ANDREW DAVIDSON & CO., INC. the Pipeline

Valuation Commentary

Modeling Home Prices as Dynamic Assets

by Alex Levin

The credit/default modeling efforts are receiving considerable attention these days and they will be a prime focus during the afternoon session at AD&Co.'s upcoming 2006 Annual Conference. This report summarizes some of our current views on this topic.

One factor that drives a borrower's decision to default is the home price of his/her property. The owner with grim personal financial circumstances has an option to sell the property or to let the bank take it and foreclose. This decision will be based, primarily, on the amount of outstanding debt and the value of the house.

From the option-theoretic stand-point, the default process is a complex derivative of the home value process, among other things. Therefore, unlike many econometric models, a model for home prices needs to include random disturbances, or noise, as part of the model. Capturing volatility and correlation structures is the goal of current home price modeling efforts at AD&Co. What we are looking for is a model for randomness and a relationship, if any, between house prices and interest rates.

Factors

AD&Co. perceives that

- Individual home prices are related to a state's (or region's) home index plus a random idiosyncratic factor. The latter does not need to be "randomized;" its volatility lets us predict the probability of negative equity analytically.
- States' factors have (generally, limited) correlations to the U.S. home price index (HPI), with state-level "noises." The relationship between a state HPI and the U.S. HPI can be deemed as the relationship between a single-name stock and a market index. The Beta for each state or region and properties of the idiosyncratic factor can be backed by historical data.

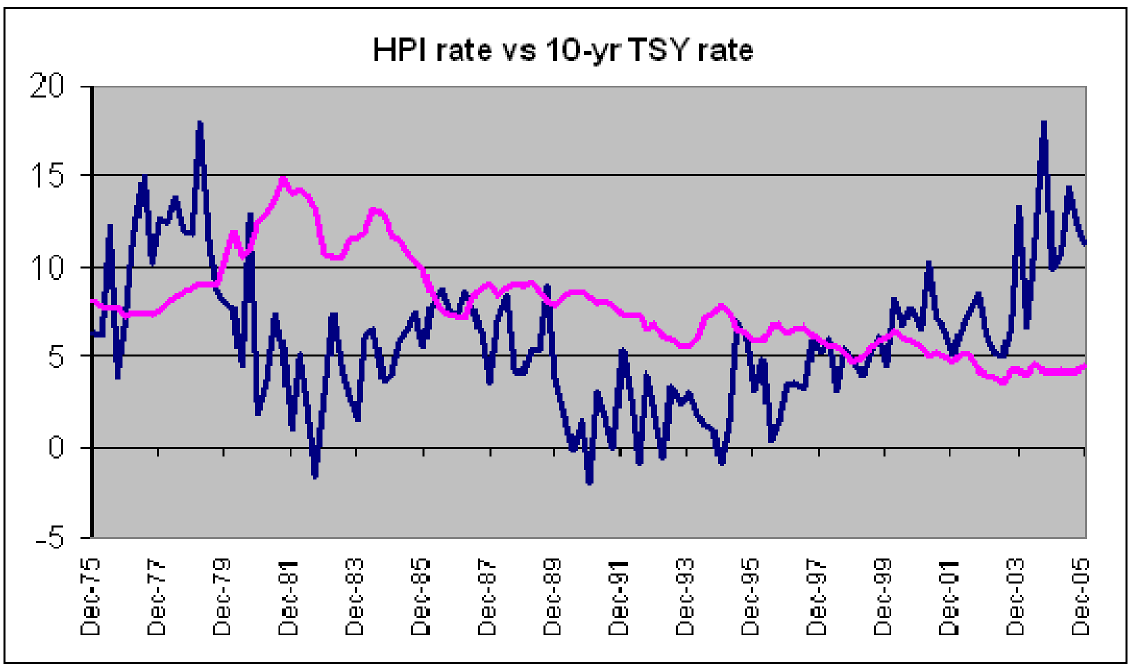
As we see further in this paper, HPIs behave like prices of dynamic assets, so the similarity between home prices and stocks was not mentioned by accident. In particular, HPI returns, which we call "HPI rates," resemble those of stocks and bonds, and a parallel to the empirical (real-life) rates and the risk-neutral ones can also be drawn.

Since the fixed income universe revolves around the concept of interest rates, it is important to find a link, if any, between them and home prices. Given known interactions between prepayments and rates, such a discovery can alter key perceptions of both prepayment and default options embedded into MBS or ABS. If, for example, home prices are proven to have a negative correlation with rates, then defaults and prepayments will have a negative correlation to each other. This finding will enlarge expected losses, and hence, valuation effect of defaults.

Dynamics of the HPI Rates: An Empirical Look

There are only a few sources for home prices and we used OFHEO as our primary source. The HPI time series is reported quarterly for all 50 states separately and for the U.S. as a whole. We computed quarterly returns and annualized them. The resultant measure, the U.S. HPI rate (hereinafter, "HPI rate"), is shown in Exhibit 1 going back to 1975. Along with the HPI rate, Exhibit 1 depicts the behavior of the 10-yr Treasury rate, the longest interest rate index available. The purpose of showing both indices on the same plot is two-fold: to assess a visual correlation (if any), and to compare the two distinctly different types of dynamics.

Exhibit 1



It is clear that the Treasury rate is continuous whereas the U.S. HPI rate is not. The latter seems to contain random jumps that occur around otherwise continuously changing mean levels. A diffusion + white noise pattern seems to resemble the dynamics of the HPI rate reasonably well. If we don’t trust our eyes, we can prove this fact by measuring empirical autocorrelation function of lag (Exhibit 2) and empirical standard deviation function of horizon (Exhibit 3).

Exhibit 2

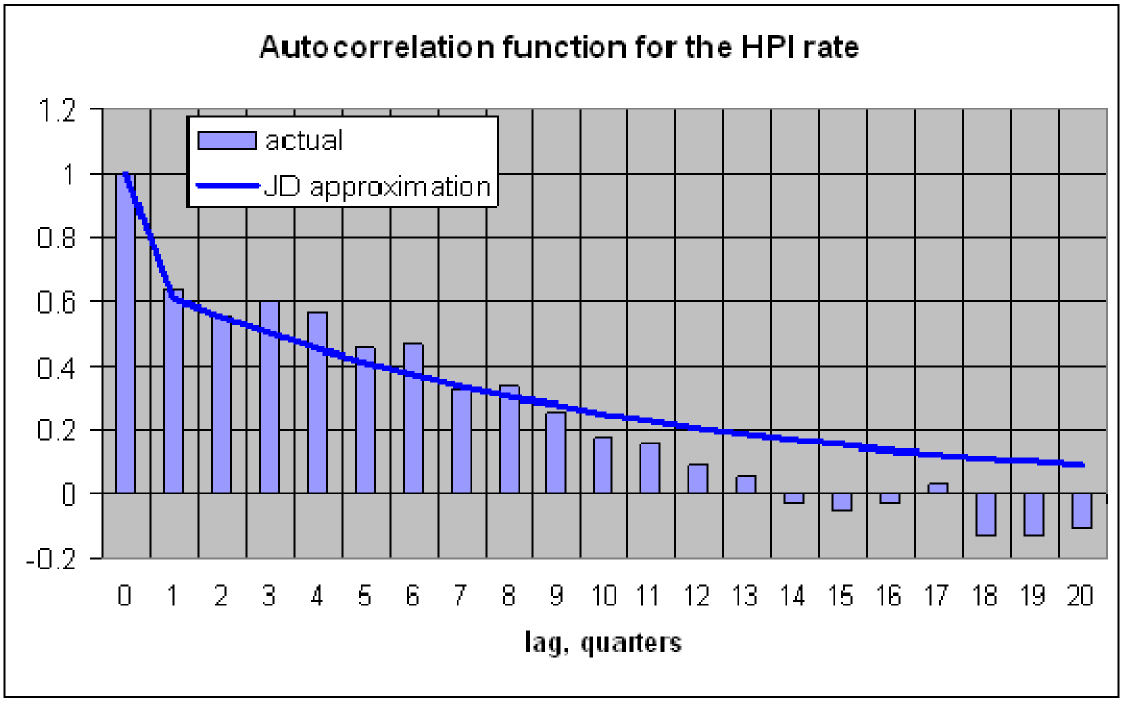
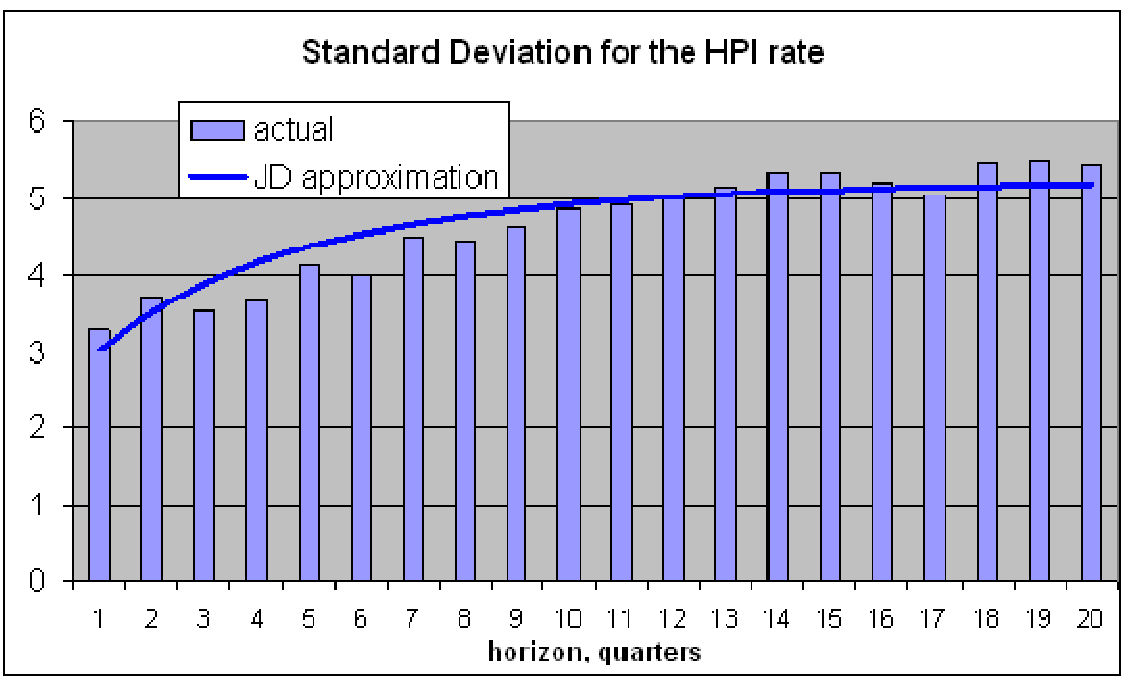


Exhibit 3



If the HPI rate followed a continuous diffusion, its autocorrelation function and its standard deviation function would be continuous as well. For example, for a 1 st-order linear model, often referred to as "AR(1)" in statistics, the stationary limit of the autocorrelation function is exp(-*at*) where *a* is the mean reversion. The standard deviation function would be equal to $\sigma\sqrt{(1-e^{-2at})/2a}$; it starts as $\sigma\sqrt{t}$ for small *t*, but then asymptotically converges to $\sigma/\sqrt{2a}$.

In contrast to these purely continuous functions, a jump is apparent and measurable in Exhibits 2 and 3 once we move from the t=0 to t=1. At first glance, the jump's size lets us assess the scale of white noise in a straightforward manner – by considering it to be equal to standard deviation (about 3% in Exhibit 3) for the minimum horizon we have, t=1. However, even for the shortest (1-quarter) horizon, the diffusion effect cannot be perceived to be negligible. Therefore, in the actual estimation, the jump's magnitude, the diffusion volatility and the mean reversion are all found concurrently. For this "AR(1) + jump" model, we added lines depicting theoretical autocorrelation and standard deviation to Exhibits 2 and 3.

The Right Theoretical Ground

Recall that the HPI rate is the annualized return of home prices. What would we expect a dynamic asset's return to be? Remember that, in the real (risky) world, the price *S* of a volatile asset paying a dividend rate of *d* should follow the stochastic differential equation,

$$\frac{dS}{S} = (r - d + \lambda\sigma)dt + \sigma dz \qquad (*)$$

where *r* is the risk-free rate, σ is volatility, λ is the price of risk and *z* is the Brownian motion. The latter is the integral of white noise (*w*), a mathematical limit for normally distributed, uncorrelated jumps. For the arbitrage-free world, λ is zero. Regardless of the case, the right-hand side of (*) is a price return for the infinitesimal horizon. To annualize, let us divide it by *dt*, we will get $(r - d + \lambda\sigma) + \sigma w$ or "diffusion + jumps." The risk-free rate, the expected dividend rate and the assumed price of risk are changing continuously. They determine the expected return. The white noise is the source of immediate next-period randomness. Therefore, if the HPI's time series represents values of a traded asset, its return must be compliant with the "diffusion + jumps" form. This proves that our modeling guess was a good one, and when looking at Exhibit 1, our vision does not malfunction. It is now clear why Treasury rates shown in Exhibit 1 are continuous: they represent **expected** (not actual) returns on the 10-yr Treasury bond and are, therefore, chiefly diffusive.

Thus, the HPI index behaves like a dynamic asset's price. Is there other evidence that the HPI can be modeled as a traded asset?

- Although the OFHEO HPI is not a direct measure of the value of the assets, like prices of bonds, it is intended to reflect the value of a constant average home over time. Although only 1-2% of individual homes get traded each quarter, it is still plausible to believe that if values for all homes were measured, they would reflect similar patterns as traded assets.

- Real estate generates “dividends” - income for investors and cost savings for owners.
- Chicago Mercantile Exchange (CME) currently initiates trading of futures and options on home price indices compiled for 10 metro areas (Read more on http://www.cme.com/trading/prd/env/housingres17858.html).

Note that the CME indices are compiled differently and independently from the OFHEO HPI index, but both apply the Case-Shiller repeat sales method and have an 80% correlation to one another. In view of the last point, the CME instruments, once established, can serve ground for an HPI risk-neutrality because they can be explicitly used to hedge the HPI-related risk. For example, one would be able to hedge credit risk by obtaining HPI puts or selling HPI forward. The forward values and volatility may follow from this market.

HPI Rate and Interest Rates

Let us revisit the main theoretical construct (*). The level of interest rates enters this equation in all 4 terms.

- First, it is the risk-free rate r: real estate is expected to earn more if r is high.
- Second, it is the dividend rate d which may contain the same inflation component as interest rates.
- Third, it is the price of risk λ to the extent of its dependence on the interest rates.
- Fourth, it is a possible correlation between the Brownian motion (z) used in (*) and the ones that drive interest rates. Indeed, if the HPI index was a bond’s price, it would have an immediate exposure to the interest rates (“duration”), i.e., random increments dz would be coming directly from an interest rate model.

One can also observe that, from a borrower perspective, the HPI index can be considered both an asset and a derived liability. A simple consideration of loan affordability leads to the conclusion that mortgage rates should negatively correlate with the HPI rates. Below is a table of historical correlations between different rates.

Exhibit 4. Historical correlations of the HPI rate's components to CMT10

1975 - 1989		
	CMT10	CMT10 increments
jump	-5.3%	**7.6%**
diffusion increments	**-28.0%**	-13.3%
diffusion	**-59.3%**	
since 1989		
	CMT10	CMT10 increments
jump	-8.5%	**-30.5%**
diffusion increments	**-29.2%**	-1.8%
diffusion	**-78.9%**	
since 1975		
	CMT10	CMT10 increments
jump	-3.8%	**4.2%**
diffusion increments	**-20.6%**	-9.3%
diffusion	**-21.9%**	

In bold, we show numbers that deserve the most modeling attention. It seems that the HPI, as an asset, is closer to a "stock" than to a "bond," and that mortgage affordability plays a key role. As seen in Exhibit 4, a negative correlation between the HPI rate's jumps to the CMT10 jumps, normally evident for a bond, has become a factor only since 1989. The diffusion component of the HPI rate has always had a strong negative correlation to the interest rates. A formally moderate -21.9% measure is explained by the difference between volatility levels in older times and now. Once we select the historical period, HPI rate and CMT10 show a strong negative correlation.

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