CoreLogic HPI Forecast

Data and Methodology

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Introduction

House Price Forecasts are vital tools for anticipating key trends and understanding potential future volatility in real-estate markets. However, HPI forecast methodologies and data drivers can vary greatly with each provider leveraging its own combination of data and analytics methodologies to yield vastly different results. Forecast accuracy is a direct function of the right balance of quality of data inputs, the expertise of the analytics staff and the analytic toolset used to produce outputs.

The CoreLogic HPI Forecast was created to help clients better understand potential future real estate risk by providing a comprehensive HPI forecast that leverages the most comprehensive housing resale data available.

The CoreLogic HPI Forecast Model is a regression-based methodology that generates predictions of returns for the CoreLogic House Price Index.

The model generates predicted returns at a monthly frequency for twenty-four-month horizons. Returns are measured as the monthly log change in the CoreLogic HPI. Forecasts are generated for all tiers (SFD, SFA, combined SFD and SFA, and distressed) and for all geographies for which CoreLogic produces an HPI index (National, State, CBSA, county and Zip codes).

The model is structured hierarchically, both in its variables and in its geography. Forecasts of the HPI are dependent upon forecasts of specific housing and economic variables, which, in turn, are dependent upon forecasts of other housing and economic variables. For geographies, forecasts for a specific geography are dependent upon the forecast of the larger geography the subject geography is embedded in.

The estimation of the model is via Maximum Likelihood. When singularity issues are occasionally encountered, the method of Conditional Least Squares is utilized.

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Data

The HPI Forecast takes a specific index from CoreLogic HPI as its input. For each index, the monthly return is computed as the log return in the index:

$$R_{j,t} = Ln\left(\frac{I_{j,t}}{I_{j,t-1}}\right) \quad (1)$$

Where:

$I_{j,t}$ = the value of the index for HPI j at time t

$I_{j,t-1}$ = the value of the index for HPI j at time t-1

The exogenous regressors in the forecast model include but are not limited to 10 Year Treasury Yields and Yield Curve Slopes, Unemployment rates, Price/Rent Ratios, Housing Inventory, Foreclosure Inventory, REO Inventory, Homebuilder Sentiment, Probability of Recession and Seasonal Factors.

Various lags, interactions and other transformations (e.g. differences) of these variables are also used in the model. In addition, the forecasts of these variables are dependent upon other variables not listed here. They are from public sources. The most locally observed level of each variable is utilized for each index when possible.

Model Specification

The model follows a unique specification, in that in the long run, house price movements are projected as an adjustment process towards equilibrium, while in the short run, they are modeled as a function of their elasticity with respect to the geography where they are embedded. The long-run adjustment process is based upon the work of Fama and French (1988), while the CAPM approach is based upon the work of Treynor (1962), Sharpe (1964) and Lintner (1965).

The model is specified as follows:

$$R_{j,t} = \lambda\left(\mathrm{Ln}\left(\mathrm{PR}^{\mathrm{e}}_{\mathrm{jt}}\right) - Ln\left(\mathrm{PR}_{\mathrm{j,t\text{-}1}}\right)\right) + \beta_1(F_{jt}) + \beta_2(ARMA) + \varepsilon_{it} \quad (2)$$

Where:

$\mathrm{PR}^{\mathrm{e}}_{\mathrm{it}}$ = the equilibrium Price-Rent ratio for HPI *j* at time *t*

$\mathrm{PR}_{\mathrm{j,t\text{-}1}}$ = the actual Price-Rent ratio for HPI *j* at time *t-1*

F_{jt}= the Forecast for the next-larger geography that HPI *j* is embedded in

ARMA = various autoregressive and moving average terms for HPI *j*

Note: The second term in equation (2) is dropped for the national forecast, since there is no HPI for a larger geography than the National HPI.

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The first term in (2) represents the difference between the equilibrium price-rent ratio in a given housing market, and the actual observed price-rent ratio in a given housing market. Since the stylized facts about house prices are that they are known to deviate around their fundamental values, this term represents the gap between where house prices should be — as explained by their fundamentals — and where they actually are. Over time, the adjustment of actual price-rent ratios around their equilibrium values is modeled as a proportion of the difference between the current period's target level and last period's actual level.

The second term in (2) represents the forecast of the HPI for the next larger geography where HPI *j* is located. For example, if HPI_j is an index for a Zip code *j*, then F_{jt} is the forecast for county *j*.

The third term in (2) is a set of autoregressive (AR) and moving average (MA) terms for HPI *j*. They are designed to pick up any residual autocorrelation left in the forecast that are not explained by the first two terms in (2).

The only term in (2) that is not directly observed is the equilibrium price-rent ratio $\mathrm{PR}_{\mathrm{it}}^{\mathrm{e}}$. This is forecast via the following specification that regresses actual price-rent ratios on each market's fundamentals:

$$PR_{it}^{e} = \beta(\text{fundamentals}) + \varepsilon_{it} \quad (3)$$

The model's specification has several unique interpretations. First, substituting equation (1) into (2) gives you:

$$Ln\left(\frac{I_{j,t}}{I_{j,t-1}}\right) = \lambda\left(\mathrm{Ln}\left(\mathrm{PR}_{\mathrm{jt}}^{\mathrm{e}}\right) - Ln\left(\mathrm{PR}_{\mathrm{j,t\text{-}1}}\right)\right) + \beta_1(F_{jt}) + \beta_2(ARMA) + \varepsilon_{it} \quad (4)$$

Since it is one of the rules of logarithmic transformations that:

$$Ln(a) - Ln(b) = Ln\left(a/b\right) \quad (5a)$$

Then equation (4) can be rewritten as:

$$Ln\left(I_{j,t}\right) - Ln\left(I_{j,t-1}\right) = \lambda\left(\mathrm{Ln}\left(\mathrm{PR}_{\mathrm{jt}}^{\mathrm{e}}\right) - Ln\left(\mathrm{PR}_{\mathrm{j,t\text{-}1}}\right)\right) + \beta_1(F_{jt}) + \beta_2(ARMA) + \varepsilon_{it} \quad (5b)$$

In this specification, the coefficient λ has the interesting interpretation of being the speed at which a given housing market adjusts to its equilibrium value. Such an interpretation has precedence in the academic literature, in which the work of Greene (1993), Pindyck and Rubinfeld (1991) specify similar specification for partial adjustment models of imperfect markets. In an econometric estimation of (5b), λ will take a value between zero and one, with values near zero indicating a market that is slow to adjust towards equilibrium, and values near one indicating a market that is quick to adjust towards equilibrium.

A similar, but alternative expression of the model can be obtained by multiplying the first term (5b) by λ and rearranging, which gives you:

$$Ln\left(I_{j,t}\right) = \lambda\left(\mathrm{Ln}\left(\mathrm{PR}_{\mathrm{jt}}^{\mathrm{e}}\right)\right) + (1-\lambda)\left(Ln\left(I_{j,t-1}\right) - Ln\left(\mathrm{PR}_{\mathrm{j,t\text{-}1}}\right)\right) + \beta_1(F_{jt}) + \beta_2(ARMA) + \varepsilon_{it} \quad (6)$$

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Equation (6) expresses the current house price level in a given market as a weighted average of its equilibrium price-rent ratio, and the difference between its actual house price levels and its actual house price-rent ratio. In this expression, λ is no longer the adjustment speed of house prices, but rather the different weights between the two terms. If λ is large, then equilibrium conditions will dominate over the intertemporal persistence in house prices, and house price appreciation should be relatively smooth and non-volatile. If λ is small, then momentum in house prices will dominate over prevailing fundamentals, and house price appreciation will likely by very cyclical and even volatile. In both of the expressions (5b) and (6), λ has a different interpretation, but similar implications. Large values of the λ coefficient are associated with housing markets that adjust smoothly and quickly to new information and conditions, whereas small values are associated with markets that have sticky and volatile prices.

In the application of a similar specification to HPI forecasts, the economic interpretation of the λ parameter is that is the speed with which house prices react to new information and move towards a new equilibrium. By contrast, the econometric interpretation of λ is that of the weight in a weighted average specification that states that current house price levels can be modeled as the weighted average of their desired (i.e. equilibrium) level and last period's deviation from the actual level.

The actual numeric interpretation of the λ parameter is interesting, as well. Since, by (6), λ is constrained to take a value from a minimum of 0 to a maximum of 1, then the magnitude of the λ reflects both the speed with which actual house price levels adjust to their equilibrium, as well as the degree to which the fundamental determinants of house prices are incorporated into house prices. At the extreme, λ=1 would imply perfectly efficient markets that immediately and completely incorporate new information into current house prices. At the other extreme, λ=0 would imply that house prices are a random walk over time, displaying enormous persistence and no mean reversion. It would also imply that the intertemporal change in house prices are zero-mean white noise.

The β coefficient on the second term in (2) is an interesting analogy to one of the most famous models in asset pricing. In the basic CAPM framework, the (excess) returns on any given asset are expressed as a linear function of the (excess) returns on the market where that asset is traded:

$$E[R_i] = R_f + \beta(E[R_m] - R_f) \quad (7)$$

Where:

$E[R_i]$ = the expected return on individual asset *i*

R_f = the risk-free rate of return, such as interest on government bonds

$E[R_m]$ = the expected return on the market

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In this expression of expected (i.e. forecasted) asset return, the β coefficient represents the sensitivity of the returns of asset i to returns in the overall market. Values less than one indicate a relative insensitivity to market returns, values greater than one indicate a hyper-responsiveness to market returns, and a value equal to one indicates a perfect correlation with the market. Using our notation for the housing market, the CAPM version of returns on housing would be:

$$E[R_j] = R_f + \beta(E[R_m] - R_f) \quad (8)$$

Where:

R_j = the house price returns of HPI *j*

R_m= the house price returns of the larger market where that HPI *j* is located

Since the HPI model forecasts nominal, not real, returns, we can remove the risk-free rate from the model:

$$E[R_j] = \beta(E[R_m]) \quad (9)$$

In this specification, the returns on house price *i* are modeled as a function of house price returns in the market where house *i* is located; for example, its CBSA. Since the HPI Forecast is concerned with indices rather than individual house prices, the l.h.s. of (8) can be the expected return on HPI j, and the r.h.s. can be the expected return on the larger market HPI j is embedded in. For example, modeling Zip-level HPI returns as a function of county-level HPI returns, county-level returns as a function of CBSA-level returns, CBSA-level returns as a function of State-level returns, and State-level returns as a function of National-level returns. In this way, the forecast utilizes a hierarchical structure of geography to incorporate two economic insights into patterns of house price returns: housing returns in any locality typically have some covariance with housing returns in the larger geographic market where locality is embedded. Housing also is an asset in addition to being consumption good. Hence, returns should exhibit some conformance with the extensive research on asset pricing.

Lastly, since the forecast model allows for time-varying changes in house price returns, we remove the expectation operator from (9), add the time subscript to the variables and replace the term on the r.h.s. of (9) with the actual forecast of market returns:

$$R_{j,t} = \beta(F_{jt}) \quad (10)$$

The term on the r.h.s. of (9) is the second term in our forecasting model in (2). Hence, the CAPM version of housing with time-varying returns is included in our HPI forecasting model's specification.

As a final step we may apply the logarithmic transformation rule in (5b) to the second term in (2). This allows us to rewrite the model as follows:

$$R_{j,t} = \lambda\left(\mathrm{Ln}\left(\mathrm{PR}^{\mathrm{e}}_{\mathrm{it}} / \mathrm{PR}_{\mathrm{i,t-1}}\right)\right) + \beta_1(F_{jt}) + \beta_2(ARMA) + \varepsilon_{it} \quad (11)$$

This is a tremendously parsimonious specification of house price returns. It is a simple regression of the (log) change in the house price index on only two exogenous variables: the (log) difference in the equilibrium price-rent ratio from the actual price-rent ratio, and the forecast of the larger housing market where the observed index is located. The first term represents the long-term adjustment of house prices towards their equilibrium. The second term represents their short-term CAPM-like elasticity with house price changes in the surrounding market. And, rather than substituting for unobserved variables, the third terms represent any residual variation in house price returns not explained by the two exogenous variables.

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Data and Model Validation

The degree to which the value of λ varies, both across housing markets and across different points in the housing cycle, further informs us of the nature of both the market and the cycle. Since it represents the adjustment speed of house prices to equilibrium, it is reasonable to expect that not only are house prices affected by their fundamentals, but that their adjustment speeds also can be affected by the fundamental characteristics of the subject housing market.

It is a central theorem of economics that prices are located at the intersection of supply and demand. However, housing is a durable good; it takes a substantial amount of time to provide new housing, and once provided it remains in the housing stock for a typically long period of time. This implies that housing supply is relatively inelastic, at least in the short run. By contrast, housing demand is relatively more elastic. Household formation rates, interest rates, rents, incomes and household mobility are always changing; at least at a speed that is faster than the change in housing supply.

If the supply is relatively slow in adjusting to changes in demand, then, in the short run, prices must adjust to clear the market. However, the speed with which prices can adjust is affected by the relative elasticity of supply. If supply can adjust relatively easily to demand, then house prices should be relatively stable over time. By contrast, if supply is difficult, costly or lengthy to adjust, then house prices over time should exhibit greater volatility and cyclicality. The extent to which a particular housing market is more like one or the other should be reflected in the value of its λ parameter.

To tie these economic relationships of housing to the structure of the forecast model, we need a measurement of housing supply elasticity for each market that we estimate an HPI for. We use the Wharton Residential Land Use Regulatory Index©, developed by Gyourko, Saiz and Summers (2007).

The Wharton Residential Land Use Regulatory Index (referred to as WRLURI hereafter) is an index that characterizes the relative degree with which land use in a given U.S. jurisdiction is regulated for residential development. The index is derived from a periodic survey sent to municipal officials, and it covers a broad array of questions concerning the housing development process in that municipality. The survey attempts to identify the degree to which certain types of development are prohibited, the extent to which regulations affect design and permitting, the ease with which court suits or political coalitions can challenge development, the cumulative magnitude of barriers and hurdles to development, the pervasiveness of regulations that drive up the cost of development (e.g. minimum lot size requirements, affordable housing requirements, open space dedications and requirements to pay for infrastructure), the trend in local construction costs over the past decade, and the standard review time for a project change (e.g. zoning variances).

The responses to the questionnaire are compiled to create an index for each municipality that characterizes the costliness, lengthiness and difficulty with which new housing can be developed. The higher the level of the index, the greater each of these aforementioned characteristics, and hence, the greater the housing supply elasticity in that market. Furthermore, the index is standardized to have a standard normal distribution with a mean of zero and standard deviation of one. Therefore, the actual level of the index is not as important as its relative level, since it identifies each municipality's location on the spectrum of housing supply elasticity across the U.S.

Figure 1 shows the distribution of the most recent WRLURI for all municipalities in the sample, while Table 1 gives the percentiles of the distribution[1]:

[1] We do not report the moments of the distribution because it is standard normal and the moments are known; e.g. mean of zero and standard deviation of one.

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Figure 1

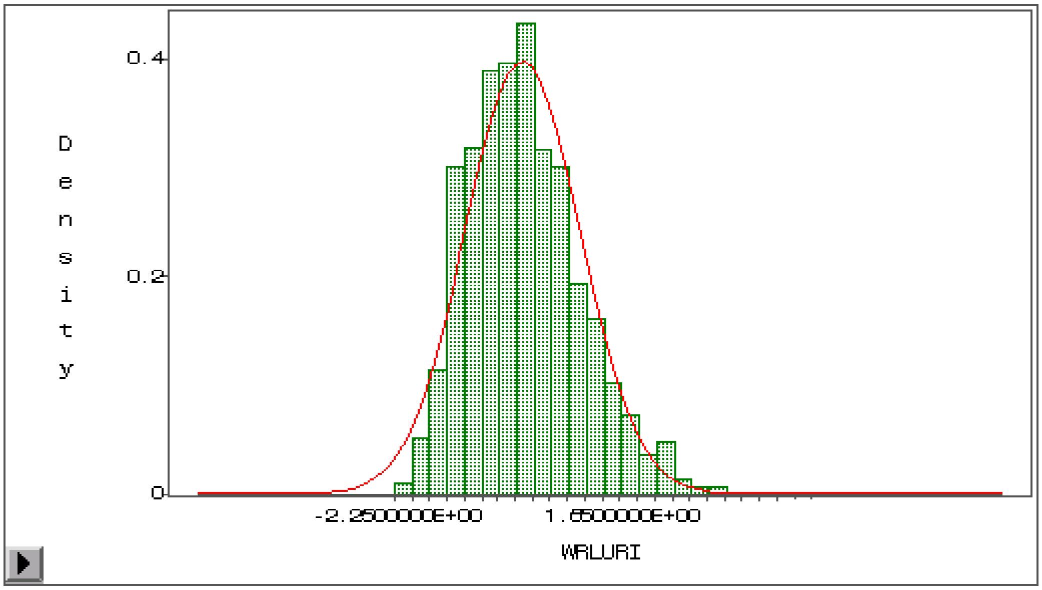

Table 1: Distribution Percentiles

Quantiles			
100% Max	4.7961	99.0%	2.8308
75% Q3	0.5882	97.5%	2.3393
50% Med	-0.0945	95.0%	1.8464
25% Q1	-0.7300	90.0%	1.3169
0% Min	-2.1523	10.0%	-1.1854
Range	6.9484	5.0%	-1.3884
Q3-Q1	1.3182	2.5%	-1.5712
Mode	-1.2046	1.0%	-1.7647

As Table 1 indicates, the 25% of U.S. municipalities where it is easiest/cheapest/quickest to build new housing have a value of -0.73 or lower, while the top 25% of U.S. municipalities where it is difficult/costliest/lengthiest to build have a value of 0.5882 or higher. This is our proxy for housing supply elasticity.

To gain further intuition and insight into the degree with which housing supply elasticity varies across the U.S., Figure 2 color-codes each county in the U.S. where FA produces an HPI by the value of its regulatory index[2]. A red-to-blue color ramp is used, with red denoting relatively elastic markets and blue denoting relatively inelastic markets. The categorization of colors is based upon the quintiles (i.e. fifths) of the distribution, so that exactly 20% of all municipalities are assigned to each of the five categories:

[2] Although the index is observed at the municipal level, FA does not estimate municipal-level HPIs. County-level elasticities were computed by averaging the values of the WRLURI across all municipalities in a given county,

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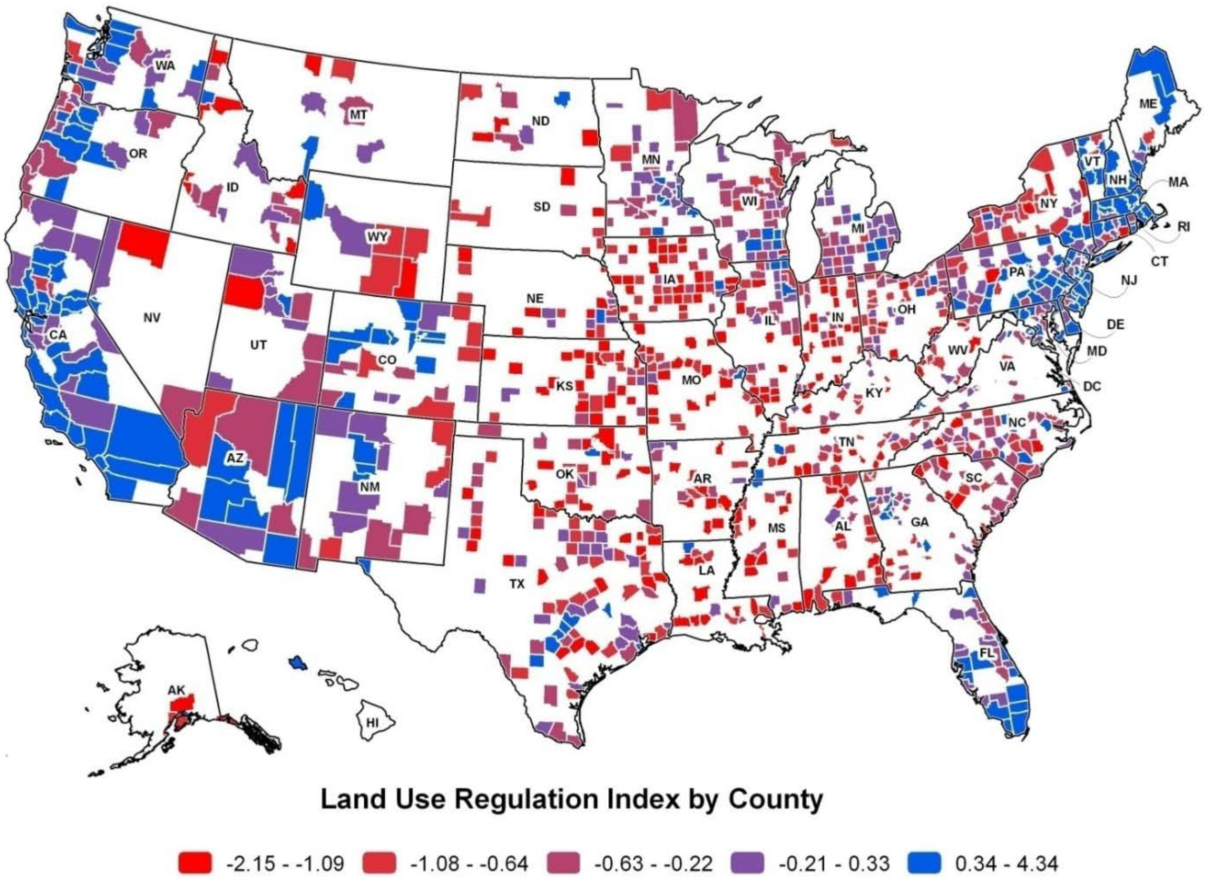
Figure 2: Land Use Regulation Index by County



The geographic pattern in housing supply elasticity is evident. Counties with high index scores (and a low implied elasticity) are disproportionately clustered along the respective coasts of the country, in the Northeast, Pacific and Mountain regions, and in larger and older metropolitan areas. Counties with low index scores (and high implied elasticity) are disproportionately clustered in the interior regions of the country, in the South and Midwest, and in smaller and younger metropolitan areas.

weighted by the number of housing units in each municipality. However, for many large cities in the U.S. the city and county are geographically synonymous.

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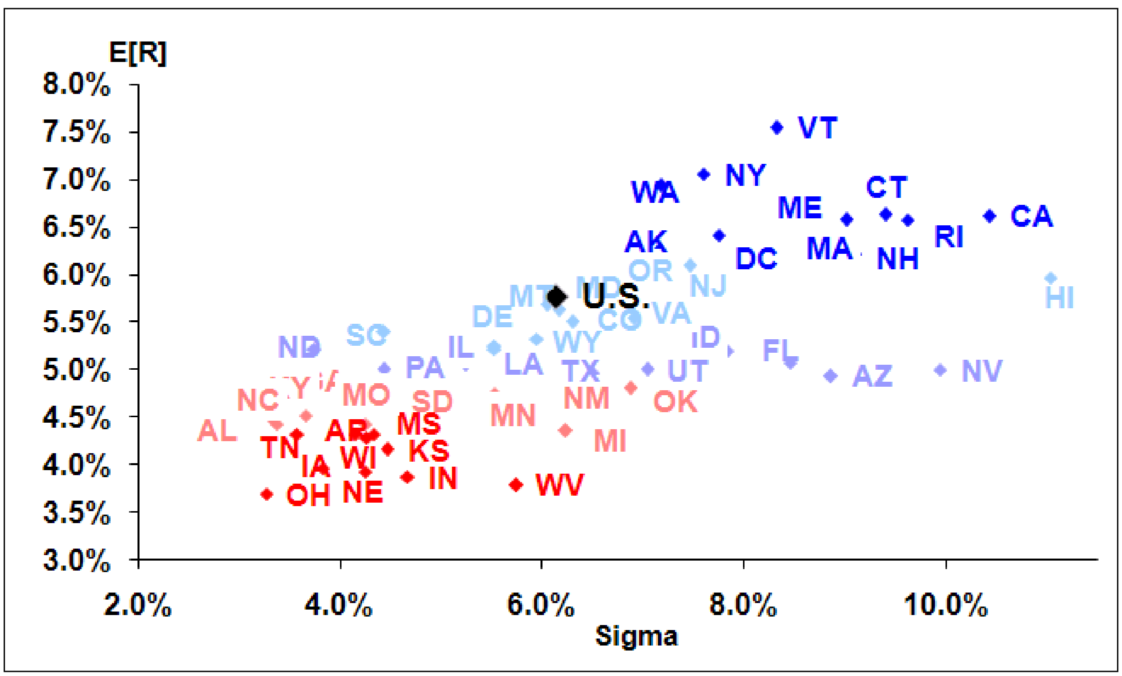
The correlates of the index score are tied to the geographic constraints and political preferences of the localities. Areas with a high score have a higher probability of possessing both limited and high-priced land due to their coastal locations, be in larger and older metropolitan areas where taxes are higher and the permit/zoning process is more pervasive, have unionized building trades that increase the cost of construction, and have stronger anti-development sentiment due to preferences for such things as less sprawl, more historic preservation, mandatory affordability guidelines, stringent building codes and preservation of green space. All of these factors contribute to land that is pricier, a development process that is longer and construction costs that are higher. By contrast, areas with a low score have a higher probability of possessing both larger amounts of and lower-priced land, be in smaller and younger metropolitan areas where taxes are lower and the permitting/zoning process more straightforward, have non-unionized building trades that keep construction costs relatively lower, and have a more pro-growth, pro-development political culture compared to their high elasticity counterparts.

If local housing supply elasticity is correlated with the general level of house price volatility, then the central results of the CAPM model should apply. Markets with relatively low levels of elasticity should not only have higher house price volatility and cyclicality over time, but they must offer homebuyers a higher average rate of appreciation over time to compensate them for this volatility. Conversely, markets with relatively high levels of elasticity should have lower levels of volatility and cyclicality over time, as well as a lower average rate of house price appreciation due to this greater certainty over future returns.

We test this in two stages. First, we perform an explicit estimation of the CAPM version of the housing using the annualized returns on each HPI. For each State HPI and the National HPI, we compute a time series of annualized returns, and then compute the mean and standard deviation of returns for each market. Figure 3 provides a scatterplot that shows each state's location in the risk-return space.

Figure 3: State House Price Return vs. Risk



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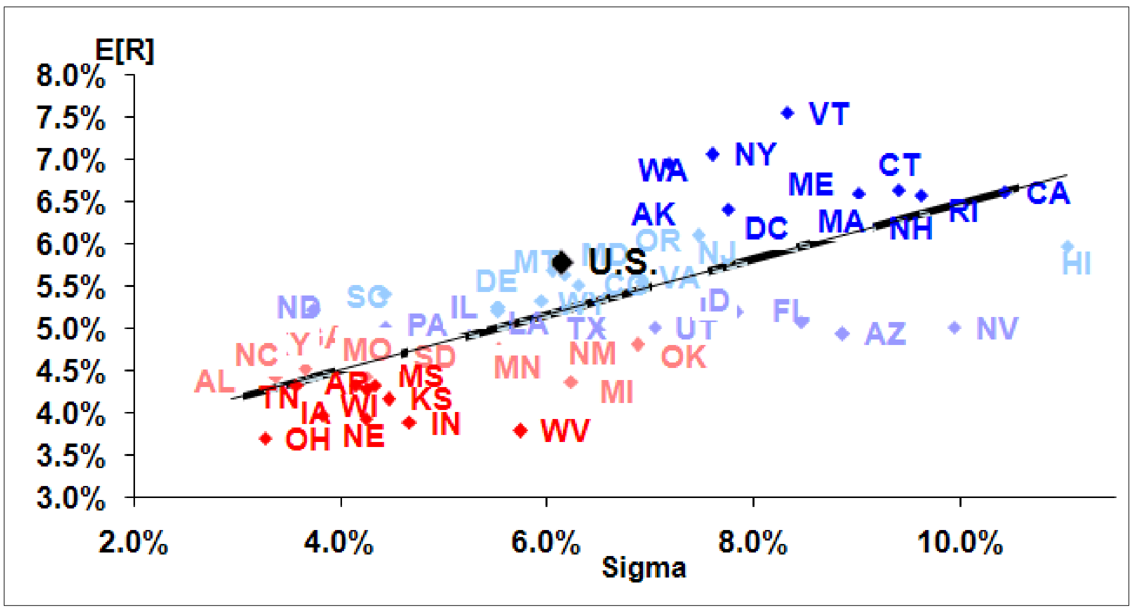
The standard deviation of returns is displayed on the horizontal axis, while the average return is plotted on the vertical axis. States in the lower left-hand side of the plot have relatively lower levels of both risk and return in house prices, and therefore they have lower levels of house price appreciation and cyclicality over time. States in the upper right-hand side have relatively higher levels of both risk and return in house prices, and hence higher levels of house price appreciation and cyclicality over time. The correlation of an individual State's position in the risk-return space with its housing supply elasticity presented in Figure 3 is evident:

- Low-risk, low-return states have abundant and cheap land (Nebraska, Kansas), low levels of taxation and regulation (Indiana, Tennessee), non-coastal locations in the country's interior (Wisconsin, Missouri) and relatively fewer large, older cities (South Dakota, Kentucky).
- High-Risk, high-return state have limited and expensive land (Hawaii, Rhode Island), high levels of taxation and regulation (California, Massachusetts), coastal locations (Connecticut, Washington) and relatively larger, older cities (New York, D.C.).

Readers with a finance background may recognize the similarity of the scatterplot of Figure 4 to Markowitz's famous "Efficiency Frontier" (1952). We provide a formal test of this by estimating the housing version of the CAPM. Basically, this is a regression of expected returns on the standard deviation of returns

Figure 4: Regression of Average Annual HPI Return on Std. Dev. of Returns



The black line represents the fitted regression line; the regression results are displayed in the inset text box within the chart. The upward slope of the line indicates that that higher-appreciation States experience more volatile returns.

The empirical results provide formal confirmation of this: house price appreciation in zero-volatility (i.e. linear appreciation) housing markets are 3.2% per year, and increase by about 33 basis points for every one percentage point increase in the standard deviation of annual house price returns. This 33 bps can be interpreted intuitively as the "price of risk." It is the additional return that the market demands in order to invest in a relatively riskier (i.e., more volatile) housing asset. With a t-score of 7.43 and R-squared of 52.44%, the results are statistically significant and provide empirical support for the model's specification and structure.

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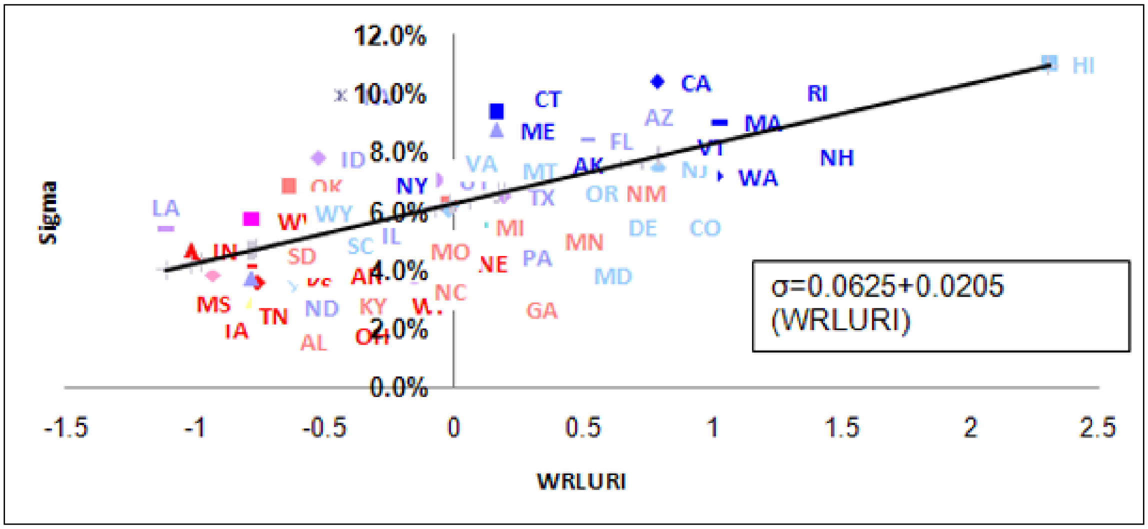
Then, we then test the exogeneity of the volatility of house price returns by regressing the standard deviation of HPI returns on each State's WRLURI score.

Figure 5: State Risk vs. Regulation



The value of the WRLURI is the exogenous variable, because its value results from either geographic factors beyond the market's control (e.g. land constraints) or policy choices made by the community (e.g. extensive land use regulation). The regression results confirm the correlation, and possibly the causation between the degree of housing supply inelasticity and the volatility of house price appreciation. States where it is relatively easier to add to the supply of housing have a lower volatility of returns. This, in turn, translates into relatively linear house price appreciation, with little cyclicality over the course of the housing or economic cycle. Conversely, states, where it is relatively more difficult or costly to add to the supply of housing, have a greater volatility of returns. This translates into more cyclical house price appreciation, with greater responsiveness of house prices to the changes in the housing market or economy.

The results of this section provide empirical evidence in favor of the model's specification and structure. In the long run, house prices gravitate toward their equilibrium values, as determined by their fundamentals. In the short run, they exhibit significant intertemporal persistence that is correlated with movement in house prices in the market where they are located. But, most importantly, the long-term components of house prices are linked to the short-term behavior of house prices by the local elasticity of supply. Where supply is inelastic, the adjustment to equilibrium is slow, house price movements are more volatile and the limited supply promotes a greater rate of appreciation. Where supply is elastic, the adjustment of equilibrium is faster, house price movements are less volatile, and the ability of supply to adjust to demand inhibits above-market rates of appreciation. In this way, not only does the model capture the most salient and known stylized facts about house price movements, but it ties these components together in the model's specification.

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Model Estimation

The model is estimated through maximum likelihood. The likelihood function is maximized through an iterative process that stops when the gains in the model's fit, due to a change in the parameters, becomes sufficiently small. If this objective is not reached within a sufficient number of iterations, the number of iterations is increased. In the few cases where convergence to a satisfactory solution is not achieved, usually due to the presence of a "ridge" in the data, the method of Conditional Least Squares is used.

Because of the model's hierarchical geographic structure, wherein the forecasts of smaller geographies use the forecasts of larger geographies, forecasts are generated from the top down. The forecasts are estimated for the National HPI tiers first. These forecasts are then input into the forecasts for the states. State-level forecasts are inputs into the CBSA-level forecasts, which are inputs into the county-level forecasts, which are inputs into the Zip-level forecasts.

Forecast Output

The model outputs the predicted log return of each HPI at a monthly frequency. A separate prediction is output for each month. This allows for both non-linearity and non-monotonicity in the forecast.

Forecasts are generated in monthly intervals for 24 months for the following geographies:

- National
- State
- CBSA
- County
- Zip

And, for the following tiers for each geography:

- Single-Family Detached (SFD)
- Single-Family Attached (SFA)
- Combined SFD and SFA
- Combined SFD and SFA, excluding distressed sales (e.g. REOs, short sales, etc.)

The deliverable product is the predicted value of the HPI in each future month, plus the predicted YoY change in the HPI for each future month.

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Model Validation and Performance Monitoring

In both the model's development and forward implementation, the outputs are subjected to thorough back-testing. This procedure is designed to simulate an out-of-sample forecast. In this simulation, specific sequential time periods from 6 months to 24 months are deleted from all time series, and the model is re-estimated to generate predictions for these time periods. The out-of-sample forecast is then compared to the actual realization of the time series to identify how well the model predicted.

To quantify the model's out-of-sample performance, predicted HPI returns are regressed on actual HPI returns and the various regression diagnostic statistics are examined. A statistically significant slope coefficient, a high R-squared, a low level of heteroscedasticity and small number of outliers all indicate strong forecast accuracy and model stability. This out-of-sample simulation is not only run for the typical periods in the housing cycle when prices are either rising or falling, but also for the critical turning points and inflection points in the housing cycle, when house prices either change direction or change their rate or increase/decrease.

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