What Unemployment Data Can Tell Us about House Prices: Stabilizing a Strong but Unstable Connection

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Abstract
It is well known that long periods of high unemployment have a significant adverse effect on real estate prices. However, the connection between unemployment and house price is very unstable. It varies significantly for different historical periods and, if no stabilizing technique is applied, the unemployment-based house price estimates produced by regression models fitted into different historical periods are vastly different and cannot be considered reliable for practical purposes. We have developed a method for building robust models for calculating unemployment-based house price estimates under given unemployment scenarios. This method was employed to build a library of unemployment-to-house price index models which includes a nationwide model and 20 MSA level models that encompass all areas covered by the Case-Shiller Indices.

Key Words: house price index, unemployment rate, finance, forecasting, regression models averaging

0. Introduction

On May 15, 2006 the Association of Realtors released the report (see, for example, [1]) showing that in the first quarter of 2006, median house prices nationwide dropped 3.3 % from the fourth quarter of 2005. That was among the first enunciations of the U.S. housing bubble bursting. In accordance with Standard & Poor's Case-Shiller House Price Indices CSXR (Composite-10) and SPCS20R (Composite-20) (see, for example, [2]), the nationwide house price reached its maximum in June-July 2006 and then declined for 33 months in a row. The steady decline of house prices set forth the down ward spiral of the American real estate market which eventually brought one of the worst U.S. recessions since World War II. From that time on, the development of house prices has become one of the major, if not the major, risk factors that determines management of any sizeable portfolio of residential mortgage-backed securities (RMBS) or whole mortgages.

In the most recent report ([3]) released by CoreLogic, the leading provider of residential real estate market data, shows that 10.8 million, or 22.3 percent, of all residential properties with a mortgage owed more on their mortgages than their homes are worth (i.e. were in "negative equity" or "underwater") at the end of the second quarter of 2012. An additional 2.3 million borrowers possessed less than 5 percent equity in their homes, (i.e. were in "near-negative equity"). Totally, in the second quarter of 2012, negative equity and near-negative equity mortgages accounted for 27% of all residential properties with a mortgage nationwide.

Obviously, negative equity borrowers have a significantly higher propensity to default on their mortgages, and any negative movement of house prices which can increase the percentage of such loans in a mortgage portfolio or diminish the equity the borrowers have on their loans constitutes a clear and present danger, which should be analyzed and properly addressed. It is common practice that asset managers run a set of declining house price scenarios to see how mortgages would perform under adverse market conditions.

There are a number of ways to create house price scenarios. This can be done, and it is frequently done in practice, in a "short and dirty" way when it assumed that house prices all over the country will drop, let us say 3% or 5% or 10%. However "unscientific" and rude it appears, it serves the trading floor reality when a trader needs to go though a long bid list of RMBS in a very short time and make a "to buy – not to buy" decision. For more fundamental and long term analysis, the majority of financial companies have developed their own HPI forecasting analytics or use commercially available house price forecast models and/or services.

In this paper, we present our approach to building scenarios for possible future development of house prices. Following this approach, we have created a library of models that yield HPI scenarios for twenty Metropolitan Statistical Areas (MSA) covered by the Case-Shiller Indices and a model producing nationwide house price scenarios (Case-Shiller Composite-10). These models have been developed and calibrated to assist investors and asset managers in selecting HPI stress scenarios that provide adequate risk evaluation of mortgage products (whole mortgages, RMBS, mortgage related securities and indices) they hold in their portfolios. These models have been solely designed for risk management and, by no means, are they intended to facilitate making bets on the HPI near-term movements.

The paper adheres to the following outline: Section 1 provides a rationale to use unemployment as the only economic input for house price models. Section 2 describes our method for creating the library of HPI models. Section 3 shows how the unemployment-based HPI models work in practice, and Section 4 demonstrates practical implications of model runs for portfolio management. Section 5 describes how our models are benchmarked against the house price analytics employed by a large group of economists and market strategists. Section 6 is a technical appendix containing "bulky" formulae.

1. House Prices and Unemployment

Over the years a number of financial companies, data providers, rating agencies, and academic institutions developed advanced house price models. A short and very incomplete list of the most "popular" providers of house price analytics and services would include such names as CoreLogic (see [3]), Moody's Analytics (see [4]), Andrew Davidson & Co. (see [5]), Fannie Mae (see [6]), and Freddie Mac (see [7]). Those models are based on fundamental econometric research (see, for example, [8], [9], and [10]) and leverage a vast amount of historical data accumulated over the last several decades. They frequently combine time series techniques with regression analysis which captures the connections between the time development of house prices and such key economic factors as housing supply and demand, rental and construction cost, income level, inflation rate, basic interest rates (Treasury or LIBOR are the most commonly used), mortgage rates, unemployment rate, and economy activity index (GDP).

In our approach, we consider only one economic factor – unemployment rate: local when dealing with MSA level model or USA when building a nationwide model. While it may look overly simplistic from the fundamental academic perspective, we believe it can provide a good "match" to the country's current economic conditions with unemployment rate hovering above 8% (see [11]) since February 2009, i.e. during the last 43 months as of the moment, September 2012, when this paper was written. Since January 1948, when the Bureau of Labor Statistics (BLS) started reporting its nationwide unemployment series, this is the longest period of high unemployment. In combination with the huge drop in house values, it has been putting tremendous stress on all consumer related credit; and mortgages are hit especially badly.

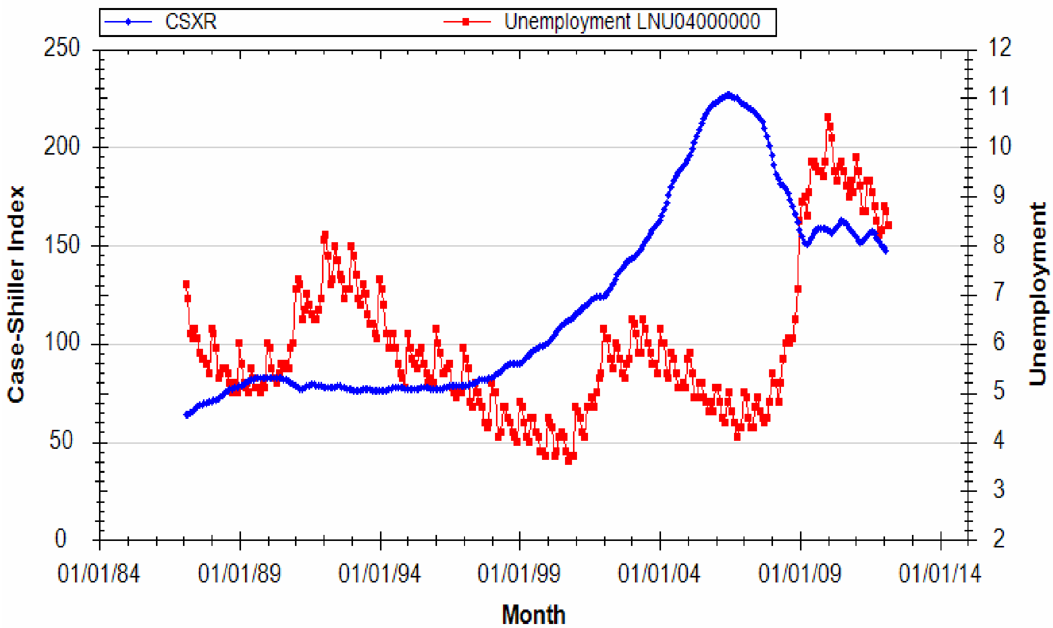

Figure 1: Case-Shiller Composite-10 house prices index CSXR vs. nationwide seasonally unadjusted unemployment LNU04000000.

There is a straightforward line of reasoning which connects high unemployment with falling house prices: if a person does not have a job, a bank will not give him or her a mortgage; if there is a significant drop among the people who could get a mortgage, then the number of people who can buy a house also drops, which, in turn, diminishes house demand and, therefore, brings house prices down. This is a quite unforgiving environment, when classical remedies like lowering interest rates is not working – a bank does not give a mortgage to an unemployed under any rate, period. It creates a vicious circle when falling house prices spook potential buyers who do not want to see the value of the house they just purchased go down, which again leads to a further decline of house prices.

Figure 1 provides the reader with a vivid illustration of the strong negative connection between unemployment and house prices. The challenge, however, rises in quantifying this connection for building a robust model that can yield unemployment-based house price estimates. The statistical analysis of the historical data shows that the connection between house prices and unemployment is very unstable. It significantly varies from one historical period to another; and other factors, such as a lag between unemployment index and HPI and the size of moving average for smoothing unemployment index, can also add to the connection instability.

To illustrate the point, let us look at Figure 2 showing the historical time development of the correlation between nationwide seasonally unadjusted unemployment series LNU04000000 reported by the Bureau of Labor Statistics ([11]) and Case-Shiller Composite-10 house prices index CSXR reported by Standard & Poor ([2]) calculated over the period of January 1987 (the first month CSXR was available) through June 2010.

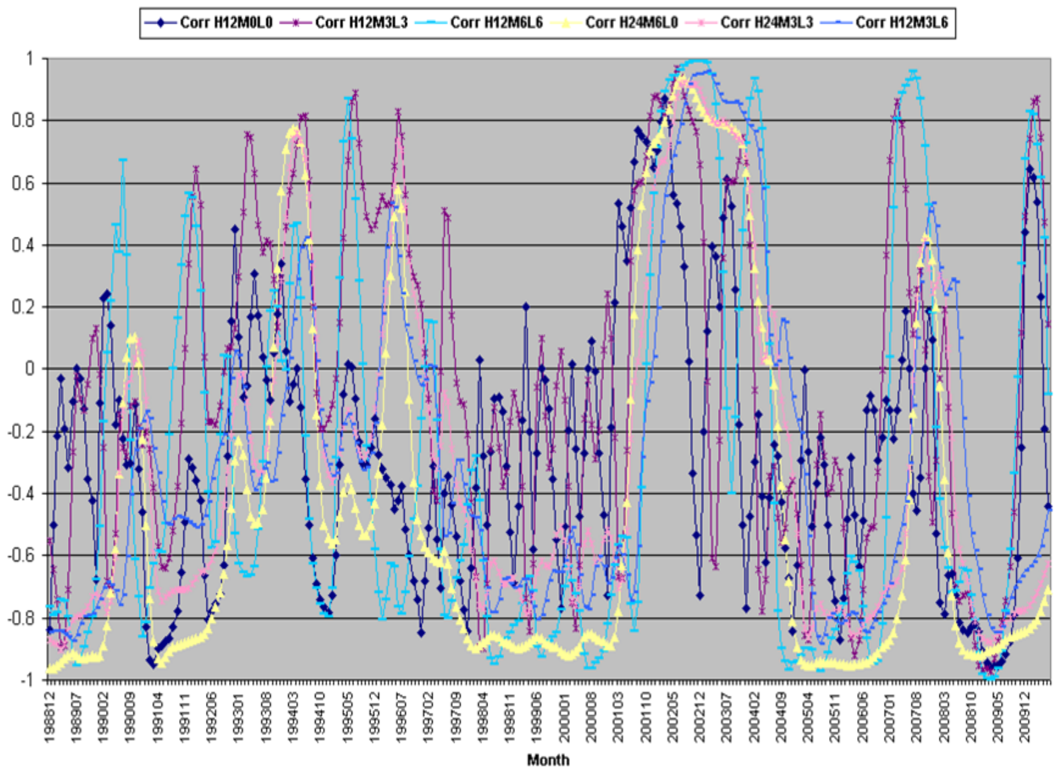

Figure 2: Correlation functions between *U(t)*=LNU04000000 (unemployment) and *S(t)*=CSXR (house prices). H is the length of historical period; M is the size of moving average for smoothing unemployment; L is the lag between CSXR and LNU04000000. CorrH12M0L0 $= Corr[U,S;12,0,0](t)$, CorrH12M3L3 $= Corr[U,S;12,3,3](t)$, CorrH12M6L6 $= Corr[U,S;12,6,6](t)$, CorrH24M6L0 $= Corr[U,S;24,6,0](t)$, CorrH24M3L3 $= Corr[U,S;24,3,3](t)$, and CorrH12M6L3 $= Corr[U,S;12,6,3](t)$ Please see Appendix for the notation explanation.

2. Building HPI Models

Figure 2 clearly shows that if no stabilizing technique is applied, the model and its HPI estimates will depend heavily on the historical period and other parameters that were chosen to build the model. This creates a level of instability which cannot be tolerated in any time constrained business environment. We developed an approach that allows overcoming the unemployment – house price connection instability and building robust models yielding unemployment-based HPI estimates. This approach is a variation of the well-known method for building a model average estimator (see, for example, [12], [13], [14], and [15]), and, the in most general form, can be described as the following two-step process:

1. Build a set of so-called Base Models for different historical periods, unemployment moving averages and lags.
2. Combine Base Models into the Final Model - contribution of each Base Model to the Final Model is proportional to its ability to estimate accurately the latest house prices.

Each Base Model (BM) is a simple linear regression model:

$$s(t) = \alpha + \beta \cdot u(t)\,, \tag{1}$$

where *s(t) = log [S(t)]*, *S(t)* is a Case-Shiller HPI and *u(t)* is a BLS unemployment series , which was smoothed over the period $[t, t-M]$ and taken with a lag L.

$$u(t) = U_M(t-L) = \frac{1}{M}\sum\nolimits_{\tau=t-M+1}^{t} U(\tau - L) \text{ (please see also Appendix)}$$

Given that a base model is fitted into the historical period $[T_C - H_V - H, T_C - H_V]$, where T_C is a date when the most recent unemployment and house price data are available, H_V is a size of validation period which is reserved for evaluating the model performance, and one can create a set of basic models by varying the length of historical period *H*, the sizes of moving average *M* and lag *L*. In such way, a set of base models can be formally described as set

$$BM = \{BM_j = (\alpha_j, \beta_j; H_j, M_j, L_j, \varepsilon_j) \mid j = 1,2,..., J\}\,, \tag{2}$$

where α_j and β_j are regression coefficients, H_j, M_j, L_j are model parameters, and ε_j is the sum of squared errors the model BM_j exhibited over the valuation period $[T_C - H_V, T_C]$.

Given a set of base models *BM*, the final model *FM* is defined as

$$FM = \sum\nolimits_{j=1}^{J} w_j BM_j\,,\; w_j = \lambda / \varepsilon_j\,,\; \lambda = \left(\sum\nolimits_{j=1}^{J} 1/\varepsilon_j\right)^{-1}, \text{ i.e.} \sum\nolimits_{j=1}^{J} w_j = 1\,. \tag{3}$$

3. How It Works In Practice

We have implemented this two-step methodology to create a library of 21 models: a nationwide model and twenty Metropolitan Statistical Areas (MSA) level models. Each model was built and recalibrated monthly as soon as new data on unemployment and HPI are posted by the Bureau of Labor Statistics and, correspondingly, Standard & Poor, on their websites. Table 1 below provides the reader with the list of matching BLS series and Case-Shiller's HPIs that are used for model building and monthly recalibration. Both BLS unemployment series and Case-Shiller's HPIs are seasonally unadjusted. The house prices are greatly defined by local conditions, and we find it very important that local unemployment data is used for each and every model.

Table 1: Historical Series Used to Build the Models

Geographical Area	*Case- Shiller HPI*	*BLS Unemployment Series*
Nationwide	SCXR	LNU04000000
AZ-Phoenix	PHXR	LAUMT04380603
CA-Los Angeles	LXXR	LAUMT06311003
CA-San Diego	SDXR	LAUMT06417403
CA-San Francisco	SFXR	LAUMT06418603
CO-Denver	DNXR	LAUMT08197403
DC-Washington	WDXR	LAUMT11479003
FL-Miami	MIXR	LAUMT12331003
FL-Tampa	TPXR	LAUMT12453003
GA-Atlanta	ATXR	LAUMT13120603
IL-Chicago	CHXR	LAUMT17169803
MA-Boston	BOXR	LAUCA25715003
MI-Detroit	DEXR	LAUMT26198203
MN-Minneapolis	MNXR	LAUMT27334603
NC-Charlotte	CRXR	LAUMT37167403
NV-Las Vegas	LVXR	LAUMT32298203
NY-New York	NYXR	LAUMT36356203
OH-Cleveland	CEXR	LAUMT39174603
OR-Portland	POXR	LAUMT41389003
TX-Dallas	DAXR	LAUMT48191003

Strictly speaking, the models we built are not forecasting ones. They require the user to come up with a number of scenarios for unemployment development for the next 60 months for each MSA region and nationwide. Then the model “converts” each unemployment scenario into an HPI estimate.

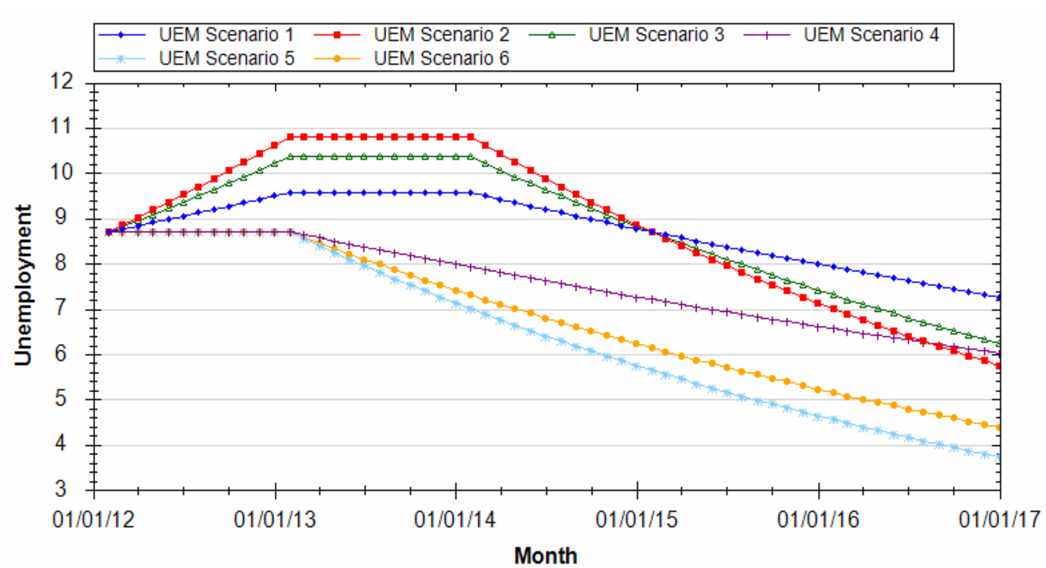

Figure 3: Model inputs: Nationwide Unemployment Scenarios for nationwide seasonally unadjusted unemployment series LNU04000000

Figure 3 above shows an example of six possible unemployment scenarios, and Figure 4 below demonstrates how the model maps those scenarios into nationwide HPI projections.

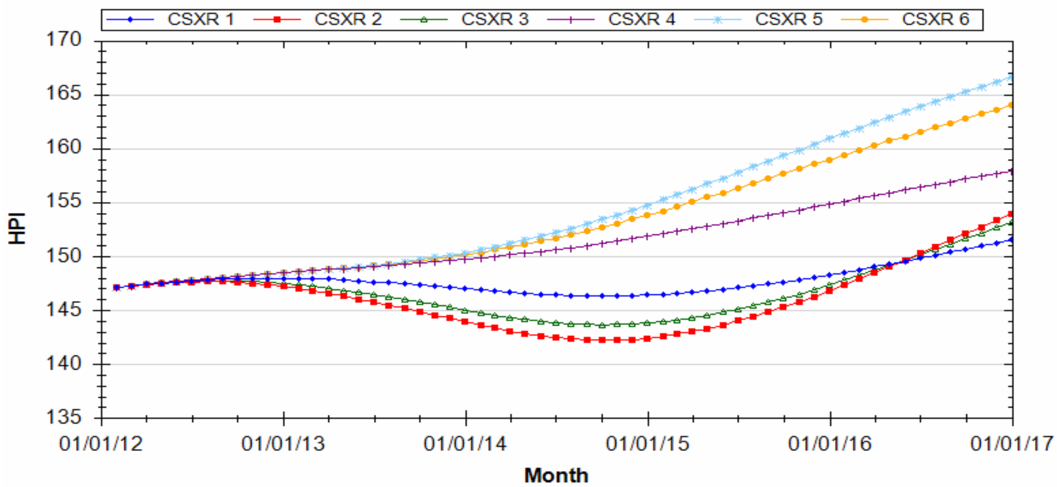

Figure 4: Model outputs: Unemployment-based CSXR estimates calculated for the scenarios in Figure 3

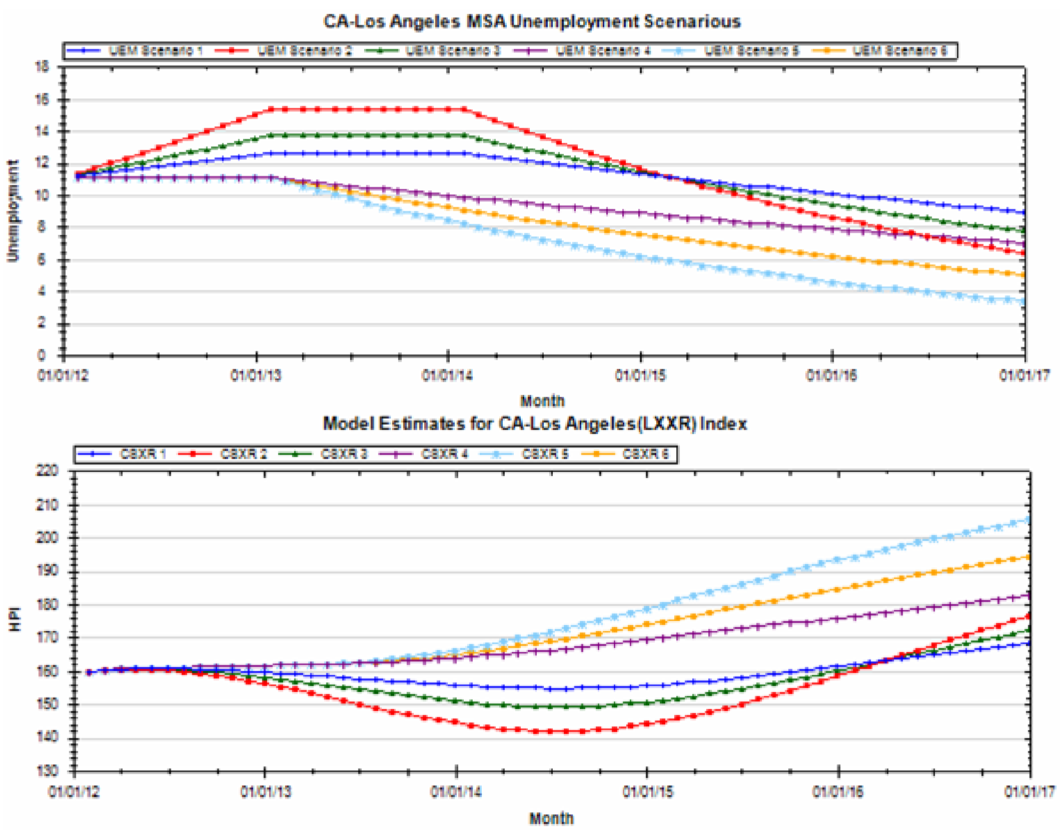

Figure 5: Model inputs - outputs: Unemployment scenarios (LAUMT06311003) and their corresponding HPI projections (LXXR) for Los Angeles, CA MSA

Figure 5 above and Figure 6 below show unemployment scenarios and their corresponding HPI projections for CA-Los Angeles MSA and, TX - Dallas MSA.

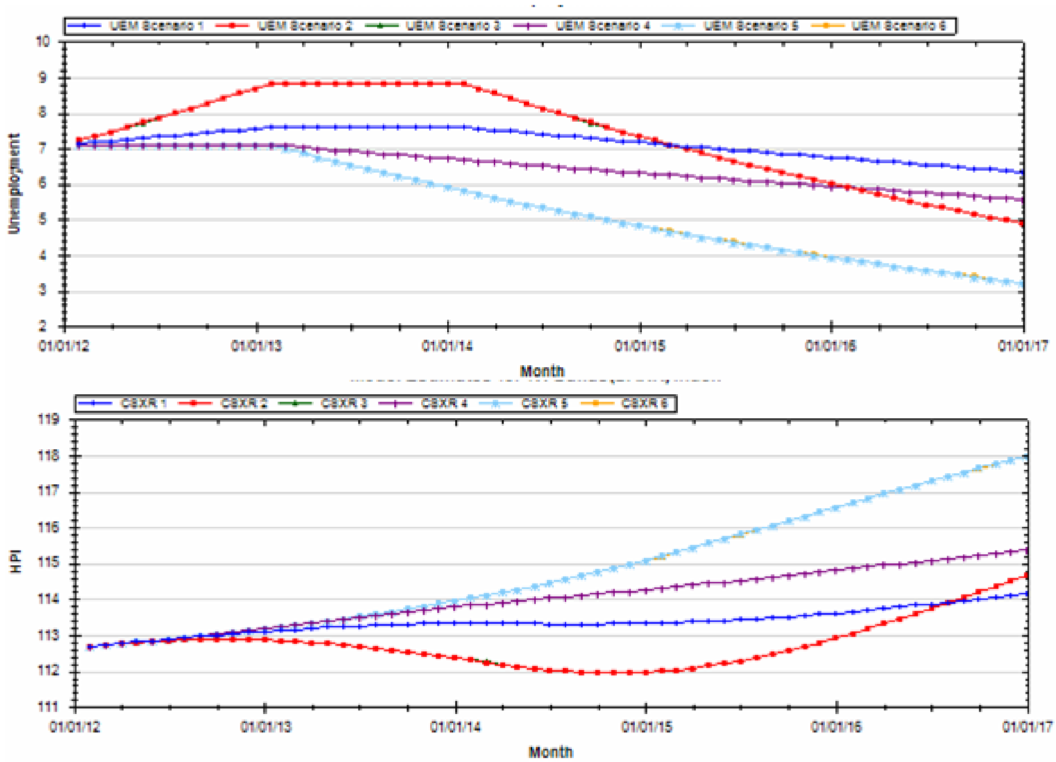

Figure 6: Model inputs - outputs: Unemployment scenarios (LAUMT48191003) and their corresponding HPI projections (DAXR) Dallas, TX MSA

The reader can see that while unemployment scenarios in Figures 3, 5, and 6 adhere to the same shapes (up-then-flat-then-down or flat-then-down), they vary in their slopes and levels. For example, Los Angeles unemployment level is higher than Dallas one, and it has a steeper upward slope in the first three scenarios. Those differences reflect the variation in local unemployment history: Los Angeles experienced a fast unemployment increase in its recent history (that suggested the steeper slope), and its unemployment rate is higher than the nationwide. Dallas' unemployment rate is well below the nationwide level, and, over the last four years, it did grow more slowly than around the country, much slower than in Los Angeles.

Figures 4, 5, and 6 show how the unemployment scenarios were mapped by the corresponding models into the HPI projections. The reader can see that two different shapes of unemployment scenarios pronounced themselves in two different shapes of HPI projections. It is also clearly visible how the difference in the slopes and levels of unemployment scenarios propagated into the difference in HPI projections. For example, comparing HPI projections corresponding the worst unemployment Scenario 1 (the red lines on all Figures 3 through 6), we can observe that while Los Angeles HPI is expected to have a significant drop in the 3rd quarter of 2014, Dallas HPI just shows a minor decline by the end of the year 2014.

4. Model Application to HPI Stress Testing of Mortgage Portfolio

When it comes to the HPI stress testing of a mortgage portfolio, the ability to differentiate between geographical regions becomes crucial. To illustrate the point let us consider two investment portfolios holding residential mortgages – directly as whole loans, or as

RMBS holdings. The 2nd and the 3rd columns of Table 2 show the geographical distribution of mortgages held in those portfolios across twenty MSAs (see Table 1). A few mortgages with property located outside of those MSAs are treated by the nationwide model. Columns 4 through 9 show the largest house price drops by markets and scenarios that were projected by the corresponding models for the next 60 months.

Table 2:	Portfolio Geographic Exposure		Model Estimations of Largest House Price Drops by Markets and Scenarios					
Market	*Portfolio 1*	*Portfolio 2*	*CS1*	*CS2*	*CS3*	*CS4*	*CS5*	*CS6*
Nationwide	0.50%	0.50%	-2.39%	-5.13%	-4.17%	-1.89%	-1.89%	-1.89%
AZ-Phoenix	2.70%	5.00%	2.53%	-4.63%	-0.26%	2.53%	2.53%	2.53%
CA-Los Angeles	7.00%	12.00%	-4.55%	-12.64%	-7.99%	-1.37%	-1.37%	-1.37%
CA-San Diego	5.00%	3.00%	-1.85%	-6.38%	-4.18%	-0.86%	-0.86%	-0.86%
CA-San Francisco	8.00%	5.00%	-3.68%	-8.78%	-6.31%	-2.95%	-2.95%	-2.95%
CO-Denver	0.70%	0.00%	-1.52%	-2.61%	-2.34%	-1.43%	-1.43%	-1.43%
DC-Washington	3.00%	3.00%	-3.59%	-6.53%	-5.66%	-2.15%	-2.15%	-2.15%
FL-Miami	7.50%	9.00%	1.39%	-4.27%	-2.27%	1.39%	1.39%	1.39%
FL-Tampa	4.50%	7.00%	-0.83%	-5.75%	-1.82%	-0.83%	-0.83%	-0.83%
GA-Atlanta	5.00%	8.00%	-5.14%	-8.36%	-6.78%	-4.88%	-4.88%	-4.88%
IL-Chicago	7.00%	7.00%	-4.27%	-7.34%	-5.69%	-4.27%	-4.27%	-4.27%
MA-Boston	3.00%	2.00%	-1.51%	-2.31%	-2.14%	-1.51%	-1.51%	-1.51%
MI-Detroit	4.00%	3.50%	0.51%	0.51%	0.51%	0.51%	0.51%	0.51%
MN-Minneapolis	2.00%	1.00%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%
NC-Charlotte	7.00%	4.00%	-1.56%	-3.15%	-1.83%	-1.56%	-1.56%	-1.56%
NV-Las Vegas	4.10%	12.00%	-6.22%	-11.06%	-8.93%	-0.96%	-0.96%	-0.96%
NY-New York	8.00%	8.00%	-5.54%	-8.94%	-8.16%	-3.17%	-3.04%	-3.05%
OH-Cleveland	9.00%	4.00%	-4%	-5.92%	-5.90%	-3.64%	-3.64%	-3.64%
OR-Portland	1.00%	1.00%	-2.17%	-3.66%	-2.18%	-2.17%	-2.17%	-2.17%
TX-Dallas	9.00%	3.00%	-0.47%	-1.13%	-1.13%	-0.47%	-0.47%	-0.47%
WA-Seattle	2.00%	2.00%	-1.48%	-3.18%	-2.57%	-1.48%	-1.48%	-1.48%

Combining the largest house price drops with the portfolio geographic exposures yields the overall portfolio losses shown in Table 3. One can see that the employment of MSA specific loss projections creates a significant difference in the assessments of how much house values underlying portfolio mortgages can drop under adverse real estate market conditions. Portfolio 2, which has larger than Portfolio 1 exposure to such "bad" MSAs as CA-Los Angeles, GA-Atlanta, GA-Atlanta, and IL-Chicago, looks definitely more risky than Portfolio 1. Assuming that both portfolios are of the same size, let us say $2 Billion, the difference in the potential decline in underlying house values (please see Table 4) should really catch the attention of portfolio managers and investors.

Table 3: Model Estimations of Portfolio Largest Drop in House Values by Scenarios

Portfolio	*CS1*	*CS2*	*CS3*	*CS4*	*CS5*	*CS6*
Portfolio 1	-2.57%	-5.98%	-4.40%	-1.74%	-1.73%	-1.73%
Portfolio 2	-2.92%	-7.15%	-5.05%	-1.57%	-1.56%	-1.57%
Portfolio 1 & 2 given the same nationwide model was applied to the whole portfolio	-2.39%	-5.13%	-4.17%	-1.89%	-1.89%	-1.89%

Table 4: Model Estimations of Largest Drop in House Values by Scenarios for $2 Billion Portfolio (in $ Millions)

Portfolio	*CS1*	*CS2*	*CS3*	*CS4*	*CS5*	*CS6*
Portfolio 1	51.36	119.60	87.98	34.81	34.60	34.62
Portfolio 2	58.49	143.00	101.08	31.50	31.29	31.30
Portfolio 1 & 2 given the same nationwide model was applied to the whole portfolio	47.80	102.60	83.40	37.80	37.80	37.80

5. Benchmarking the Model

Every quarter MacroMarkets LLC posts on its website a home price expectations survey of about 100 leading economists, real estate experts, investment and market strategists employed by industry and academia (see [16]). The list of experts includes such names as chief economists from Moody's Analytics, Freddie Mac, Barclays Capital, and professors from UCLA and Columbia Business Schools. The survey is based upon the projected path of the S&P/Case-Shiller U.S. National Home Price Index over the coming five years.

We use this report to benchmark our unemployment based HPI estimates. Figure 7 shows that our projections lie well inside of the lowest (most pessimistic) and highest (most optimistic) opinions expressed by survey participants in the 4th quarter of 2011 and the 1st quarter of 2012. Our HPI projections based on the more optimistic unemployment scenarios (see Scenarios 4, 5, and 6 in Figure 3) are very close to the survey median, while our HPI projections based on the more pessimistic unemployment scenarios (see Scenarios 1, 2, and 3 in Figure 3) fall below the median.

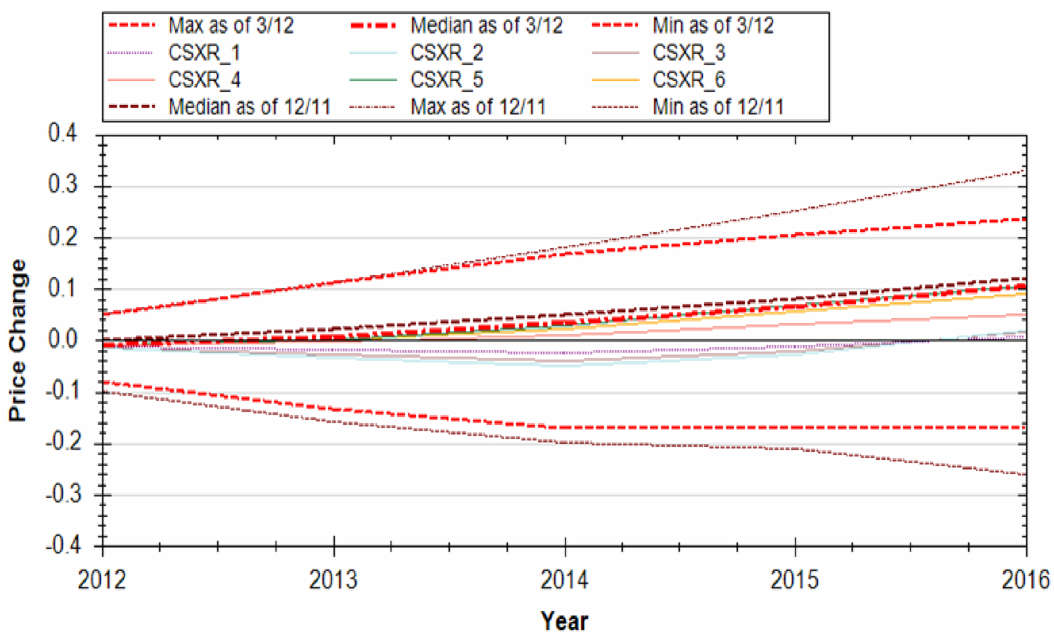

Figure 7: Unemployment-based nationwide HPI (CSXR) estimates vs. MacroMarkets home price expectations survey.

These results give us confidence that our simple one-variable HPI analytics does a decent job. Nobody in the market possesses a crystal ball-type house price model which foresees exact movements of real estate prices. Everybody is doing his best to figure out what is going to happened; and the question is not whether you turn out to be right or wrong, but whether your miscalculations will be worse or better than the others.

6. Appendix: Notation for Figure 2

We used the following notation for the chart in Figure 2:

For two time series *X(t)* and *Y(t)* defined for $t \in Z$ and parameters $L \in Z$ and $H, M \in Z_+ = \{z \in Z \mid z \geq 0\}$, Z is the set of all integers numbers, we define

$$X_M(t) = \frac{1}{M}\sum_{\tau=t-M+1}^{t} X(\tau), \qquad \text{(A.1)}$$

$$E[X;H,M,L](t) = \frac{1}{H}\sum_{\tau=t-H+1}^{t} X_M(\tau - L), \qquad \text{(A.2)}$$

$$\sigma[X;H,M,L](t) = \sqrt{\frac{1}{H}\sum_{\tau=t-H+1}^{t}\left[X_M^2(\tau-L) - E^2[X;H,M,L](t)\right]}. \qquad \text{(A.3)}$$

Assuming that time series X and Y are such that $E[X;H,M,L](t)$ and $E[Y;H,0,0](t)$ are bounded, and $\sigma[X;H,M,L](t)$, $\sigma[Y;H,0,0](t)$ are bounded and non-negative, we define the correlation between X and Y as the following function of time *t*:

$$Cor[X,Y;H,M,L](t) = \frac{\frac{1}{H}\sum_{\tau=t-H+1}^{t} X_M(\tau-L)\cdot Y(t)}{\sigma[X;H,M,L]\cdot\sigma[Y;H,0,0]} \qquad \text{(A.4)}$$

Consider two time series *U(t)*, $t \in [t_0^u, t_c^u]$ and *S(t)*, $t \in [t_0^s, t_c^s]$ containing historical data for correspondingly unemployment rate as reported by BLS and Case-Shiller HPI as reported by S&P for the same region (an MSA or country-wide). BLS has data that goes farther back than Case-Shiller; i.e. $t_0^u < t_0^s$. Also, for all regions, BLS reports the most recent unemployment rate before or at the same time as S&P reports Case-Shiller house price indices; i.e. $t_c^s \leq t_c^u$. Thus, $[t_0^s, t_c^s] \subset [t_0^u, t_c^u]$ and the amount of data that was used for the historical analysis is limited by the availability of Case-Shiller HPI data.

Given the length of historical period *H*, the lag *L* between *U(t)* and *S(t)*, the size of smoothing average *M*, the formulae (A.1) – (A.4) can be used to calculate the correlation between a Case-Shiller HPI and an unemployment rate

$$\boxed{Corr[U,S;H,M,L](t) = \frac{\frac{1}{H}\sum_{\tau=t-H+1}^{t} U_M(\tau-L)\cdot S(t)}{\sigma[U;H,M,L]\cdot\sigma[S;H,0,0]}} \qquad \text{(A.5)}$$

for $\forall t \in [t_0^s, t_c^s] : t - M - L \geq t_0^u$ if $L \geq 0$ and $\forall t \in [t_0^s, t_c^s + L] : t - M \geq t_0^u$ if $L < 0$.

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