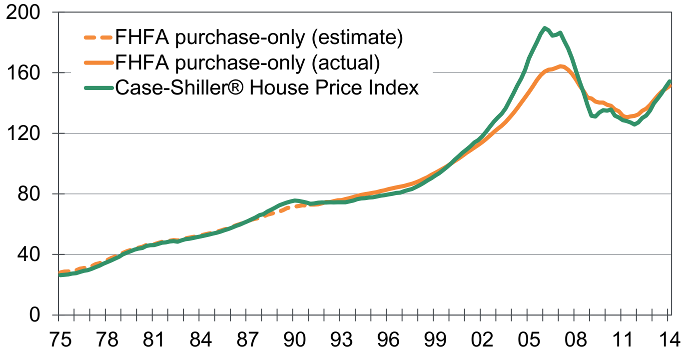
3 CoreLogic uses FHFA purchase-only indexes to fill in for Case-Shiller if these are available; otherwise, it uses FHFA all-transactions indexes, which include refinancing appraisal values in addition to purchase transactions.

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 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.

Chart 2: Deviation Varies, but Trend Is Similar

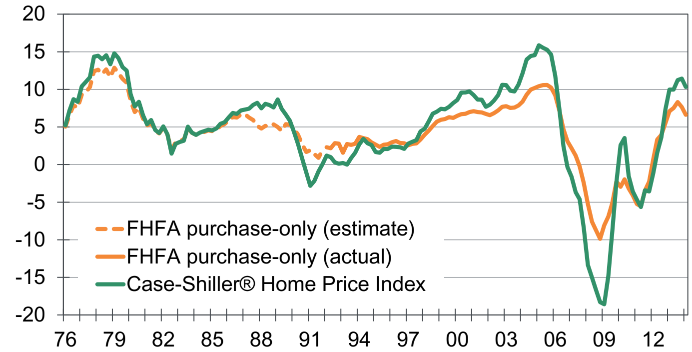
U.S. house price, 2000Q1=100



Sources: CoreLogic, FHFA, Moody's Analytics

Chart 3: Growth Rates Also Tend to Converge

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



Sources: CoreLogic, FHFA, Moody's Analytics

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 co-integrated. That is, there is 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 tend to track 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 and differences in the source data, 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 2013.[6] For these tests and co-integration tests, an anticipated difficulty crops up: The period of the housing bubble reduces the evidence for non-stationarity and co-integration, in some cases to the point where the tests did not prove successful. To underline the importance 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 at the metro area level rejected the null hypothesis of a unit root at the 5% confidence level, though not as low as the 1% level. However, for the restricted sample, the test failed to reject the null hypothesis of a unit root and non-stationarity. For the U.S. and states, tests with both a full and restricted sample failed to reject the null hypothesis of non-stationarity. 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 co-integration 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 co-integration even with the distorting effects of the housing bubble. The effects of the housing bubble, when overall prices rose at a much higher rate than FHFA-monitored prices, resulted in the U.S. test rejecting the null hypothesis of co-integration only at a 10% confidence level for the full sample. For the restricted sample, the U.S. test rejected the null hypothesis at a 1% confidence level. We can therefore conclude that the housing bubble notwithstanding, the Case-Shiller and FHFA indexes are non-stationary and are co-integrated, so that each can be modeled based on an error correction process with respect to the other.

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.	1975Q1-2014Q1	157	-1.0823	--	0.7221
State pool *	1991Q1-2013Q4	3,312	--	70.0951	0.5416
Metro area pool **	1990Q1-2013Q4	20,736	--	490.6920	0.0265
	Restricted sample	**Observations**	**t-statistic**	**Fisher Chi-square Statistic**	**Prob.**
U.S.	1975Q1-2001Q4	104	-1.3704	--	0.5941
State pool *	1991Q1-2001Q4	1,584	--	19.8467	1.0000
Metro area pool **	1990Q1-2001Q4	10,368	--	255.9540	1.0000

* 36 states
** 216 metro areas

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

6 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 1991-2014 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	1975Q1-2014Q1	153	-1.9037	--	0.3300
State pool *	1991Q1-2014Q1	3,187	--	67.1939	0.6383
Metro area pool **	1990Q1-2014Q1	20,838	--	492.9910	0.0224

	Restricted sample	Observations	t-statistic	Fisher Chi-square Statistic	Prob.
U.S.	1975Q1-2001Q4	103	-2.0797	--	0.2533
State pool *	1991Q1-2001Q4	1,496	--	58.3641	0.8771
Metro area pool **	1990Q1-2001Q4	10,259	--	255.2090	1.0000

* 36 states, FHFA purchase-only index
** 216 metro areas, FHFA all-transactions index

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

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.	1975Q1-2014Q1	157	-18.3085	--	0.0693
State pool *	1991Q1-2013Q4	3,312	--	-4.2145	0.0000
Metro area pool **	1990Q1-2013Q4	20,736	--	-8.6750	0.0000

	Restricted sample	Observations	z-statistic	Group ADF Statistic †	Prob.
U.S.	1975Q1-2001Q4	108	-31.4558	--	0.0026
State pool *	1991Q1-2001Q4	1,584	--	-14.5318	0.0000
Metro area pool **	1990Q1-2001Q4	10,368	--	-60.9311	0.0000

* 36 states
**216 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 co-integrated.

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.7 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 similar. The model drives 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:

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

Where:

- » CSI = Case-Shiller index for region,
- » FHFA = FHFA purchase-only index for U.S. and states, or all-transactions index for metro areas,
- » 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.

The error correction term with the coefficient β_3 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.[8] 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 house 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

7 For modeling purposes, the Case-Shiller and FHFA indexes are benchmarked to their own values from the first quarter of 2000 in order to minimize comparability problems. 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.

8 It should also be noted that the model includes neither a constant term nor fixed effects, mainly because either term would 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.

Table 5: U.S. Case-Shiller® Home Price Index Forecast Equation

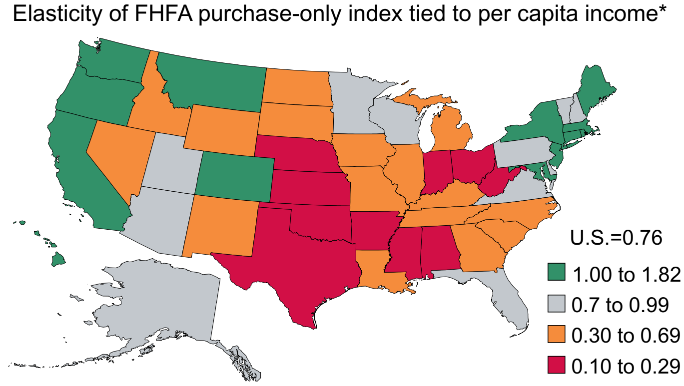
Dependent variable: DLOG(Case-Shiller® House Price Index)
Method: Least squares
Sample (adjusted): 1991Q2-2014Q1
Included observations: 92 after adjustments

Variable	Coefficient	Std. error	t-statistic	Prob.
DLOG Case-Shiller® Home Price Index, lagged 1 qtr	0.3555	0.0778	4.5690	0.0000
DLOG(FHFA Purchase-Only Index)	0.7745	0.0949	8.1656	0.0000
LOG Case-Shiller® Home Price Index, lagged 1 qtr - LOG FHFA Purchase-Only Index, lagged 1 qtr	-0.0251	0.0132	-1.9054	0.0599

R-squared	0.8775	**Mean dependent var**	**0.0083**
Adjusted R-squared	0.8748	**S.D. dependent var**	**0.0163**
S.E. of regression	0.0058	**Akaike info criterion**	**-7.4413**
Sum squared resid	0.0030	**Schwarz criterion**	**-7.3596**
Log likelihood	349.02	**Hannan-Quinn criter.**	**-7.4083**
Durbin-Watson stat	1.8320		

Chart 4: Income Effect Predominates in Coasts

Elasticity of FHFA purchase-only index tied to per capita income*



Sources: FHFA, BEA, Moody's Analytics

*1991Q1-2014Q1 sample

helps to predict future behavior—and prevents the Case-Shiller index from reverting too quickly to the level of the FHFA index.

It is difficult to find data at the subnational level that can explain short-term differences between behavior of the Case-Shiller and FHFA indexes. Any such a variable would have to measure transactions that are included in the Case-Shiller index but not in the FHFA indexes: cash purchases, federal-insured mortgages, jumbo and private-label mortgages. Or it would have to estimate the effect of refinancing appraisals, which are present in FHFA all-transactions indexes but not Case-Shiller indexes. There is no subnational data that tracks the former category, so the only additional driver that was added attempts to measure the effects of the refinancing inertia in FHFA all-transactions indexes.

Tables 5 and 6 present the results of the model for the U.S. and the 36 states with independent CoreLogic data. The coefficients in Tables 5 and 6 are as expected, and of the right signs. The coefficient on the mean reversion term for the states is approximately 0.05, which indicates that other things being equal, the Case-Shiller index tends to converge with the FHFA index over a period of five to six years, which corresponds with historical experience as seen in Chart 2.

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, thus the all-transaction index was used.[9] 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 nearby homes that can lag by as much as several months, and consequently do not provide an up-to-date measure of house prices.

To compensate for refinancing inertia, the metro area forecast model introduces an additional driver, which is the share of refinancing mortgage originations out of total originations that quarter, interacting with a two-quarter moving average of the change in the FHFA all-transactions index lagged one quarter. 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 regression are shown in Table 7. The results for the first four drivers are similar to the regres-

9 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 of a single regression pool with a single FHFA index driver.

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

Dependent variable: DLOG Case-Shiller® Home Price Index
Method: Pooled least squares
Sample: 1991Q2-2013Q4
Included observations: 91
Cross sections included: 36
Total pool (balanced) observations: 3,276
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
DLOG Case-Shiller® Home Price Index, lagged 1 qtr	0.2002	0.0102	19.5448	0.0000
DLOG FHFA Purchase-Only Index	0.8000	0.0106	75.7349	0.0000
LOG Case-Shiller® Home Price Index, lagged 1 qtr - LOG FHFA Purchase-Only Index, lagged 1 qtr	-0.0556	0.0052	-10.7559	0.0000

Weighted statistics			
R-squared	0.7730	**Mean dependent var**	**0.0107**
Adjusted R-squared	0.7729	**S.D. dependent var**	**0.0227**
S.E. of regression	0.0106	**Sum squared resid**	**0.3674**
Durbin-Watson stat	2.2955		

Unweighted statistics			
R-squared	0.6735	**Mean dependent var**	**0.0081**
Sum squared resid	0.4502	**Durbin-Watson stat**	**2.2965**

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

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

Dependent variable: DLOG Case-Shiller® Home Price Index
Method: Pooled EGLS (cross section weights)
Sample: 1990Q1-2013Q4
Included observations: 96
Cross sections included: 216
Total pool (unbalanced) observations: 20,615
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
DLOG Case-Shiller® Home Price Index, lagged 1 qtr	0.0927	0.0055	16.9963	0.0000
DLOG FHFA All-Transactions Index	0.7451	0.0043	171.6217	0.0000
LOG Case-Shiller® Home Price Index, lagged 1 qtr - LOG FHFA Purchase-Only Index, lagged 1 qtr	-0.0740	0.0025	-29.2712	0.0000
Refinancing share of mortgage originations * 2-qtr MA of DLOG FHFA All-Transactions Index, lagged 1 qtr	0.4033	0.0125	32.3498	0.0000

Weighted statistics			
R-squared	0.7248	**Mean dependent var**	**0.0099**
Adjusted R-squared	0.7247	**S.D. dependent var**	**0.0267**
S.E. of regression	0.0137	**Sum squared resid**	**3.8558**
Durbin-Watson stat	1.9663		

Unweighted statistics			
R-squared	0.6341	**Mean dependent var**	**0.0072**
Sum squared resid	4.2455	**Durbin-Watson stat**	**1.8885**

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

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

Forecast period: 2011Q1 to 2014Q1
Observations: 13

	Root mean squared error	Normalized root mean squared error
In-sample *	2.1922	0.0152
Out-of-sample, ex post *	2.2596	0.0157
Out-of-sample, ex ante **	6.4198	0.0446

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

sion for the states. The coefficient on the 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. As such, the additional driver does a good job of showing the greater variability of the Case-Shiller index and the FHFA purchase-only index relative to the all-transactions index.

Validation

The Case-Shiller forecast models were validated by evaluating both in-sample and out-of-sample root mean square errors for forecasts in the most recent sample period. In-sample forecasts are obtained using the coefficients for the regression for the full sample period, whereas out-of-sample forecasts are obtained using coefficients for a regression where observations are limited to the historical period before the sample range being forecast.

In attempting to judge the accuracy of the model, Moody's Analytics gives priority to the normalized root mean squared error (NRMSE) from an out-of-sample regression forecast.[10] By comparison, an in-sample NRMSE test tends to overestimate forecast accuracy because it picks up unusual market conditions during the forecast period such as housing booms, which may cause the Case-Shiller index to diverge from the FHFA index.

In addition, the out-of-sample tests were split into two types. *Ex post* out-of-sample tests use the actual values of the FHFA index regression drivers to obtain a forecast for the Case-Shiller index in that time period. *Ex post* tests thus test only the validity of the regression model rather than the validity of the regression drivers, and are thus open to the criticism that they are not a true forecast since they use actual values of the regression drivers that could not have been known ahead of time.

Ex ante out-of-sample tests use forecast values of the FHFA index drivers and are thus closer to a true blind forecast.[11] All three tests are reported in Tables 8, 9 and 10 for the U.S., states and metro areas, respectively, in the 2011Q1-2014Q1 sample period. For the state and metro area pools, both simple and household-weighted average NRMSEs are reported. Both the in-sample and *ex post* out-of sample forecasts do exceedingly well. For the U.S., the NRMSEs for both tests are about 1.5% of the historical values. As the geographical coverage becomes more granular, outliers increase and push up the NRMSE values, especially for out-of-sample tests. Even so, the household-weighted average NRMSEs are about 2% of actuals for the states, and about 3.5% of actuals for metro areas, which is a good overall showing.

Ex ante, out-of-sample forecast accuracy is a sterner test of the model. In Table 8, using a U.S. Case-Shiller index forecast derived from a FHFA purchase-only index forecast rather than its actual values more than doubles the root mean squared error. Nevertheless, the normalized root mean squared error is only 4.4% of the sample mean for the period, which is still a good performance. For the states, using *ex ante* forecasts also doubled the NRMSE, which is at 5% for a simple average of states and 4.4% for a household-weighted average as shown in Table 9. For metro areas, using *ex ante* forecasts also doubled the NRMSE to about 7.5% of the sample mean for a simple average and 6.6% of the sample mean for a household-weighted average.

It should be noted that the household-weighted average NRMSEs for the states and metro areas in ex-ante tests are slightly lower than the simple average NRMSEs. This is a good sign and an expected one, as metro areas with larger housing markets tend to have steadier trends and lower volatilities for the actual historical data, which reduces the likelihood of substantial forecast inaccuracy.

Overall, the lack of any NRMSEs above 10% of the sample means indicates that the Case-Shiller forecasts, building on the FHFA index forecasts, perform quite well and are robust to standard backtesting procedures.

Alternative specifications

Being a model in which economic and demographic drivers flow through the FHFA index, the basic model for the Case-Shiller

10 Root mean squared errors are calculated by taking the sum of squared differences between forecast and actual values, dividing by the number of observations, and then taking the square root. The root mean squared error can then be normalized by dividing by the average of the actual values for the sample period. Root mean squared errors punish outliers more than do mean absolute errors, the other frequent measure of forecast accuracy.

11 This third test is not 100% *ex ante* since actual values of the other drivers such as the refinancing share of mortgage originations are still being used. But these drivers have much less influence on the forecast than the co-integrated FHFA index regressors.

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

Forecast period: 2011Q1 to 2013Q4
States: 36 †
Observations: 432

	Household weight, 2010 census	Normalized root mean squared errors		
		In-sample *	Out-of-sample, ex post *	Out-of-sample, ex ante **
Alabama	0.0197	0.0052	0.0056	0.0174
Arkansas	0.0120	0.0057	0.0054	0.0353
Arizona	0.0249	0.0192	0.0257	0.1602
California	0.1315	0.0090	0.0090	0.0437
Colorado	0.0206	0.0275	0.0308	0.0265
Connecticut	0.0143	0.0125	0.0120	0.0591
District of Columbia	0.0028	0.1088	0.1156	0.0325
Delaware	0.0036	0.0193	0.0202	0.1228
Florida	0.0776	0.0148	0.0169	0.0175
Georgia	0.0375	0.0965	0.0982	0.0838
Hawaii	0.0048	0.0197	0.0209	0.0485
Iowa	0.0128	0.0041	0.0041	0.0236
Illinois	0.0506	0.0240	0.0242	0.0663
Kentucky	0.0180	0.0034	0.0035	0.0267
Louisiana	0.0181	0.0058	0.0059	0.0303
Massachusetts	0.0266	0.0071	0.0068	0.0357
Maryland	0.0226	0.0353	0.0364	0.0498
Michigan	0.0405	0.0259	0.0222	0.0261
Minnesota	0.0218	0.0105	0.0110	0.0288
North Carolina	0.0392	0.0048	0.0049	0.0537
Nebraska	0.0075	0.0084	0.0080	0.0492
New Hampshire	0.0054	0.0181	0.0176	0.0926
New Jersey	0.0336	0.0134	0.0139	0.0682
Nevada	0.0105	0.0185	0.0190	0.0721
New York	0.0765	0.0231	0.0244	0.0301
Ohio	0.0481	0.0120	0.0124	0.0286
Oklahoma	0.0153	0.0048	0.0046	0.0145
Oregon	0.0159	0.0135	0.0149	0.0915
Pennsylvania	0.0525	0.0137	0.0149	0.0131
Rhode Island	0.0043	0.0285	0.0274	0.0973
South Carolina	0.0188	0.0060	0.0060	0.0546
Tennessee	0.0261	0.0466	0.0487	0.0256
Virginia	0.0320	0.0518	0.0525	0.0595
Vermont	0.0027	0.0135	0.0139	0.0341
Washington	0.0274	0.0078	0.0095	0.0264
Wisconsin	0.0238	0.0044	0.0050	0.0776
	Simple avg	**0.0206**	**0.0214**	**0.0506**
	Household-weighted avg	**0.0193**	**0.0200**	**0.0444**

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

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

Forecast period: 2011Q1 to 2013Q4
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	0.0394	0.0418	0.0786
Albany NY	0.0048	0.0195	0.0196	0.0347
Allentown PA	0.0042	0.0254	0.0273	0.0692
Altoona PA	0.0007	0.0080	0.0078	0.0180
Anderson SC	0.0010	0.0078	0.0075	0.0923
Ann Arbor MI	0.0018	0.0595	0.0627	0.0428
Asheville NC	0.0024	0.0077	0.0076	0.0212
Athens GA	0.0010	0.0140	0.0139	0.0702
Atlanta GA	0.0260	0.0575	0.0587	0.1154
Atlantic City NJ	0.0014	0.0251	0.0235	0.0649
Augusta GA	0.0028	0.0082	0.0084	0.0698
Bakersfield CA	0.0034	0.0835	0.0858	0.0484
Baltimore MD	0.0139	0.0329	0.0334	0.0597
Barnstable Town MA	0.0013	0.0188	0.0191	0.1323
Bellingham WA	0.0011	0.0319	0.0319	0.0392
Bend OR	0.0009	0.0123	0.0125	0.0563
Bethesda MD	0.0059	0.0293	0.0302	0.0284
Binghamton NY	0.0014	0.0216	0.0230	0.0804
Boston MA	0.0098	0.0399	0.0392	0.0577
Boulder CO	0.0016	0.0210	0.0217	0.0289
Bowling Green KY	0.0007	0.0304	0.0301	0.0989
Bridgeport CT	0.0045	0.0214	0.0228	0.1338
Brunswick GA	0.0006	0.0171	0.0171	0.0944
Buffalo NY	0.0064	0.0157	0.0163	0.0879
Burlington VT	0.0011	0.0034	0.0032	0.0347
Cambridge MA	0.0078	0.0230	0.0227	0.0627
Camden NJ	0.0062	0.0300	0.0330	0.0874
Canton OH	0.0022	0.0476	0.0521	0.0527
Cape Coral FL	0.0035	0.0820	0.0868	0.0326
Cedar Rapids IA	0.0014	0.0027	0.0026	0.0377
Champaign IL	0.0013	0.0037	0.0037	0.0567
Charleston SC	0.0035	0.0205	0.0245	0.0373
Charlotte NC	0.0090	0.0160	0.0201	0.0500
Charlottesville VA	0.0011	0.0088	0.0090	0.0380
Chattanooga TN	0.0028	0.0039	0.0039	0.0427
Chicago IL	0.0390	0.0324	0.0357	0.0916
Chico CA	0.0012	0.0381	0.0398	0.0807
Cincinnati OH	0.0111	0.0193	0.0220	0.0742
Clarksville TN	0.0014	0.0274	0.0266	0.0077
Cleveland OH	0.0115	0.0330	0.0354	0.0864
Colorado Springs CO	0.0033	0.0308	0.0325	0.0361
Columbia SC	0.0040	0.0276	0.0288	0.0662
Columbus OH	0.0097	0.0349	0.0375	0.0425
Corvallis OR	0.0005	0.0102	0.0103	0.0550
Crestview FL	0.0010	0.0459	0.0488	0.0722
Dalton GA	0.0007	0.0199	0.0200	0.0925
Danville IL	0.0004	0.0089	0.0090	0.0723
Davenport IL	0.0021	0.0025	0.0025	0.0712
Dayton OH	0.0046	0.0395	0.0408	0.0829
Deltona FL	0.0028	0.0514	0.0580	0.1260

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

Forecast period: 2011Q1 to 2013Q4
Metro areas: 216 †
Observations: 2,592

		Normalized Root Mean Squared Errors		
	Household weight, 2010 census	In-sample *	Out-of-sample, ex post *	Out-of-sample, ex ante **
Denver CO	0.0135	0.0262	0.0280	0.0304
Des Moines IA	0.0030	0.0039	0.0040	0.0405
Detroit MI	0.0094	0.0485	0.0687	0.0587
Dover DE	0.0008	0.0112	0.0113	0.0934
Duluth MN	0.0016	0.0065	0.0067	0.0616
Durham NC	0.0027	0.0057	0.0058	0.0108
Eau Claire WI	0.0009	0.0050	0.0052	0.0527
Edison NJ	0.0115	0.0148	0.0158	0.0543
El Centro CA	0.0007	0.0350	0.0361	0.1932
Elmira NY	0.0005	0.0535	0.0531	0.0161
Erie PA	0.0015	0.0029	0.0028	0.0612
Eugene OR	0.0020	0.0149	0.0150	0.0910
Fayetteville AR	0.0023	0.0029	0.0028	0.0573
Fayetteville NC	0.0019	0.0079	0.0081	0.0339
Flagstaff AZ	0.0006	0.0485	0.0543	0.0713
Florence SC	0.0011	0.0068	0.0069	0.0535
Fort Collins CO	0.0016	0.0212	0.0213	0.0147
Fort Lauderdale FL	0.0092	0.0550	0.0570	0.0497
Fort Smith AR	0.0015	0.0028	0.0028	0.0273
Fresno CA	0.0039	0.0667	0.0685	0.0627
Gainesville FL	0.0014	0.0345	0.0405	0.1265
Gainesville GA	0.0008	0.0520	0.0536	0.1766
Glens Falls NY	0.0007	0.0095	0.0094	0.0534
Grand Junction CO	0.0008	0.0653	0.0695	0.0349
Greeley CO	0.0012	0.0516	0.0547	0.0269
Green Bay WI	0.0016	0.0053	0.0054	0.0860
Greensboro NC	0.0039	0.0273	0.0304	0.0352
Greenville SC	0.0033	0.0523	0.0550	0.0237
Hanford CA	0.0006	0.0646	0.0657	0.1378
Harrisburg PA	0.0030	0.0031	0.0031	0.0571
Hartford CT	0.0063	0.0084	0.0088	0.1300
Honolulu HI	0.0042	0.0702	0.0664	0.0642
Hot Springs AR	0.0006	0.0114	0.0112	0.0465
Ithaca NY	0.0005	0.0593	0.0570	0.0553
Jackson TN	0.0006	0.0064	0.0065	0.0820
Jacksonville FL	0.0070	0.0348	0.0410	0.0926
Johnson City TN	0.0011	0.0115	0.0122	0.0512
Kennewick WA	0.0012	0.0035	0.0036	0.0231
Kingsport TN	0.0017	0.0065	0.0068	0.0348
Kingston NY	0.0010	0.0170	0.0204	0.1192
Knoxville TN	0.0038	0.0419	0.0430	0.0100
Lake County IL	0.0041	0.0304	0.0307	0.1175
Lake Havasu AZ	0.0011	0.0114	0.0117	0.0375
Lakeland FL	0.0031	0.0417	0.0547	0.1092
Lancaster PA	0.0026	0.0094	0.0094	0.0362
Lansing MI	0.0025	0.0277	0.0336	0.1179
Las Vegas NV	0.0096	0.0930	0.0941	0.0839
Lawton OK	0.0006	0.0068	0.0070	0.0894
Lima OH	0.0005	0.0048	0.0047	0.0721
Little Rock AR	0.0037	0.0173	0.0180	0.0147

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

Forecast period: 2011Q1 to 2013Q4
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 **
Longview WA	0.0005	0.0159	0.0160	0.1374
Los Angeles CA	0.0435	0.0596	0.0623	0.0616
Louisville KY	0.0069	0.0221	0.0234	0.0162
Lynchburg VA	0.0013	0.0051	0.0052	0.0437
Macon GA	0.0012	0.0141	0.0142	0.1038
Madera CA	0.0006	0.0154	0.0157	0.2224
Madison WI	0.0032	0.0056	0.0057	0.0264
Manchester NH	0.0021	0.0346	0.0337	0.1027
Manhattan KS	0.0006	0.0070	0.0070	0.0699
Mankato MN	0.0005	0.0088	0.0086	0.1038
Medford OR	0.0011	0.0161	0.0161	0.0845
Memphis TN	0.0066	0.0636	0.0529	0.1515
Merced CA	0.0010	0.0832	0.0853	0.1935
Miami FL	0.0116	0.0742	0.0790	0.0457
Milwaukee WI	0.0084	0.0448	0.0447	0.0452
Minneapolis MN	0.0171	0.0425	0.0489	0.0523
Modesto CA	0.0022	0.0799	0.0801	0.0998
Monroe MI	0.0008	0.0071	0.0070	0.1515
Mount Vernon WA	0.0006	0.0175	0.0177	0.1400
Myrtle Beach SC	0.0015	0.0285	0.0354	0.1284
Napa CA	0.0007	0.0397	0.0427	0.1105
Naples FL	0.0018	0.0880	0.0908	0.0860
Nashville TN	0.0083	0.0309	0.0330	0.0230
Nassau NY	0.0127	0.0212	0.0224	0.0403
New Haven CT	0.0045	0.0146	0.0149	0.1239
New Orleans LA	0.0061	0.0270	0.0282	0.0367
New York NY	0.0583	0.0226	0.0239	0.0447
Newark NJ	0.0104	0.0078	0.0107	0.0686
North Port FL	0.0042	0.0500	0.0513	0.0366
Norwich CT	0.0014	0.0293	0.0297	0.1428
Oakland CA	0.0124	0.0297	0.0341	0.0832
Ocala FL	0.0018	0.0575	0.0691	0.1463
Ocean City NJ	0.0005	0.0250	0.0274	0.1313
Oklahoma City OK	0.0066	0.0294	0.0298	0.0205
Olympia WA	0.0014	0.0168	0.0185	0.1186
Omaha NE	0.0045	0.0192	0.0217	0.0386
Orlando FL	0.0107	0.0639	0.0716	0.0498
Oxnard CA	0.0036	0.0339	0.0348	0.1057
Palm Bay FL	0.0031	0.0793	0.0816	0.0520
Palm Coast FL	0.0005	0.0564	0.0602	0.0727
Panama City FL	0.0009	0.0263	0.0279	0.1532
Peabody MA	0.0038	0.0235	0.0244	0.0905
Pensacola FL	0.0023	0.0367	0.0412	0.0883
Peoria IL	0.0020	0.0031	0.0031	0.0804
Philadelphia PA	0.0206	0.0119	0.0129	0.0348
Phoenix AZ	0.0206	0.0579	0.0659	0.0881
Pittsburgh PA	0.0134	0.0090	0.0113	0.0444
Pittsfield MA	0.0008	0.0241	0.0251	0.1213
Port St. Lucie FL	0.0023	0.0615	0.0657	0.0480
Portland OR	0.0116	0.0376	0.0407	0.0480

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

Forecast period: 2011Q1 to 2013Q4
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 **
Poughkeepsie NY	0.0031	0.0160	0.0169	0.1231
Prescott AZ	0.0012	0.0500	0.0541	0.0417
Providence RI	0.0084	0.0248	0.0254	0.0998
Pueblo CO	0.0008	0.0070	0.0070	0.1309
Punta Gorda FL	0.0010	0.0892	0.0967	0.0444
Raleigh NC	0.0058	0.0317	0.0317	0.0302
Reading PA	0.0021	0.0072	0.0073	0.0770
Redding CA	0.0009	0.0604	0.0627	0.0352
Reno NV	0.0022	0.0178	0.0179	0.1143
Richmond VA	0.0066	0.0623	0.0650	0.0418
Riverside CA	0.0174	0.0448	0.0485	0.0644
Roanoke VA	0.0017	0.0065	0.0067	0.1027
Rochester MN	0.0010	0.0062	0.0063	0.0590
Rochester NY	0.0056	0.0172	0.0179	0.0908
Rockford IL	0.0018	0.0117	0.0118	0.1720
Rockingham County NH	0.0022	0.0303	0.0313	0.0879
Rome GA	0.0005	0.0230	0.0238	0.1076
Sacramento CA	0.0106	0.0617	0.0645	0.0895
Salem OR	0.0019	0.0178	0.0179	0.1333
Salinas CA	0.0017	0.0373	0.0460	0.0962
Salisbury MD	0.0006	0.0177	0.0211	0.1409
San Diego CA	0.0146	0.0324	0.0340	0.0826
San Francisco CA	0.0095	0.0321	0.0373	0.0453
San Jose CA	0.0083	0.0274	0.0306	0.0476
San Luis Obispo CA	0.0014	0.0641	0.0650	0.0745
Sandusky OH	0.0004	0.0074	0.0073	0.1019
Santa Ana CA	0.0133	0.0529	0.0538	0.0680
Santa Barbara CA	0.0019	0.0226	0.0245	0.1236
Santa Cruz CA	0.0013	0.0274	0.0298	0.0765
Santa Rosa CA	0.0025	0.0457	0.0483	0.0643
Savannah GA	0.0018	0.0210	0.0215	0.0341
Seattle WA	0.0142	0.0377	0.0414	0.0460
Sebastian FL	0.0008	0.0497	0.0545	0.0708
Shreveport LA	0.0021	0.0044	0.0044	0.0160
Spokane WA	0.0025	0.0297	0.0317	0.0856
Springfield IL	0.0012	0.0026	0.0025	0.0402
Springfield MA	0.0036	0.0230	0.0237	0.0800
Springfield OH	0.0007	0.0400	0.0431	0.0947
St. Cloud MN	0.0010	0.0086	0.0088	0.0868
St. Louis MO	0.0150	0.0359	0.0378	0.0474
Stockton CA	0.0029	0.0510	0.0518	0.1139
Syracuse NY	0.0035	0.0192	0.0186	0.0937
Tacoma WA	0.0040	0.0225	0.0233	0.1626
Tallahassee FL	0.0019	0.0423	0.0460	0.0782
Tampa FL	0.0155	0.0326	0.0370	0.0767
Toledo OH	0.0035	0.0361	0.0392	0.0994
Trenton NJ	0.0018	0.0504	0.0511	0.0450
Tucson AZ	0.0052	0.0372	0.0421	0.0997
Tulsa OK	0.0049	0.0259	0.0260	0.0702
Utica NY	0.0016	0.0202	0.0212	0.0970

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

Forecast period: 2011Q1 to 2013Q4
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 **
Valdosta GA	0.0007	0.0141	0.0144	0.0992
Vallejo CA	0.0019	0.0560	0.0585	0.1300
Vineland NJ	0.0007	0.0127	0.0132	0.1430
Visalia CA	0.0017	0.0680	0.0703	0.0993
Warner Robins GA	0.0007	0.0065	0.0064	0.0919
Warren MI	0.0131	0.0474	0.0537	0.0296
Washington DC	0.0219	0.0178	0.0182	0.0346
Waterloo IA	0.0009	0.0531	0.0576	0.0527
Wilmington DE	0.0036	0.0218	0.0241	0.0650
Wilmington NC	0.0020	0.0119	0.0119	0.0809
Winston NC	0.0026	0.0359	0.0403	0.0244
Worcester MA	0.0041	0.0196	0.0207	0.1149
York PA	0.0023	0.0099	0.0100	0.0811
Youngstown OH	0.0031	0.0307	0.0349	0.0746
Yuba City CA	0.0007	0.0148	0.0146	0.1917
Yuma AZ	0.0009	0.0125	0.0127	0.0673
Simple average		**0.0291**	**0.0308**	**0.0754**
Household-weighted avg		**0.0341**	**0.0365**	**0.0660**

* Uses actual historical values for the FHFA all-transactions index regressor.
** Uses forecast 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

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 since they often rely on non-standard financing, but the new CoreLogic Case-Shiller indexes exclude most REO sales, and there is no good way of separating out short sales. Also, total distress sale 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.

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 area 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, though these adjustments are usually minor.[12]

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 in-

12 For Case-Shiller calibration, only the states and metro areas with independent CoreLogic data are calibrated; states and metro areas that use infilled FHFA indexes are ignored.

clude different levels of geography (regions, counties and ZIP codes) and other price measures (condo indexes and single-family indexes by price 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.13

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 was calculated 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 metro area price. The regression is a pooled cross section regression with fixed effects:

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

13 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. For example, National Association of Realtors data on state home sales were discontinued and end in 2011.

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): 1980Q2-2012Q4
Included observations: 131 after adjustments
Cross sections included: 479
Total pool (balanced) observations: 62,749
Linear estimation after one-step weighting matrix
Cross sections without valid observations dropped

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-9.40E-05	5.69E-06	-16.5329	0.0000
DLOG Case-Shiller metro area index	0.9989	0.0003	3643.3920	0.0000
LOG Case-Shiller county index, lagged 4 qtrs - LOG Case-Shiller metro area index, lagged 4 qtrs	-0.0119	0.0008	-14.4082	0.0000
DLOG ratio of county to metro area median income, 4-qtr MA	0.0123	0.0050	2.4886	0.0128

Weighted Statistics

R-squared	0.9954	**Mean dependent var**	0.0333
Adjusted R-squared	0.9954	**S.D. dependent var**	0.1217
S.E. of regression	0.0079	**Sum squared resid**	3.9016
F-statistic	27928.17	**Durbin-Watson stat**	2.2183
Prob(F-statistic)	0.0000		

Unweighted Statistics

R-squared	0.8082	**Mean dependent var**	0.0084
Sum squared resid	5.7322	**Durbin-Watson stat**	1.8841

Fixed effects coefficients available on request.

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 incomes.

The most important explanatory variable in the house price equation is the county effect of growth the corresponding metro area's CSI. On average, a 1% increase in the metro area (or state) house price leads to a proportional increase in county house prices (Table 11).

To keep metro area forecasts in line with its constituent county 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 nearly 0.12 percentage point.

The model also includes the median household income. 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 0.1 percentage point.

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 data exist but the county's do not, the metro area forecast is used. If the ZIP code is not within a metro area, the state 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 pool cross-sectional 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 rate 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 adjustment 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.

Fourteen pools have been constructed across the 6,200 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 1 and 1.06. Also, the large number of observations and the use of fixed effects almost guarantee that the adjusted R^2 statistic for each pooled regression will be close to 1. 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.

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 0.8 and 0.9. In addition, the error correction term is positive 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 condos and tiers prices within a metro area would move in sync with the broader housing market of the metro area.[14] Since these price indexes 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 price index is a main driver of the condo and tier forecast models. As with standard error correction models, the lagged difference in the condo and aggregate single-family indexes is also a good prediction of reversion tendencies, as condo prices cannot indefinitely stay too high or too low compared with single-family prices. Since condo purchases tend to rely more on conventional mortgage financing, a user cost driver is 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:

$$\Delta\log(CSI_{co}) = \beta_0 + \beta_1 \Delta\log(CSI_{msa}) + \beta_2(\log(CSI_{co,t-1}) - \log(CSI_{msa,t-1})) + \beta_3 UC_{msa}$$

where CSI_{co} is the condo house price index and CSI_{msa} is the aggregate Case-Shiller house price for the corresponding metro area; β_0 is a constant term, β_1, β_2 and β_3 are the other regression coefficients. UC_{msa} 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.

Tables 13 and 14 present the regression results for state and metro area condo indexes. 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 0.9 percentage point increase in condo house prices. On the other hand, the user cost of owning a home, which takes into account institutional variables such as property taxes, mortgage rates, and maintenance and obsolescence, adds information to the regression and is negatively related to prices. Therefore, as user costs increase, individuals prefer to rent rather than own a condo unit. Finally, while the reversion term is statistically significant and of the right sign, it has only a weak effect, indicating that deviations of condo prices from the single-family index take many years to correct.

14 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.

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	1.0016	0.0003	3216.3490	0.0000	0.9919	555
New York state	LOG county Case-Shiller index	1.0085	0.0002	4152.1290	0.0000	0.9959	437
New Jersey, Pennsylvania	LOG county Case-Shiller index	1.0136	0.0003	2952.2250	0.0000	0.9862	762
South Atlantic census division, except Florida	LOG county Case-Shiller index	1.0182	0.0004	2882.3920	0.0000	0.9842	804
Florida	LOG county Case-Shiller index	1.0336	0.0006	1829.5600	0.0000	0.9689	669
East North Central census division, eastern half	LOG county Case-Shiller index	1.0293	0.0006	1669.8890	0.0000	0.9792	401
East North Central census division, western half	LOG county Case-Shiller index	1.0008	0.0006	1820.6900	0.0000	0.9821	402
East South Central census division	LOG county Case-Shiller index	1.0419	0.0012	869.9405	0.0000	0.9748	126
West North Central census division	LOG county Case-Shiller index	1.0243	0.0007	1406.0510	0.0000	0.9864	170
West South Central census division	LOG county Case-Shiller index	1.0606	0.0011	962.9885	0.0000	0.9748	156
Mountain census division	LOG county Case-Shiller index	1.0148	0.0005	2198.6150	0.0000	0.9859	423
Southern California	LOG county Case-Shiller index	1.0097	0.0004	2851.8980	0.0000	0.9903	454
Northern California	LOG county Case-Shiller index	1.0073	0.0003	3405.7570	0.0000	0.9934	454
Pacific census division, except California	LOG county Case-Shiller index	1.0148	0.0004	2610.8720	0.0000	0.9902	389
						Total ZIP codes	6,202

Constant terms and fixed effects coefficient are available on request.

†Each ZIP code has 160 to 177 observations between 1970 and 2014.

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 †
New England census division	DLOG county Case-Shiller index	0.8740	0.0016	530.2896	0.0000		
	LOG countyCase-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0149	0.0007	21.0205	0.0000	0.7706	555
New York state	DLOG county Case-Shiller index	0.8400	0.0020	424.8001	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0204	0.0010	21.1422	0.0000	0.7260	437
New Jersey, Pennsylvania	DLOG county Case-Shiller index	0.8012	0.0017	460.8001	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0181	0.0005	35.3317	0.0000	0.6455	762
South Atlantic census division, except Florida	DLOG county Case-Shiller index	0.8354	0.0015	543.6196	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0097	0.0004	25.3555	0.0000	0.7008	804

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

Dependent variable: DLOG ZIP code Case-Shiller index

Pool	Regressor	Coefficient	Std. error	t-statistic	Prob.	Adj. R squared	Cross Sections †
Florida	DLOG county Case-Shiller index	0.8668	0.0017	515.8229	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0136	0.0005	27.7168	0.0000	0.7165	669
East North Central census division, eastern half	DLOG county Case-Shiller index	0.7882	0.0027	291.6294	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0091	0.0007	13.8375	0.0000	0.5802	401
East North Central census division, western half	DLOG county Case-Shiller index	0.8963	0.0023	383.3611	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0044	0.0007	6.2666	0.0000	0.7016	402
East South Central census division	DLOG county Case-Shiller index	0.8218	0.0043	191.0771	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0030	0.0009	3.4275	0.0006	0.6599	126
West North Central census division	DLOG county Case-Shiller index	0.8078	0.0035	229.1304	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0095	0.0009	10.0954	0.0000	0.6651	170
West South Central census division	DLOG county Case-Shiller index	0.9179	0.0033	280.7549	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0019	0.0010	1.9983	0.0457	0.7699	156
Mountain census division	DLOG county Case-Shiller index	0.8990	0.0018	497.7839	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0180	0.0006	28.3695	0.0000	0.7836	423
Southern California	DLOG county Case-Shiller index	0.9241	0.0019	495.7543	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0329	0.0006	54.3261	0.0000	0.7678	454
Northern California	DLOG county Case-Shiller index	0.8796	0.0016	555.4021	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0254	0.0006	39.2440	0.0000	0.8016	454
Pacific census division, except California	DLOG county Case-Shiller index	0.8941	0.0017	514.7712	0.0000		
	LOG county Case-Shiller index, lagged 4 qtrs - LOG ZIP code Case-Shiller index, lagged 4 qtrs	0.0083	0.0006	14.8707	0.0000	0.8000	389
						Total ZIP codes	**6,202**

Constant terms and fixed effects coefficient are available on request.

†Each ZIP code has 156 to 173 observations between 1970 and 2014.

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 to 2014Q1
Included observations: 165 after adjustments
Cross sections included: 26 *
Total pool (unbalanced) observations: 3,294
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.0065	0.0010	6.5454	0.0000
DLOG Case-Shiller single-family home price index	0.9479	0.0132	72.0063	0.0000
(LOG Case-Shiller condo index, lagged 1 qtr - LOG Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0094	0.0020	-4.7022	0.0000
User cost of capital	-0.1472	0.0194	-7.5865	0.0000

Weighted statistics			
R-squared	0.6226	**Mean dependent var**	**0.0103**
Adjusted R-squared	0.6222	**S.D. dependent var**	**0.0286**
S.E. of regression	0.0176	**Sum squared resid**	**1.0167**
F-statistic	1808.96	**Durbin-Watson stat**	**2.0079**
Prob(F-statistic)	0		

Unweighted statistics			
R-squared	0.4380	**Mean dependent var**	**0.0087**
Sum squared resid	1.1476	**Durbin-Watson stat**	**1.9936**

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

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): 1975Q1 to 2014Q3
Included observations: 159 after adjustments
Cross sections included: 73 *
Total pool (unbalanced) observations: 9,910
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.0066	0.0007	10.0713	0.0000
DLOG Case-Shiller single-family house price index	0.8768	0.0082	107.5687	0.0000
(LOG Case-Shiller condo index, lagged 1 qtr - LOG Case-Shiller single-family home price index, lagged 1 qtr), 4-qtr MA	-0.0080	0.0013	-6.1461	0.0000
User cost of capital	-0.1430	0.0130	-11.0291	0.0000

Weighted statistics			
R-squared	0.5525	**Mean dependent var**	**0.0094**
Adjusted R-squared	0.5524	**S.D. dependent var**	**0.0292**
S.E. of regression	0.0196	**Sum squared resid**	**3.7988**
F-statistic	4076.96	**Durbin-Watson stat**	**2.0100**
Prob(F-statistic)	0		

Unweighted statistics			
R-squared	0.5071	**Mean dependent var**	**0.0086**
Sum squared resid	3.8414	**Durbin-Watson stat**	**2.0310**

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

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 to 2014Q1
Included observations: 138 after adjustments
Cross sections included: 101 *
Total pool (balanced) observations: 13,138
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.0005	0.0002	2.8305	0.0047
DLOG Case-Shiller aggregate index	1.0898	0.0071	152.4826	0.0000
(LOG Case-Shiller low-tier index, lagged 1 qtr - LOG Case-Shiller aggregate price index, lagged 1 qtr), 4-qtr MA	-0.0165	0.0016	-10.2243	0.0000
LOG current unemployment rate, 8-qtr MA - LOG unemployment rate, lagged 8 qtrs, 8-qtr MA	-0.0045	0.0006	-7.3583	0.0000

Weighted statistics

R-squared	0.6948	Mean dependent var	0.0116
Adjusted R-squared	0.6948	S.D. dependent var	0.0332
S.E. of regression	0.0183	Sum squared resid	4.3818
F-statistic	9968.97	Durbin-Watson stat	2.1293
Prob(F-statistic)	0		

Unweighted statistics

R-squared	0.6730	Mean dependent var	0.0105
Sum squared resid	4.3884	Durbin-Watson stat	2.1130

* Metro areas without tier indexes are excluded

In forecasting the house price tier indexes, Moody's Analytics assumes that tier prices within a metro area would move in sync with the broader housing market of the metro area, with modifiers included that can explain any deviations from the market average. Therefore, the tier indexes are forecast using the following pooled cross-section regression with fixed effects:

$$\Delta \log(CSI_{low}) = \beta_0 + \beta_1 \Delta \log(CSI_{msa}) + \beta_2\big(\log(CSI_{low,t-1}) - \log(CSI_{msa,t-1})\big) + \beta_3 \Delta(U_{msa})$$

$$\Delta \log(CSI_{med}) = \beta_0 + \beta_1 \Delta \log(CSI_{msa}) + \beta_2\big(\log(CSI_{med,t-1}) - \log(CSI_{msa,t-1})\big)$$

$$\Delta \log(CSI_{high}) = \beta_0 + \beta_1 \Delta \log(CSI_{msa}) + \beta_2\big(\log(CSI_{high,t-1}) - \log(CSI_{msa,t-1})\big) + \beta_3(\log(SP_{t-1}) - \log(SP_{t-5})) + \beta_4 \Delta\log(Y_{dis})$$

CSI_{msa} is the aggregate price in a metro area and CSI_{low}, CSI_{med} and CSI_{high} refer to indexes 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. U_{msa} is the difference between a two-year moving average of the current unemployment rate and that same average from the previous two years intended to model a persistent labor market shift, and Y_{dis} is the ratio of average to median household income, used to proxy income distribution in the metro area. Lastly, SP is the Standard & Poor's 500 stock index, included in the hypothesis that good stock market gains over the previous year would tend to make wealthier households spend more on purchasing high-tier homes. Tables 15A, 15B and 15C present the regression results for metro area indexes.

The main explanatory variable is the metro area house price; the coefficient on this driver is between 0.9 and 1.1 depending on the tier; the low-tier index regression has a coefficient of 1.1, reflecting the much larger percentage increase in the price of low tier homes made possible by unrestricted subprime lending during the housing bubble. To keep the tier forecasts in line with their constituent aggregate index forecasts, lagged reversion terms are included in all three regressions; these drivers measure the gap between the previous quarter's tier index and the aggregate index for a given metro area. For example, if housing is much more expensive in the high tier in the same metro area, new homebuyers will favor houses priced in the middle tier, all else being equal. Therefore, in the long run, prices among tiers within a metro area should converge to the aggregate index. When a tier index is 1% above the metro area aggregate index in the previous quarter, that tier index will fall by 0.1 to 0.2 percentage point in the following quarter. The reversion effect is strongest for the middle tier regression in Table 15B. The higher sensitivity of the mid-tier price index to the gap with the aggregate index reflects the tendency of the mid-tier index to track the aggregate index more closely than the low and high tiers.

The model for low tiers includes an additional explanatory variable, a two-year moving average of the unemployment rate minus the same moving average lagged two years; the long lags and moving averages are introduced to offset volatility in the jobless rate, which can be substantial, especially for smaller metro areas. Changes in the long-term unemployment rate are relevant since the buyers of lower-cost homes tend to be lower income and are thus more sensitive to the local business cycle and job prospects than higher-income households.

The first explanatory variable in the high-tier index regression equation that can lead to short-term deviations is the previous year's growth rate of the S&P500 index, which proxies the change in the asset position of wealthier households. However, this effect is not large, most likely due to the geographical concentration of higher-wealth households, which are a very small share of the total in most metro areas. A better

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 to 2014Q1
Included observations: 173 after adjustments
Cross sections included: 101
Total pool (balanced) observations: 16,445
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.0002	0.0001	2.5511	0.0107
DLOG Case-Shiller aggregate index	0.9869	0.0026	377.4511	0.0000
(LOG Case-Shiller middle-tier index, lagged 1 qtr - LOG Case-Shiller aggregate price index, lagged 1 qtr), 4-qtr MA	-0.0199	0.0019	-10.6084	0.0000

Weighted statistics			
R-squared	0.8966	Mean dependent var	0.0143
Adjusted R-squared	0.8966	S.D. dependent var	0.0290
S.E. of regression	0.0092	Sum squared resid	1.4029
F-statistic	71311.76	Durbin-Watson stat	2.5411
Prob(F-statistic)	0		

Unweighted statistics			
R-squared	0.8668	Mean dependent var	0.0124
Sum squared resid	1.4071	Durbin-Watson stat	2.6012

* Metro areas without tier indexes are excluded.

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): 1979Q2 to 2014Q1
Included observations: 140 after adjustments
Cross sections included: 101
Total pool (balanced) observations: 14,140
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	-0.0002	0.0001	-3.3739	0.0007
DLOG Case-Shiller aggregate index	0.9542	0.0023	413.8138	0.0000
(LOG Case-Shiller high-tier index, lagged 1 qtr - LOG Case-Shiller aggregate price index, lagged 1 qtr), 4-qtr MA	-0.0115	0.0014	-8.4362	0.0000
LOG S&P 500 index, lagged 1 qtr - LOG S&P 500 index, lagged 5 qtrs	0.0032	0.0003	10.9709	0.0000
DLOG ratio of avg to median household income	0.0104	0.0031	3.3279	0.0009

Weighted statistics			
R-squared	0.9269	Mean dependent var	0.0114
Adjusted R-squared	0.9268	S.D. dependent var	0.0265
S.E. of regression	0.0071	Sum squared resid	0.7182
F-statistic	44782.15	Durbin-Watson stat	2.3131
Prob(F-statistic)	0		

Unweighted statistics			
R-squared	0.9084	Mean dependent var	0.0096
Sum squared resid	0.7195	Durbin-Watson stat	2.3943

* Metro areas without tier indexes are excluded.

explanatory variable 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 0.1 percentage point.

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Celia Chen is a managing director of the Moody's Analytics research staff, specializing in housing economics. Celia manages the Moody's Analytics regional house price forecast models, develops proprietary housing market indicators, and writes extensively about housing issues. Based in the West Chester PA office, Dr. Chen has participated in numerous consulting projects, including econometric modeling of regional house price forecasts, consumer lending, and mortgage lending.

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