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Integrating Real Estate Market Conditions into Home Price Forecasting Systems

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Abstract

Market condition indicators are reviewed here as candidates for improved short-term home price forecasting. Medium- to longer-term housing price primary drivers are quite well known, such as employment, income, supply constraints, and interest rates. Shorter-term forecasts with improved accuracy on turning points present a greater challenge and require the use of market condition indicators. Here we demonstrate the power of a variety of market-based variables that might be considered in any future research on short-term home price forecasting. Such research may help us better understand potential housing bubbles and turning points in market prices. As data continues to improve, we can perform such analysis across much of the United States on a near-real time basis in smaller and smaller sub-markets.

Housing market analysis and the forecasting of prices is both an art and a science. The art comes from good economic theory and from the selection and integration of variables that capture the behavior component of the market. The science comes from using appropriate statistical modeling approaches. Here we focus on the art of forecasting housing processes over the short to intermediate time horizons by reviewing variables that we have observed as correlated positively or negatively with home prices, especially those that have proven to be leading indicators.[1]

We understand that over the years more sophisticated statistical tools have become available for forecasting, although we embrace them with some caution. For example, among the latest approaches, described by Kaboudan (2011) as ''agent-based modeling,'' combines two computational techniques, genetic programming (GP) and neural networks (NN), in a sequence of three stages. In the first stage the methods compete, in the second they cooperate, and in the third stage they use a best fit two-stage algorithm. There are two such problems with such ''statistically advanced'' techniques. Like all forecast models built from copious data sets, they are not immune to spurious correlations and data fitting. When you can test millions of variables in myriad exotic functional forms there is a greater likelihood that spurious results can occur.[2] The other problem is the challenge of interpretability, which may not matter if all we want to do is forecast prices. For those seeking the most advanced forecast techniques, see Dua and Miller (1996), Dua, Miller and Smyth (1999), Conway (2001), Crawford and Fratanoni (2003), Kaboudan (2008, 2011), Kaboudan and Sarkor (2008), among others.

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We argue that good forecasting requires both robust modeling techniques and expert intuition for the purpose of including the right variable selection. Here we define ''right'' as theoretically based with sound logic on cause and effect. We focus on the selection of variables we have found as significant for short- to intermediate-term forecasts. Over the long run it is clear that fundamentals will dominate, such as employment, income, supply constraints, and interest rates. But in the short run we find a rich set of market information embedded in market condition indicators, such as sales volume, time on the market, months remaining inventory and sales price to list price, among others. We also know that government interference may affect short-term price trends and these must also be monitored.[3]

When we are able to put at least two components together, that is fundamental drivers of price trends and market condition indicators, we are able to do a much better job of forecasting short run prices, sometimes catching turning points or even suggesting the potential for price bubbles. Market condition indicators also reflect behavior information, which is difficult to capture in fundamental models.

There is a rich literature on asset bubbles and behavioral influences on the stock market and a significant volume of work explaining housing bubbles. See, for example, recent work by Follain and Gertz (2011) where market conditions are examined in light of the potential for explaining housing bubbles. We do not attempt to explain housing bubbles here but our work could certainly be applied to housing bubble analysis.[4]

Last, we recognize that seasonality plays a part in housing sales volume and price trends over the course of a year based on separate and prior research and models attempting monthly price forecasts might consider controlling for seasonal patterns (e.g., Goodman, 1993; Kuo, 1996; Kaplanski and Levy, 2009; Miller, Sah, Sklarz, and Pampulov, 2011).

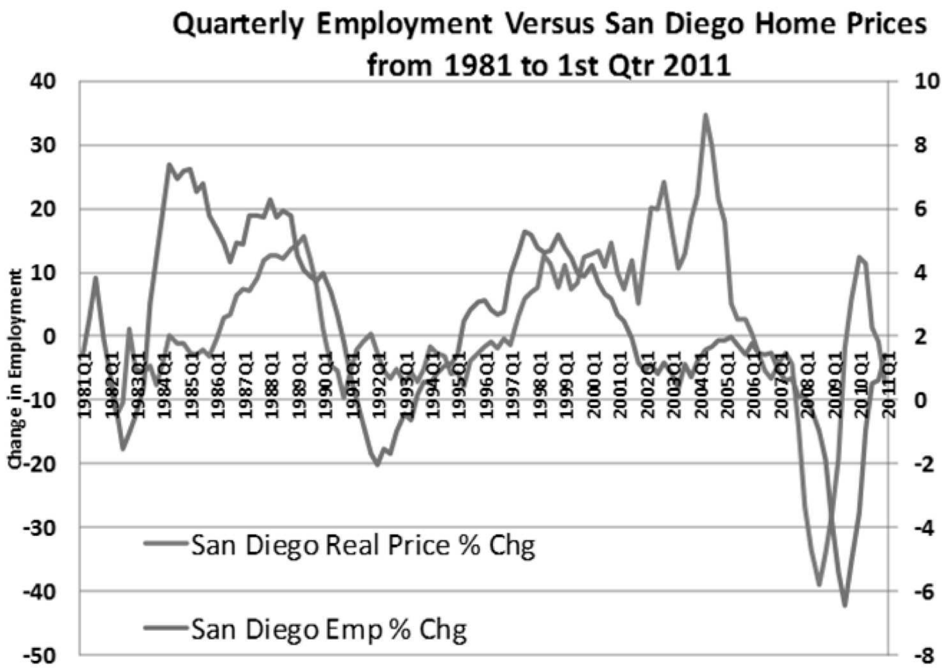
Context of Short-term Home Price Forecasting and the Supply Side of the Market

Starting With Demand

For longer-term trends and within a geographically defined market, we suggest starting with the long-term fundamentals based on known drivers of demand (i.e., employment, household formation, and affordability) and expected supply (permits and construction trends less units lost to natural forces or regulatory decisions such as eminent domain, which may require a separate forecast) and chart these out as long-term trends based on the best statistical fit using whatever functional form is most comfortable. We know, for example, that average ages of the U.S. population are increasing and thus, it is obvious that senior citizen targeted property uses will be increasing over the long term. The more localized the fundamental variables, the better they will work (i.e., local ZIP Code level demographic trends are better than metropolitan trends, although both may work well).[5] Local fundamentals include anything that drives demand like demographics (i.e., age, household size, etc.) and employment.

We also know that apartment markets and rents interact with the owner-occupied market. Quickly rising rents will drive demand for owner-occupied housing, but also provide a direct way to derive demand for housing.[6] One might argue that housing markets suffer from greater heterogeneity than apartments but they still provide some substitution at

Exhibit 1. Quarterly Employment versus Changes in Home Prices for San Diego



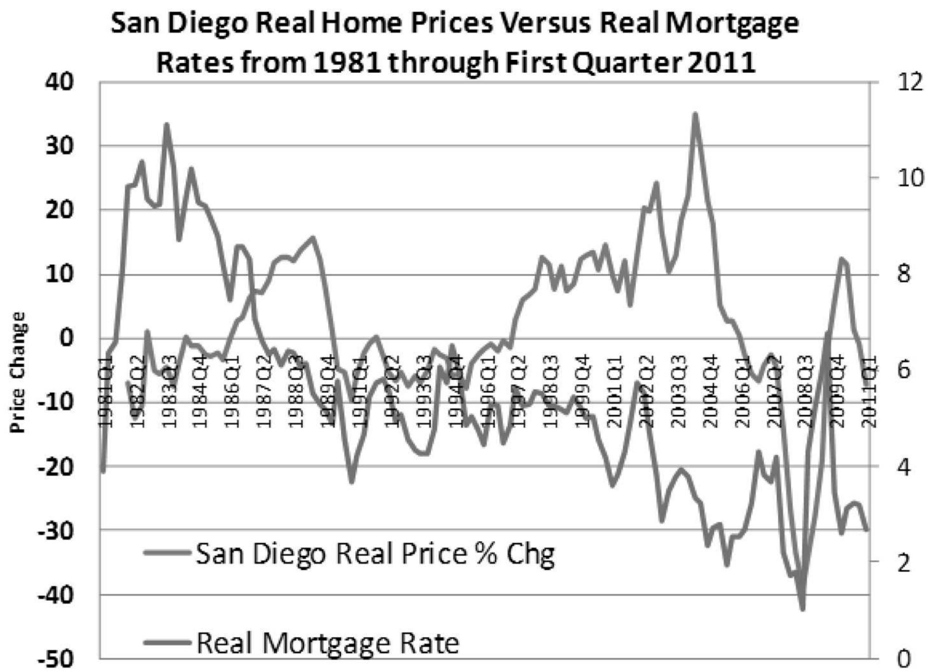
the margin and have been shown to interact with home prices (Gallin, 2008; Kim, 2009). The point is that the indicators of rental market affordability should be included in most models that forecast short- to intermediate-term housing prices.

Exhibit 1 shows one of these fundamental demand drivers, quarterly employment, versus housing real sales price percentage changes with a several quarter lead between employment and the observed changes in prices for San Diego. Note the significant lead time between changes in employment and changes in prices.

More recently we have seen models incorporating credit market conditions. During the peak of the housing boom in 2005, the average loan-to-value ratio for mortgages was much higher than historic averages. The ease of getting a loan approved was also quite high. Duca, Muellbauer, and Murphy (2010) incorporated the loan-to-value (LTV) ratio for first-time home buyers, as a proxy for credit ease, with excellent results in terms of explaining changes home prices. The authors show that LTV ratios along with the subprime boom and private label securitization trend were strong evidence of credit standard weakening. They found the best fit with an eight-quarter lead from the change in the LTV to the change in the home prices. Similarly, Brueckner, Calem, and Nakamura (2011) find that bubble conditions in the housing market spurred subprime lending as default concerns from strategic default were eased, in turn feeding into a further bubble.

We obviously need to know about capital costs (interest rates) in addition to the ease of financing. The inverse relationship between costs of capital and asset prices is well

Exhibit 2. FRM Mortgage Rates versus Home Prices



established, which we will provide further evidence of here (e.g., Harris, 1989; Reichert, 1990; Miller, Sklarz, and Thibodeau, 2005). Exhibit 2 shows one example of real fixed-rate mortgages (inflation is subtracted using the percentage change in the CPI) versus home prices for San Diego. Except for the very last quarter or so, we can clearly see the inverse relationship. Later we will show a similar chart for adjustable-rate mortgages (ARMs).

Supply

Supply is primarily driven by a difference between market values and the cost to produce the same home or condo (with normal profit, considering current and future interest rates, current and future loan terms, and current risk considerations to develop). With respect to risks that affect costs, consider, for example, the difficulty of getting zoning approved or that permits may affect risk and required returns in some markets, more so than in others. The profit required (or rate or return) is differentiated by the supply constraints, risks embedded in the challenges of the entitlement process, and these can severely affect development costs and required profit margins. The wildcard here is often land costs, which may be sticky on the downside or affected by government incentives (TIFs, bonus densities) or impact fees that can at times result in negative land values. The point is, when you move from macro national to local market trends, the local regulations, incentives, and factors affecting supply responsiveness matter much more. An excellent review of regulations and interventions affecting housing supply is provided by Glaeser and Gyourko (2008), who focus on the issue of affordability.

One way to factor in supply is to bring into the model an index that measures the difficulty of adding new supply. This supply difficulty is a function of only two categories: one natural and one human induced.[7] Glaeser and Gyourko (2008) use, among other supply-elasticity measures, permits to the existing housing stock, with significant price-inducing results.

Supply trends can be forecast using a responsiveness function to changes in price, at the margin, such as the spread between construction costs and the top quartile of current market prices. While none of this is easy as the leads vary and must be studied by market, it is possible. Natural constraints include water, topography or mountains, and existing build-out. Human constraints on supply include all land-use regulations and hurdles that must be overcome prior to gaining entitlement.[8] In general, areas that are difficult to add new supply to tend to stay that way for many years and those that are easy to secure new permits for also stay easy for many years. We also need to monitor units lost to natural, or man-made causes, and demolishing rates, which can run up to 1.5% or higher of the existing stock inventory in a given year. See HUD Cinch data as an example of such estimates.[9] These lost units are supply reductions, which may exceed new units added resulting in a net declining stock, especially in markets that have faced unusual natural disasters.

We know that areas with greater supply inelasticity (restrictions) tend to have faster growth in prices in response to any change in demand. For example, Miller, Sklarz, and Thibodeau (2005) found less elastic markets were more responsive to changes in interest rates and employment changes.

Focusing on the Short Run and Potential Market Condition Indicators

We can think of short-term forecasting as the same as analyzing deviations or residuals from the long-term trends. In the short run the market can be over-supplied or under-supplied. In a world without collusion, we should expect fluctuations (cycles) around long-term trends. We explore a variety of market condition indicators that might be described as technical in nature by stock market analysts, which are correlated with and often lead housing prices.

Examples of market condition factors for the housing market could include but are not limited to these variables or the changes in these variables: (1) volume of sales; (2) turnover ratio (percentage of total inventory sold; (3) days on market for sold properties; (4) months remaining inventory (existing units for sale divided by recent sales rate); (5) sold to list price ratio; (6) percentage of all units (inventory stock) for sale; (7) percentage of units for sale with price revisions (generally down but in some exceptional cases, upward); (8) prices of new listings adjusted for size and quality; (9) changes in the affordability of housing based on changes in LTV; (10) capital access or interest rates based on an affordable index or corresponding affordable price; and (11) price trends using longer-term and shorter-term smoothing function or h-p (hodrick-prescott) filters that enable one to separate out seasonality and or longer-term trends from short-term price trends.

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Criteria for Forecasting Success among Lenders, Investors, and Consumers of Housing

Normally, statisticians seek the best fit possible or smallest out-of-sample prediction deviation over a range of periods not used to generate the models. Our criteria are somewhat more decision based. We want as long a lead time as possible. We also want variables that allow us to catch and predict turning points as soon as possible. Last, we want the best out of sample trend fit, but this is less important than catching turning points and knowing the general trends as far in advance as possible.

Again, one of our primary goals is to find leading indicators where the longer the lead found the better. This is because we are taking the perspective of investors or lenders in the direct and somewhat illiquid housing market as opposed to derivative traders on some housing price index, where overall trend fit may be the primary goal. In the process of searching for such factors, we tested many local drivers of demand that might provide early warning signals. For example, while the orders for oil drilling equipment was successfully tested as a leading indicator of home prices in Houston, we would not expect such a variable to work as well in Austin or Atlanta. As another example, we found that the yen/dollar exchange rate explained well the prices for condos in the submarket of Waikiki on Oahu in the 1980s and did so with a significant lead of two or more quarters (Miller, Sklarz, and Ordway, 1988).

Forecast models using traditional fundamentals or market condition variables would not have done a good job of capturing the ease of credit impact that we observed in the 2000–2006 run up in prices. In many local markets where prices rose rapidly, there was rampant use of no-doc (often subprime) loans (also known as ''Alt-A'' in the mortgage securities market). If we had a variable to capture the extent of credit ease, we might better understand the impact of credit tightening observed. What might be described as changing market credit conditions are not easy to measure but LTV ratios and the percentage of homes with second mortgages seem to be logical choices. We will show one of these that worked particularly well in a later section of results.

Seasonality

In a fairly recent study of home prices, Kaplanski and Levi (2009) find a significant and persistent seasonality effect. Their study examines price changes within each year during the 1987–2007 period. They use two indices, the Case-Shiller Index and the House Price Index, to find evidence of price seasonality. Specifically, the study finds that the real rates of return on real estate are very low and even negative during the fall and early winter and are positive and relatively high during the spring and early summer. The prices are higher, on average, in the summer by 0.86% to 3.75%, depending on the real estate price index employed. However, one major drawback of the study is the use of indices to proxy for residential real estate prices. By using the Case-Shiller data, the Kaplanski and Levi (2009) study is restricted to only 20 major metropolitan statistical areas (MSAs), a fairly small set of major markets.

More recently, Miller, Sah, Sklarz, and Pampulov (2011) examined home price seasonality in most of the U.S. MSAs and found that many have pronounced and consistent seasonal price variation. They use hedonic pricing regression models for millions of homes in the

U.S. and a hierarchical regression to tease out the seasonality impact. For example, in Exhibit 3a we see price seasonality for all CBSA's using monthly data from 1999 or earlier through 2010. On average, the variation observed for January is −3.0% compared to the annual average price and a positive 2.3% for July compared to the average annual price. These calculations were based on prices controlling for several size and quality attributes. In some markets the seasonal effects were even more pronounced, and in others less pronounced. See, for example, Exhibit 3b, where Cook County (Chicago) is compared with Los Angeles County. Obviously Chicago has more pronounced seasonality and we see a greater swing in prices over the course of a year, even when controlling for property attributes. So to ignore seasonal price effects, as most appraisers do, is to miss a significant source of systematic price variation.

Explorations on Market Condition Variables that Help Predict Housing Prices

One classic technical indicator, which we see for the stock market on Yahoo! Finance websites is a price and volume of transactions chart. We have been using similar charts for at least three decades and have noticed significant lead times from peak (or trough) volumes to peak prices (or trough) prices. We provide one example in Exhibit 4 but we successfully tested sales volume on many markets with significant time leads between changes in sales volume and changes in prices.

In Exhibit 4 it is hard to decipher the seasonality from any lead time, so we provide the table below the graph. Here we see the highest correlation of sales volume with prices at a six-month lead, but note that even longer leads are possible with good results.

In some cases we can get leads of a year or more between sales volume and the eventual change in prices. One problem with using the change in sales volume is that if volumes are very low (on a long-term relative basis) they give a false signal of a significant increase when they are merely going from very low to moderately low on a historical basis. For this reason, one might also wish to consider the turnover rate as another measure that works quite well. The turnover rate is measured via the percentage of total stock sold. Rather than measure the percentage of listings sold, we measure the percentage of sold properties relative to the total stock of inventory in that market. The turnover rate not only serves as a substitute for relative volume but also provides signals on the relative life cycle of the submarket when measured on a local basis. This is because newer growing neighborhoods will tend to have higher turnover rates, as well as active markets. Granted some older markets are more stable and others more transient and one might want to be careful to use the local history, as well as some normative measures of market strength. But in general the higher the percentage of market activity as measured by sales relative to the total stock, the stronger the market demand is relative to supply. One of our key findings is that the turnover rate for REO and regular sales when combined did not work nearly as well nor as consistently across times as simply using regular (non-distressed) sales. Turnover rates for regular sales provided a very consistent and significant lead over changes in home prices throughout the market cycle. Exhibit 5 shows the regular sale turnover rate versus real price changes in San Diego. We see a significant lead here and in most markets that we have tested.

Another technical indicator is days on the market (DOM), which can be measured for a small geographic area or aggregated up to a metropolitan level or even nationally. We

Exhibit 3a. Monthly Price Seasonality in All CBSA's as of Data from 2000 to 2011

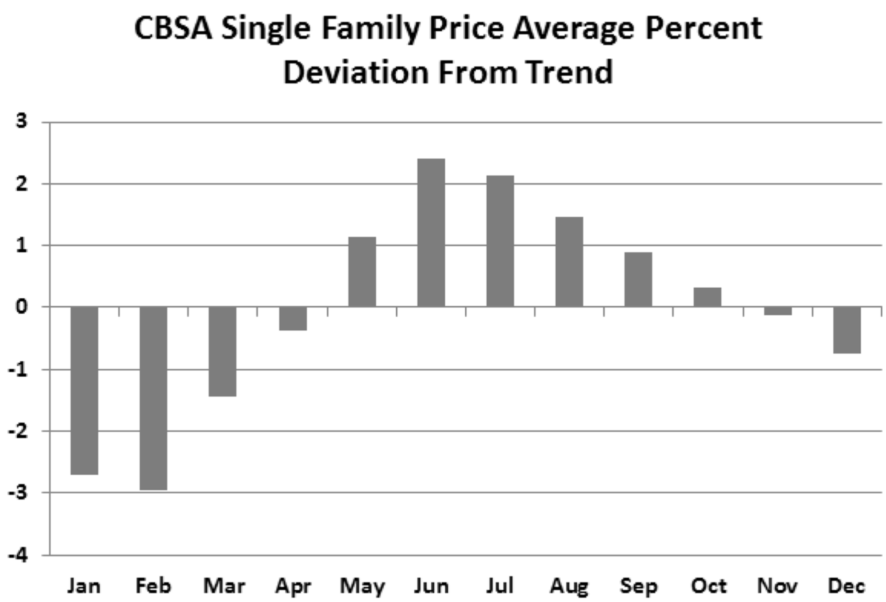
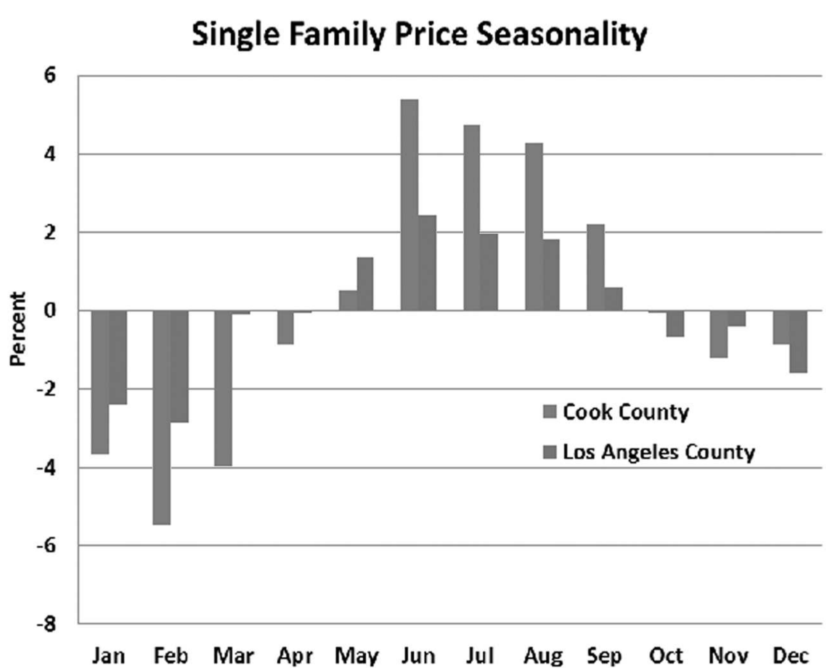
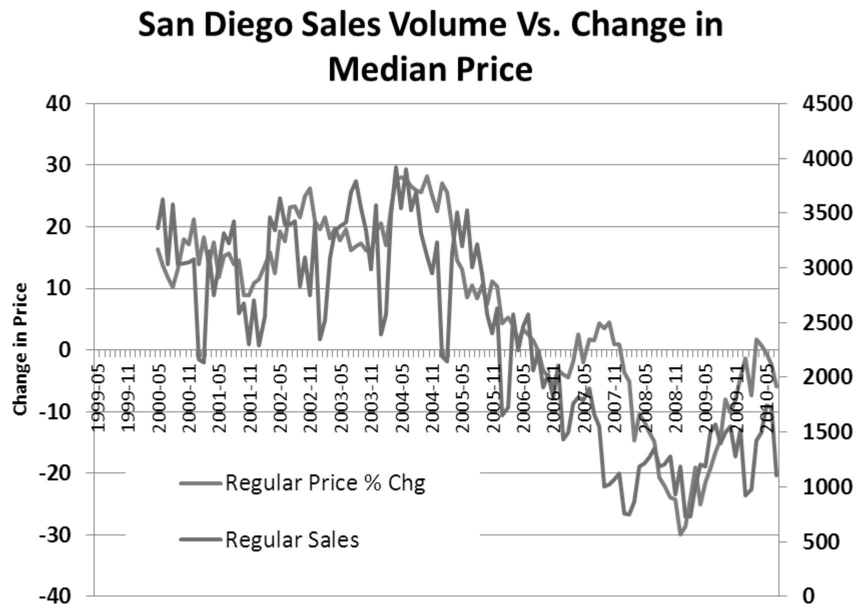


Exhibit 3b. Price Seasonality Illustrated for Cook County (Chicago) versus Los Angeles County



Source of Data: Collateral Analytics.

Exhibit 4. Sales Volume (not seasonally adjusted) in San Diego Metro versus the Change in Median Price Using Monthly Data Using Regular Non-Distressed Sales



The correlation matrix behind this graph is as follows:

Lead Time Shown in ( )	San Diego Regular Price % Change
San Diego Regular Sales	0.8329
San Diego Regular Sales (−1)	0.8374
San Diego Regular Sales (−2)	0.8398
San Diego Regular Sales (−3)	0.8445
San Diego Regular Sales (−4)	0.8495
San Diego Regular Sales (−5)	0.8470
San Diego Regular Sales (−6)	**0.8506**
San Diego Regular Sales (−7)	0.8388
San Diego Regular Sales (−8)	0.8327
San Diego Regular Sales (−9)	0.8223
San Diego Regular Sales (−10)	0.8083
San Diego Regular Sales (−11)	0.7936
San Diego Regular Sales (−12)	0.7737

can measure DOM for existing listings or for homes that have actually sold. In Exhibit 6 we see that in Honolulu when the DOM for sold listings is running under 50 days, we generally have appreciating prices. Also note that when DOM is dropping rapidly, we see more rapid appreciation, and that when graphed on a monthly basis, we see a several period lead between DOM and prices.

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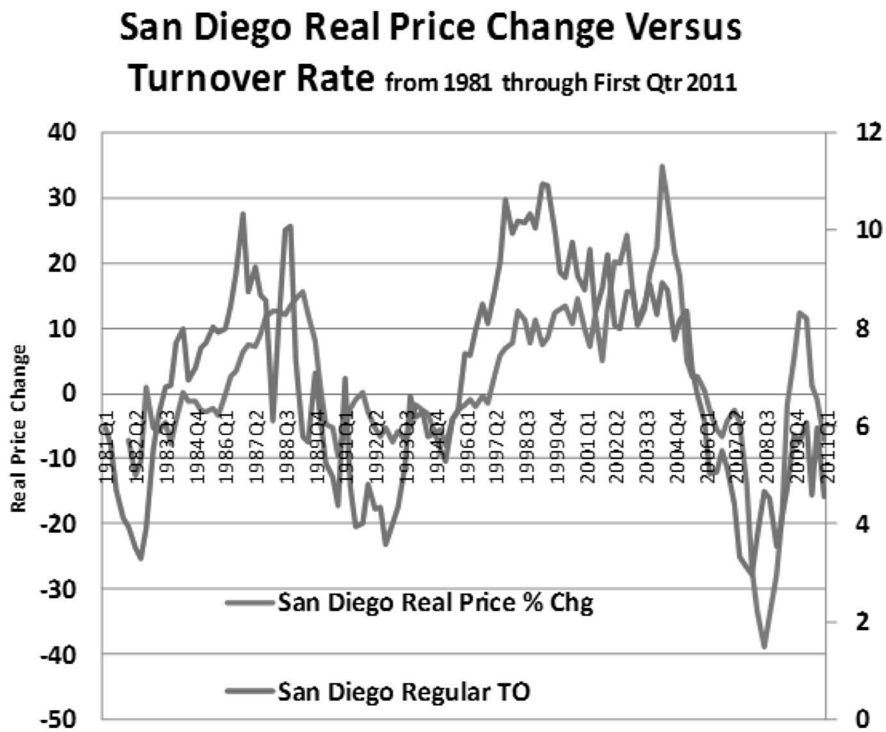
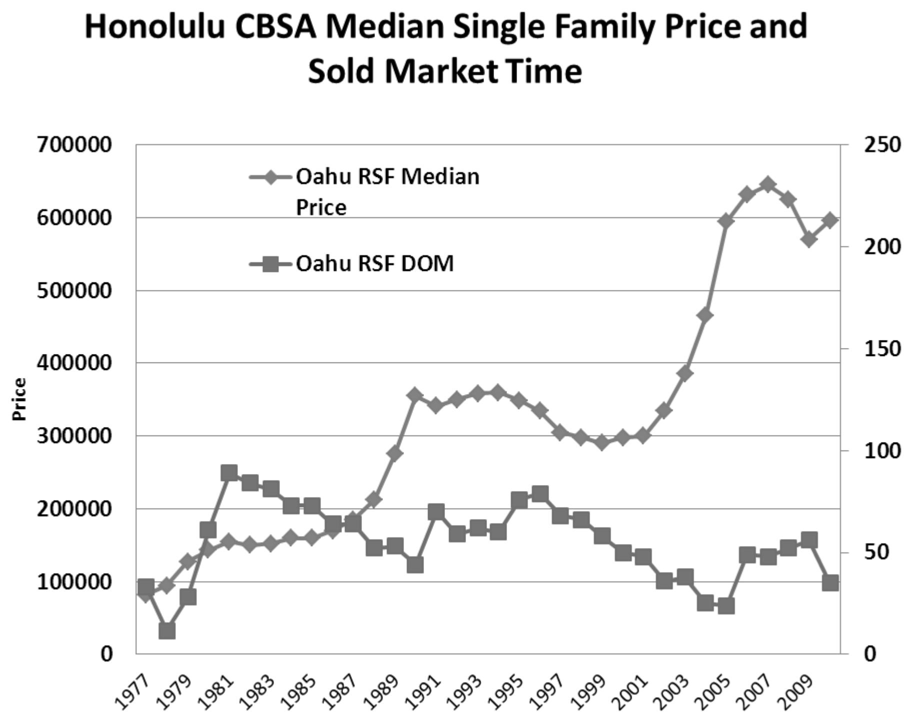
Exhibit 5. Turnover Rate versus Real Home Prices for San Diego



One problem with the days or time on market variable is that in many local markets, real estate agents game the system so as to try and avoid the stigma attached to homes on the market for a long period of time.[10] So, they take the listing off the market, adjust the price just slightly and put it back on the market a few days later as if it were a new listing. These re-listed properties show up as having much shorter DOM than is case and bias the overall figures downward. Another problem with using DOM is that different Multiple Listing Service (MLS) boards calculate DOM differently. For example, at some MLS boards DOM is the time from the original listing to the off-market date, while at others it is the time from the original listing until the actual closing, which may be much longer than the off-market date.[11] Thus, the DOM indicators, which should work as a good proxy for short-term demand and supply trends, is often quite flawed in some markets and one should be careful not to compare DOM figures between different markets unless the MLS has similar rules governing measurement of time on the market.

Months remaining inventory (MRI) is more consistent and reliable than DOM as it is harder to game the statistic. It can be calculated by taking the current number of listings in a particular geography and dividing this by the current rate of sales (typically in the most recent month or two). To avoid seasonal bias, one can also use the past 12 months average monthly sales rate and divide this into current listing inventory, which is the approach that we take here. We also note that MRI can be misleading when in a downward price cycle since there may be a significant build-up of shadow inventory (owners who would

Exhibit 6. Days on Market (Sold Market Time) versus Median Single Family Price

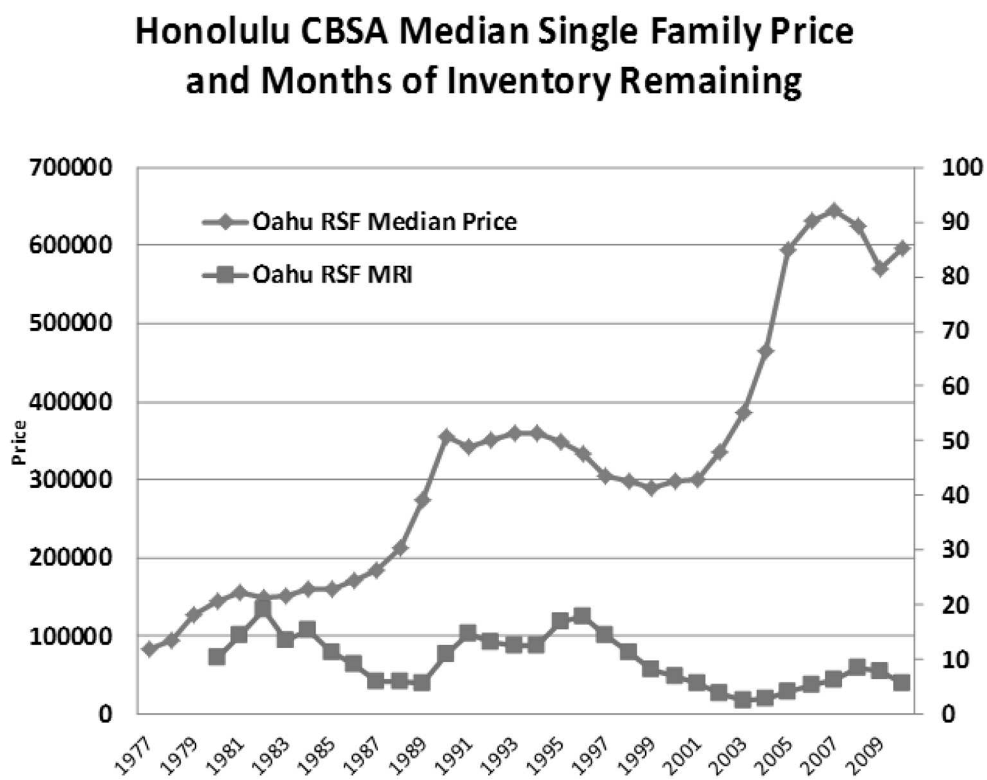


like to sell but are waiting for better market conditions) that has been pulled from the market but will return as soon as prices stabilize, start to head up or when sellers accept the inevitable declines. So the actual MRI when the shadow inventory is considered can sometimes appear to be lower than the true inventory once sellers see an opportunity to sell with less pain or an actual gain. In Exhibit 7, we take a fairly long-term view and see that in this market, Honolulu, prices tend to be heading up when MRI is less than 10 months. The lower the MRI, the hotter the market; in fact, we can characterize most markets in this fashion, where an MRI less than three months would be a ''hot'' market at the one end of the spectrum with increasing prices and MRI of more than 24 months would be a very slow market on the other extreme. Again, the lead varies by market but could run three to six months or even more.

Typically we use the following characterizations based on MRI, given many years of historical review:

Market Characterization	Months Remaining Inventory
Very Strong to Hot	0 to 5
Balanced	6 to 10
Soft	11 to 15
Weak	16 to 20
Very Weak to Distressed	21 or more

Exhibit 7. Months Remaining Inventory versus Honolulu Median Single Family Prices

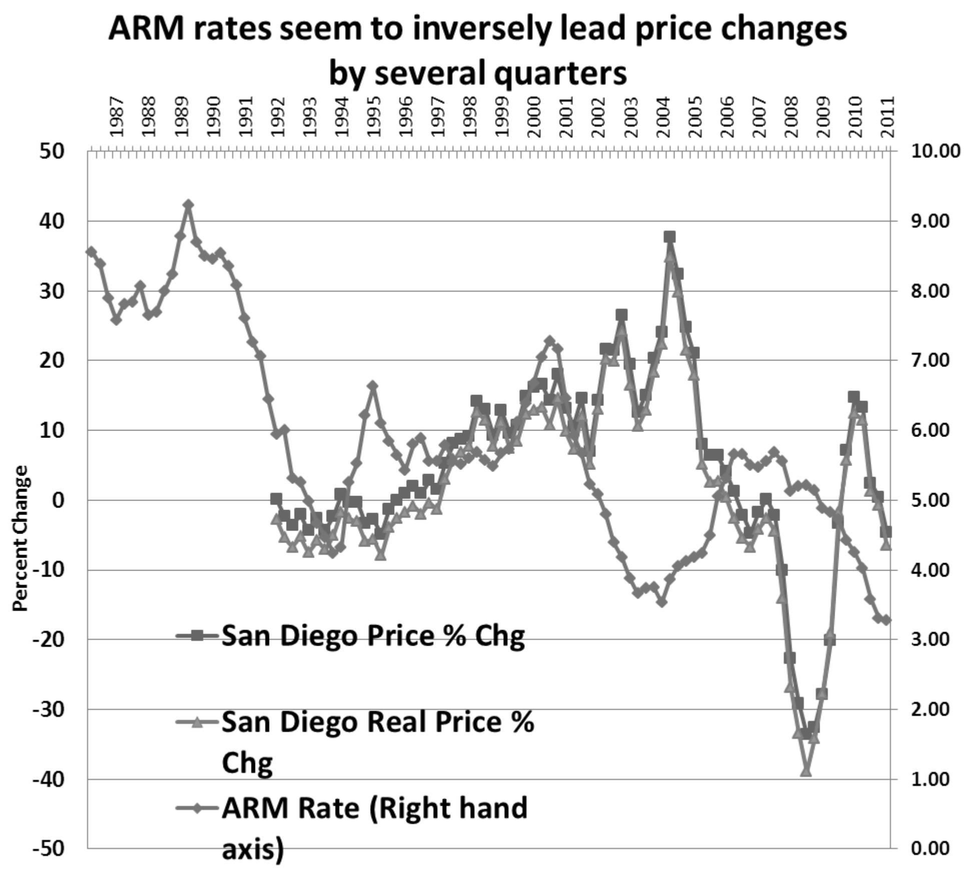


Source of Data: Collateral Analytics.

Mortgage rates directly affect affordability and thus move inversely with prices, although we often find that when mortgage rates are in decline, some home buyers wait and as soon as there is a signal that rates have stopped dropping or moved up a touch we see many buyers, who had been fence sitting, jumping into the market. Yet, we observe fairly consistent inverse relationships between interest rates and prices. In some markets like California from 2000 through 2010, adjustable-rate mortgages (ARMs) seem to be the dominant choice of mortgages while in most other markets, fixed-rate mortgages (FRMs) seem to dominate. Based on the dominant choice in the local market, one might include either a proxy for FRMs or ARMs or both for capturing the effect of mortgage costs. In Exhibit 8 we graph ARM rates versus San Diego real home prices. We see a slight lead and a general inverse relationship with prices.

An alternative to using mortgage rates is to combine household income trends, mortgage rates, LTV trends, and median prices in the form of an affordability index or ratio. Since interest rate changes dominate this index on a short-term basis, it is essentially a proxy for mortgage rates. Here we convert the affordability index to an affordable price and use this measure.

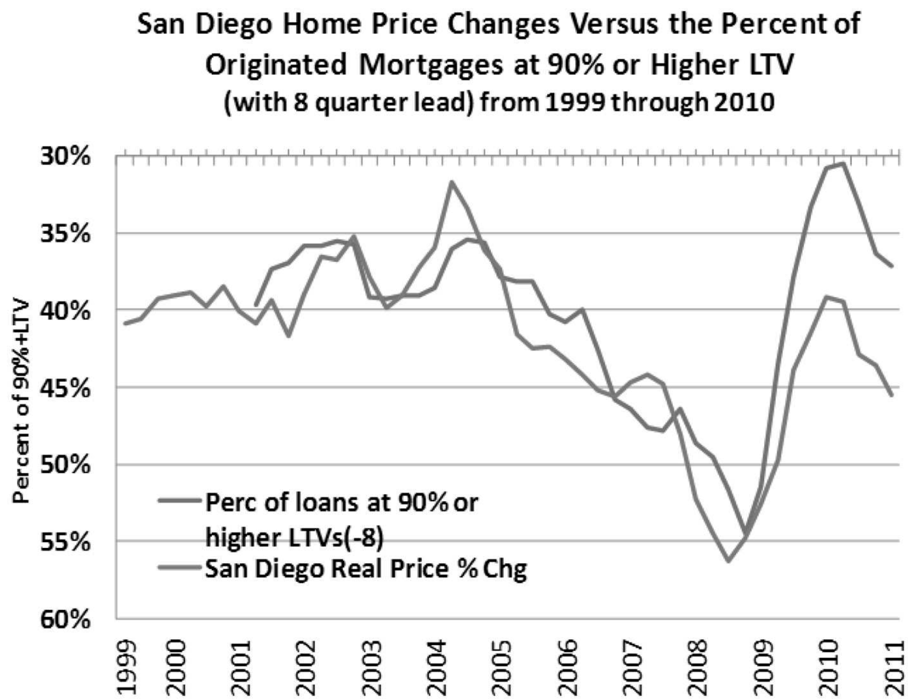
Exhibit 8. ARM Rates versus San Diego Real Home Prices



Ease of capital access is a challenge to pin down but after experimenting with various measures including the percentage of loans that are subprime mortgages and loans above 80% LTV, we settled upon the percentage of loans in the market that were at 90% or above LTV. As seen in Exhibit 9, this variable leads the change in San Diego real home price changes by seven or eight quarters, providing an excellent leading indicator. We find the same result in other markets, and it is very interesting that we find the same exact lead as Duca, Muellbauer, and Murphy (2010) when using national data on LTVs for first-time home buyers. Exhibit 10 provides the correlation matrix between real home prices and various lags of the proportion of mortgages with LTVs above 90%.

Historically, one technical indicator of changing price trends is the sale price to list price ratio. Generally a home seller reviews market price suggestions with a listing broker and then sets a price. Seldom do these prices get revised upward, but the prices may get revised downward if the home does not sell as quickly as desired by the seller. When markets are active and prices are moving up rapidly, not only will we see quicker time on market as mentioned above, but we will also see properties sell at prices closer to or at the asking price. In some cases, they even sell above the asking price. When markets

Exhibit 9. Percentage of Loans Over 90% LTV versus Home Prices



soften, we often see the reverse where sellers receive offers further below asking prices. For most markets, this is a leading indicator of prices but we show it in Exhibit 11 on a simultaneous basis for the San Diego market. A variation on this that also works equally as well is to use the percentage of properties that have revised asking prices up or down by period.

Many other technical indicators exist which help to depict market behavior including frustrated sellers who in turn allow listings to expire or withdraw them from the multiple listing service. Exhibit 12a shows the general inverse indicator provided by withdrawn listings. Exhibit 12b shows the listing expired without selling as a percentage of those that did sell by period versus price.

Naturally distress sales as a proportion of the market are a strong indicator of short-term price trends. Pennington-Cross (2006) estimated a 22% lower appreciation rate on foreclosed property compared to non-distressed property. This estimate was consistent with Forgey, Rutherford, and Van Buskirk (1994), who suggested a 23% discount on distressed sales. We have found similar if not larger discounts in more recent periods, based on longer foreclosure periods and an increased frequency of empty and deteriorated homes compared to earlier periods. We include a selection of the studies on foreclosure impacts in Exhibit 13.

While we could show markets with greater distress like Las Vegas, we show San Diego here for consistency, and we do this in three variations. In Exhibit 14a we show distressed

Exhibit 10. Correlation Matrix of 90% Plus LTV versus San Diego Home Prices at Various Leads

	Real Price % Chg	*% of Loans at 90% or Higher LTVs*	*% of Loans at 90% or Higher LTVs(−1)*	*% of Loans at 90% or Higher LTVs(−2)*	*% of Loans at 90% or Higher LTVs(−3)*	*% of Loans at 90% or Higher LTVs(−4)*	*% of Loans at 90% or Higher LTVs(−5)*	*% of Loans at 90% or Higher LTVs(−6)*	*% of Loans at 90% or Higher LTVs(−7)*	*% of Loans at 90% or Higher LTVs(−8)*	*% of Loans at 90% or Higher LTVs(−9)*	*% of Loans at 90% or Higher LTVs(−10)*
Real Price % Chg	1											
% of loans at 90% or higher LTVs	0.2181	1										
% of loans at (−1)	0.1893	0.9242	1									
% of loans at (−2)	0.136	0.7666	0.9227	1								
% of loans at (−3)	0.0256	0.5814	0.7619	0.9213	1							
% of loans at (−4)	−0.1417	0.4003	0.5679	0.7530	0.9160	1						
% of loans at (−5)	−0.3645	0.2546	0.3768	0.5531	0.7446	0.9156	1					
% of loans at (−6)	−0.5781	0.1737	0.23766	0.3648	0.5451	0.7443	0.9169	1				
% of loans at (−7)	−0.7370	0.0977	0.1448	0.2170	0.3505	0.5407	0.7404	0.9177	1			
% of loans at (−8)	−0.8013	0.0228	0.0774	0.1301	0.2061	0.3471	0.5375	0.7396	0.9181	1		
% of loans at (−9)	−0.7677	−0.0712	0.0062	0.0657	0.1215	0.2042	0.3448	0.5372	0.7403	0.9182	1	
% of loans at (−10)	−0.6671	−0.1772	−0.0966	−0.0115	0.0519	0.1088	0.1895	0.3360	0.5277	0.7354	0.9159	1

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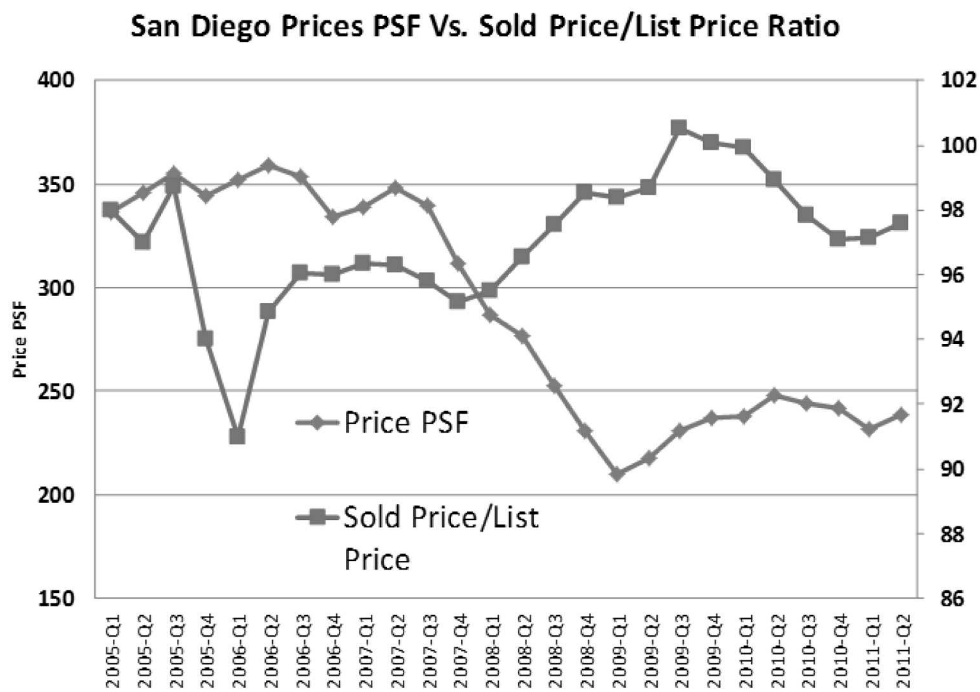
Exhibit 11. Sales Price per Square Foot versus Sale Price to List Price Ratio



sales as a percent of total sales versus price per square foot. The inverse relationship is clear. In Exhibit 14b we show a simple estimate of the discount from regular sales versus this same distress percentage. We add a no-distress sales trend line to simply smooth the data, which has significant noise. Here we observe the average discount at around 30% with the maximum discounts near 45% in 2008, far greater than earlier estimates. This suggests that disrepairs and property conditions have been more affected in this down cycle than in previous cycles. Last we show in Exhibit 13c the distress sales volume versus home prices per square foot. Again one observes the inverse relationship. Note: The last data point is incomplete and only an estimate so one should not put much weight on it.

Summary of Hypothetical Market Condition Home Price Drivers

Below we summarize the demand, supply, government interference/regulatory, and market condition factors that we postulate as driving home prices. We do this to place our work in context and not to suggest that we are addressing all the possible individual influences in this paper. We also recognize that there is a great deal of multi-collinearity among these variables and so one should not necessarily use all of them in any single forecast model.

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Exhibit 12a. Percentage of Listings Withdrawn as a % of those Sold for San Diego

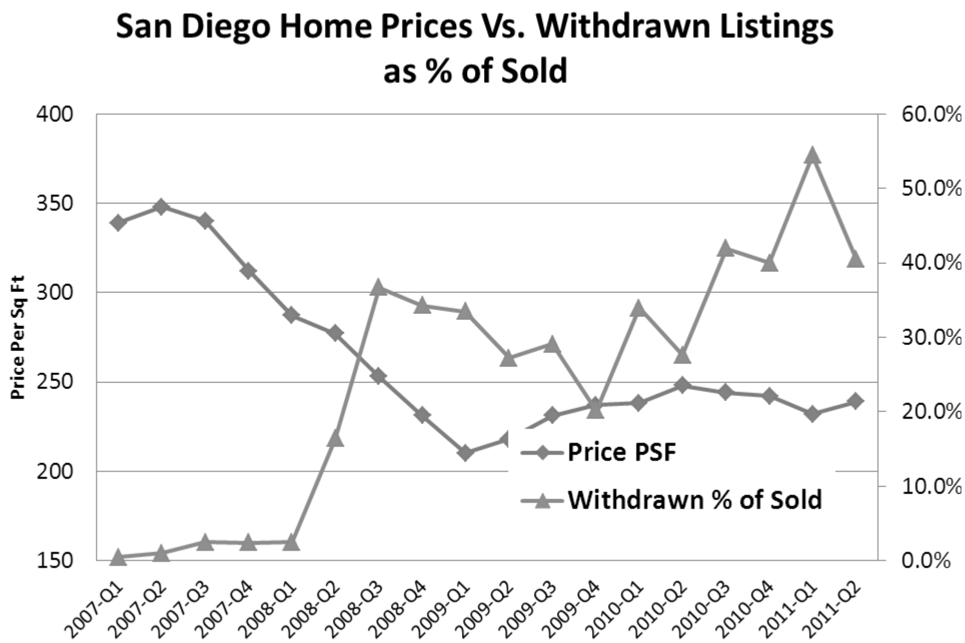

Exhibit 12b. Expired Listings as Percentage of those Sold versus Price

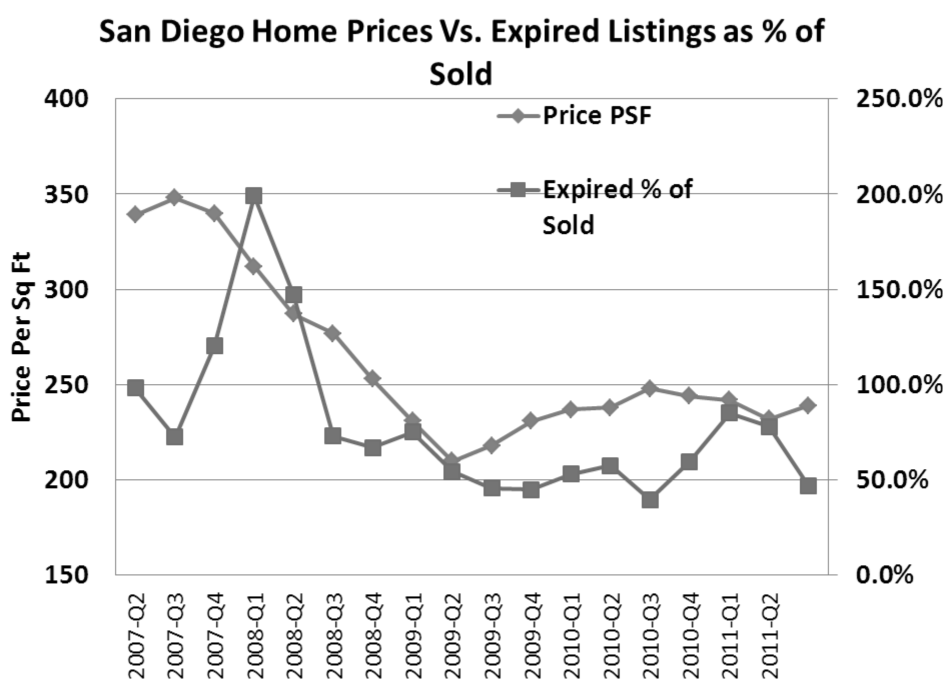

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Exhibit 13. The Impact of REO and Foreclosure Sales on Single-Family Homes

Study Title	Authors	Study Period	Geography	Typical Discount Found vs. Non-distressed
REO Properties, Housing Markets, and the Shadow Inventory	Mallach	2007–09	U.S.; Phoenix	Significantly lower prices with poor market conditions
Holding or Folding? Foreclosed Property Durations and Sales During the Mortgage Crisis	Immergluck	2005–09	Fulton County, GA	Spillover effects on homes nearby −.9% within 600 feet
REO and Beyond: The Aftermath of the Foreclosure Crisis in Cuyahoga County, Ohio	Coulton, Schramm, and Hirsh	2004–09	Cuyahoga County, Ohio	"Extreme distress" selling for under $10,000 for many properties often vacant.
Examining REO Sales and Price Discounts in Massachusetts	Lee, Federal Reserve Bank of Boston	2007–09	Mass.	−19.9%
Optimal Choice for Lenders Facing Defaults: Short Sale, Foreclose, or REO	Clauretie and Daneshvary	1985–2008	U.S.; Las Vegas	−7.8%
Realty Trac Q1 2011 REO Report: Foreclosure Homes Account for 28 Percent of Q1 2011 Sales	Realty Trac Staff	Q1, 2010 and 2011	U.S.	−35% with a large range depending on market
Short-Term Own-Price and Spillover Effects of Distressed Residential Properties: The Case of a Housing Crash	Daneshvary, Clauretie, and Kader	1990–2008	U.S.; Nevada	−13.5% for REO sales
The Contagion Effect of Foreclosed Properties	Harding, Rosenblatt, and Yao	1990–2008	Atlanta, Columbus, Vegas, LA	−1% in Las Vegas to −21% in Columbus
Forced Sales and House Prices	Campbell, Giglio, and Pathak	1987–2008	Massachusetts	−21.6% to −47.2% depending on the time on market
Agency Theory and Foreclosure Sales of Properties	Chau and Ng	1996–2000	Hong Kong	−1% to −10% depending on market conditions
Effect of Foreclosure Status on Residential Selling Price: Comment	Carroll, Clauretie, and Neill	1990–1993	Las Vegas	No significant discounts
Single-Family Housing Transactions: Seller Motivations, Price, and Marketing Time	Springer	1989–1993	Arlington, TX	−4% to −6%

Exhibit 13. The Impact of REO and Foreclosure Sales on Single-Family Homes (continued)

Study Title	Authors	Study Period	Geography	Typical Discount Found vs. Non-distressed
The Relationship between Foreclosure Status and Apartment Price	Hardin and Wolverton	1993–1994	Phoenix	−22% for apartments
Effect of Foreclosure Status on Residential Selling Price	Forgey, Rutherford, and Van Buskirk	1991–1993	Arlington, TX	−23%
Estimating Net Realizable Value for Distressed Real Estate	Shilling, Benjamin, and Sirmans	1985	Baton Rouge, LA	−24%
The Value of Foreclosed Property	Pennington-Cross	1990–2006	U.S.	−15 to −22% depending on condition and timing

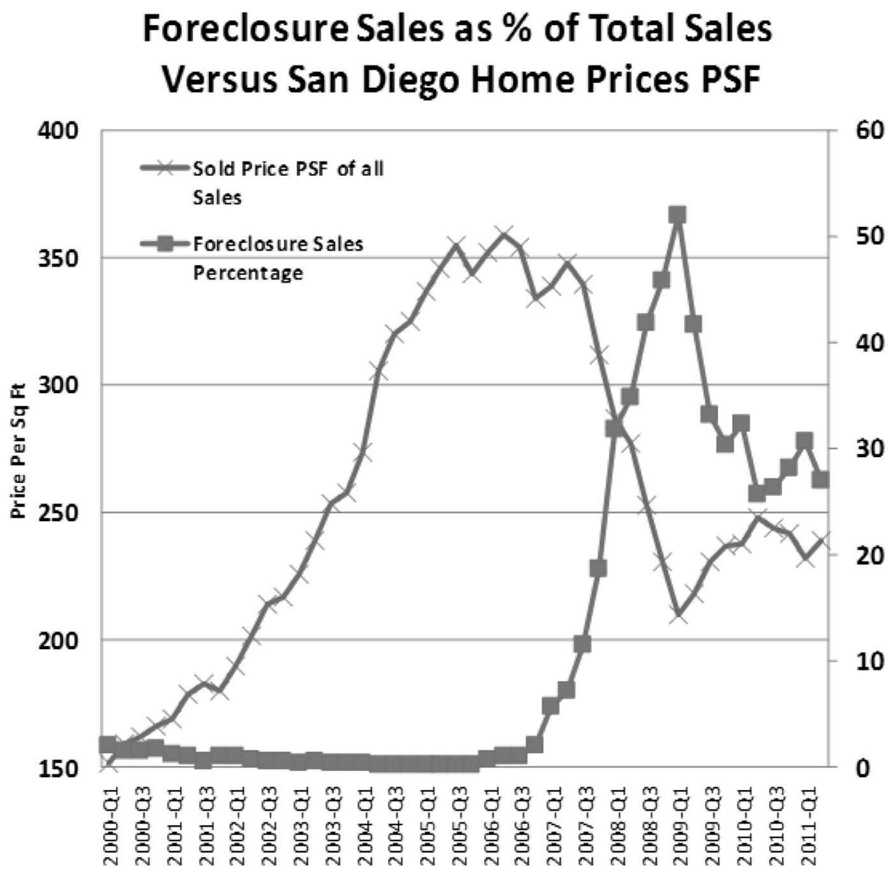
We do not consider this an exhaustive list but rather an illustrative and generally comprehensive list as there are always other proxies that may work equally well. Our ideal price driver is one with a strong influence and/or significant lead time. The longer the lead time for any significant variable, the longer we can predict future home prices with confidence, so variables with greater lead times are more valuable in this context.

We have used almost all of these variables listed with highly significant statistical influence on housing prices. That is by themselves most will add a marginal increase in the overall fit (R-squared) of at least 10% or more, but the fit is very much dependent on the frequency of the measurement. For example, time on the market changes daily for a given submarket and is fairly noisy, but when the area of testing expands and the time intervals between measurement increases (to say quarterly), the fit dramatically improves. For this reason, it is difficult to use only statistical indicators of fit. For we know that by picking intervals that smooth out the noise or using H-P filters, we can often improve the fit.

Which variables provide the longest lead? Again, this is a difficult question to answer since it depends on the market being tested. Among the variables that provide the longest lead are changes in sales volume. In some markets we see a one to two year lead between changes in sales volume and price changes but in other markets we see much less lead time as the best fit. For example, in the San Diego illustration (Exhibit 4) we see the best fit between sales volume and changes in home prices at six quarters. We believe that some markets are more informationally efficient and others less so. For example, a market with a high proportion of second homes may be less informationally efficient than a market where there is little rental-based housing stock and most occupants are owner-occupants. What factors allow us to see the longer lead times in some markets and less so in others is valuable future research, but the variation in market reaction lead times suggests that is it hard for us to generalize which variables to use in all markets.

Adding to the complexity of picking the best leading indicators is the fact that some markets have more reliable data than others. For example, time on the market is measured

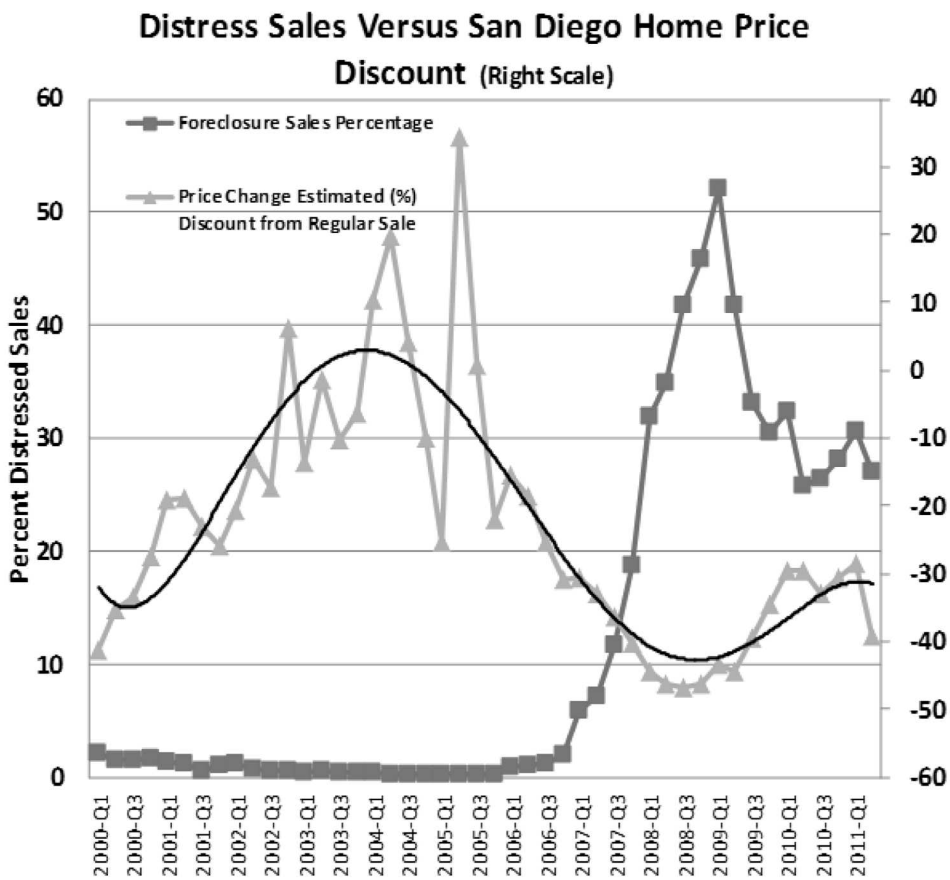
Exhibit 14a. Distressed Sales as a Percentage of Total Sales versus Price per Square Foot for All Sales



is different ways by various REALTOR boards and in some markets we see a lot of game playing that will affect the measurement of time on the market, when listings are taken off the market and re-listed a few days later and treated as new listings. Price revisions tend to be more reliable and months remaining inventory (MRI) tends to be more reliable, so we highly suggest the use of MRI not because it provides the longest lead time in all markets but because it tends to be the most consistent predictor across markets other than changes in sales volume. Exhibit 15 is a home price forecast model.

Quarterly data from 1981 through the first quarter of 2011 are utilized in the analysis presented below and comes from a variety of sources including Collateral Analytics, DataQuick, the California Association of REALTORs®, the FDIC, Federal Reserve, Bureau of Labor Statistics, and the Bureau of the Census. After a few iterations, we provide the model below for San Diego. For DOM, MRI, and foreclosures, the data starts in 1988 and runs through the first quarter of 2011. We use the following variables in the first set of models, with the correlation matrix shown below:

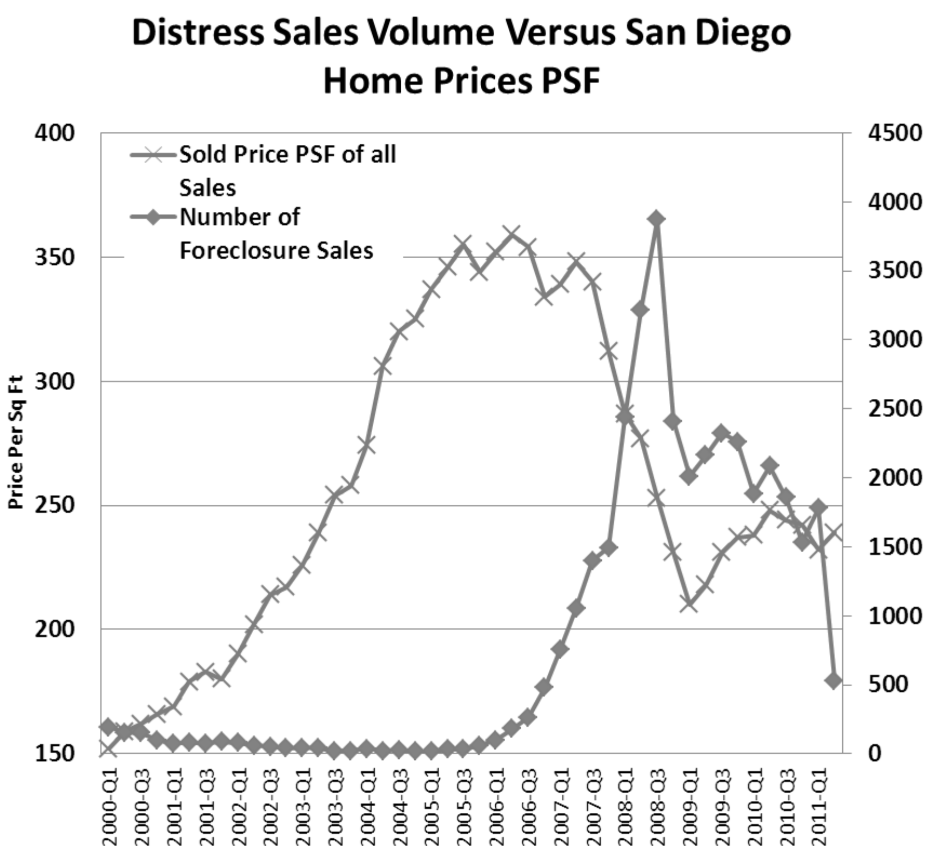
Exhibit 14b. Distressed Sales as a Percentage of Total Sales versus the Discount Estimate from Non-Distressed Sales Shown With Trend Line



Variable	Mean	Std. Dev.
San Diego Real Price % Change	1.89	11.95
San Diego Regular Sale Turnover Rate	6.83	1.98
San Diego Employment % Change	2.11	2.57
San Diego Real Afford % Change	3.93	9.65
San Diego Real Mortgage Rate	5.40	2.18
Sab Diego DOM (Days on Market)	51.95	2.78
San Diego MRI (Months Remaining Inventory)	8.29	4.28
San Diego Foreclosure Percentage of Regular and REO Sales	11.48	14.37

Exhibit 16 shows the latest graph of our forecast results, along with four model runs for San Diego with graphed results based on data stopping in the first quarter of 2011 using the variables shown. We provide models that stop in 1995, 2000, and 2005, along with the statistical results. Note that in examining the variables included, the highest *t*-values

Exhibit 14c. Distressed Sales Volume (Right Scale) versus San Diego Home Prices per Square Foot



are generally when using a two quarter lead. We include affordability, sales volume turnover, affordability, foreclosure percentages, months remaining in inventory, and employment. The employment and interest rate forecasts are those of Economy.com and we did not reflect the uncertainty behind the Economy.com forecasts for those particular variables.[12]

With respect to the actual outlooks, our models are less sanguine that those of Kaboudan (2011). His work suggests positive price trends for San Diego throughout the second half of 2011 and beyond. Our own outlook suggests that prices will decline less over the next few years (including 2011 and 2012) than in the recent past but will not show appreciation on average across the metro for several quarters. Clearly our model results are driven more by the distressed inventory and forecasts of continued foreclosures and REO sales remaining in the market. At the same time, we can show many submarkets in San Diego that are already doing quite well. However, when you use metro level indicators for price trends, the REO sales will bring down the averages, and these distress sales are affecting our overall metro results.

Exhibit 15. An Illustrated Home Price Forecast Model

Variables	**Hypothesized Relationship on Housing Prices**
Demand Drivers	
Household growth rates per year	Positive
Employment in absolute numbers and in relative growth rates	Positive
Past home price trends	Positive
Mortgage interest rates and or affordability ratios that include income, LTV, median prices, and interest rates	Inverse for mortgage rates, positive for affordability indexes
Rent (multifamily market) to price (median home) ratios	Positive
Credit access (LTV trends, % of mortgages at 90% plus LTV, % of loan applications approved, average credit score)	Positive except for credit score which is negative. Positive for % of LTVs above 90% temporarily and then negative with a substantial lead time.
Seasonal pattern of demand for localized market	Positive and negative based on month of transaction
Other Unique Factors Affecting Demand	
Currency exchange rates (stronger foreign currency may affect local prices if a significant portion of the market is international)	Positive with strength of foreign currency, inverse with US Dollar
Oil prices (may affect transportation-dependent submarkets more so than central mixed-use locations)	Inverse
Supply Drivers and Constraints	
Housing permits to total stock issued	Inverse as more elastic supply puts less pressure on price
Wharton Residential Land Use Regulatory Index	Positive as the higher the hurdle to develop property the more upward pressure on prices when trends are positive. When trends are negative, there will be less effect.
Population density (another proxy for high land costs) or land prices to median home prices	Positive
Government Interference	
Home tax credit programs	Positive and temporary
Below-market financing subsidies	Positive and temporary
Changes in tax laws on capital gains	Varies with the direction of the ruling; will affect behavior most just prior to the change.
Market Condition Drivers	
Sales transaction volume, volume % trend, by price range, by size, by age	Positive
Turnover rate as % of stock using regular (non-distress) sales only	Positive
Distress sales as percentage of total sales and % trend	Inverse
Average new listing price over past period listing price trend and the same in terms of average new listing price per square feet	Positive
Percentage of expired (off-market) listings that did not sell of the total listings, or the number of listings pulled off market (by price range and size as well)	Inverse
Sold price to listing price ratio and percentage change trend	Positive
Time on the market to sell (DOM) and the percentage change trend in DOM	Inverse

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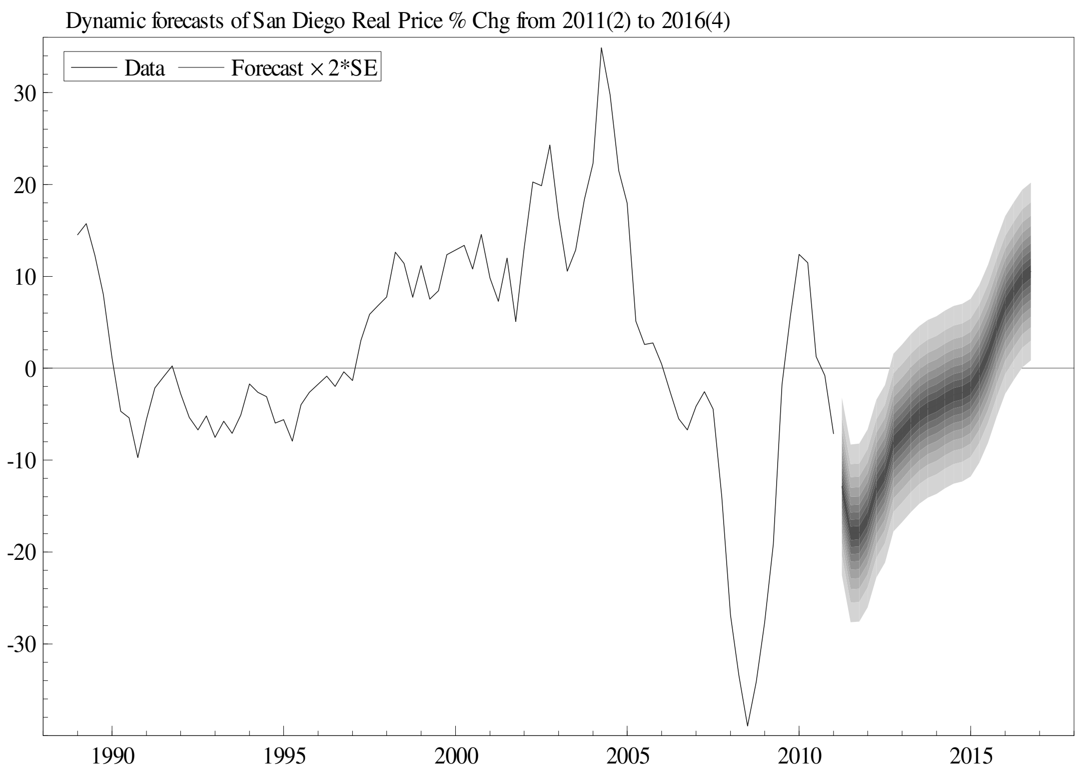
Exhibit 16. San Diego Median Home Price Forecast With the Percentage Change on the Y1 Axis



We could further improve our model results by using some of the more sophisticated techniques of combining neural networks and genetic programming suggested by Kaboudan (2011). But using roughly the same data period and the same two metro markets, our regression squared results and overall fit compare very favorably with his results. His best fit for Los Angeles was an R^2 of .87, compared to .89 for our own work. His best work for San Diego was an R^2 of .86, compared to .88 for our own work presented here. We believe that variable selection is critical to forecasting and when based on theory and experience, can perform well even with simple models.

GUM(1) Modeling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988:Q3–1995:Q1

	Coeff.	Std. Error	*t*-Value	*t*-Prob.
Constant	6.4081	6.8976	0.929	0.3728
San Diego Regular Sale TO Rate	0.0773	0.5062	0.153	0.8815
San Diego Regular Sale TO Rate_1	0.4040	0.5011	0.806	0.4372
San Diego Regular Sale TO Rate_2	0.6269	0.6230	1.006	0.3359
San Diego Emp % Chg	−0.3998	1.3280	−0.301	0.7690
San Diego Emp % Chg_1	−4.5596	1.5173	−3.005	0.0120
San Diego Emp % Chg_2	5.2743	0.9539	5.529	0.0002
San Diego Real Aff Price % Chg	0.4339	0.1075	4.038	0.0020
San Diego Real Aff Price % Chg_1	0.0197	0.1077	0.183	0.8584
San Diego Real Aff Price % Chg_2	−0.1128	0.1120	−1.007	0.3355
San Diego MRI	−0.2689	0.1519	−1.770	0.1044
San Diego MRI_1	−0.4089	0.2218	−1.891	0.0852
San Diego MRI_2	−0.4811	0.1470	−3.273	0.0074
San Diego FC % of Regular & REO Sales	−0.5691	0.3106	−1.832	0.0941
San Diego FC % of Regular & REO Sales_1	0.3563	0.4726	0.754	0.4668
San Diego FC % of Regular & REO Sales_2	0.1019	0.4052	0.251	0.8061

Notes: RSS = 30.5402; σ = 1.6663; R^2 = 0.9802; adj. R^2 = 0.9531; log-likelihood = −1.6633; AIC = 1.3084; HQ = 1.5367; SC = 2.0763.

	Value	Prob.
Chow (1991:4)	0.0000	0.0000
Chow (1994:3)	0.1284	0.8811
Normality test	4.2791	0.1177
AR 1-4 test	2.3756	0.1499
ARCH 1-4 test	0.0237	0.9983

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GUM(2) Modeling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988:Q3–2000:Q1

	Coeff.	Std. Error	*t*-Value	*t*-Prob.
Constant	7.5786	3.9114	1.938	0.0618
San Diego Regular Sale TO Rate	0.1666	0.4122	0.404	0.6888
San Diego Regular Sale TO Rate_1	0.2282	0.5521	0.413	0.6823
San Diego Regular Sale TO Rate_2	0.9310	0.4175	2.230	0.0331
San Diego Emp % Chg	−0.9449	0.9463	−0.999	0.3258
San Diego Emp % Chg_1	−1.965	1.4296	−1.374	0.1792
San Diego Emp % Chg_2	2.9757	0.8565	3.474	0.0015
San Diego Real Aff Price % Chg	0.1960	0.0729	2.688	0.0115
San Diego Real Aff Price % Chg_1	0.08921	0.1007	0.886	0.3827
San Diego Real Aff Price % Chg_2	−0.1884	0.0738	−2.553	0.0158
San Diego MRI	−0.3446	0.1696	−2.032	0.0508
San Diego MRI_1	−0.4814	0.1871	−2.572	0.0151
San Diego MRI_2	−0.3464	0.1589	−2.181	0.0369
San Diego FC % of Regular & REO Sales	−0.6280	0.3672	−1.710	0.0972
San Diego FC % of Regular & REO Sales_1	0.1492	0.5388	0.277	0.7837
San Diego FC % of Regular & REO Sales_2	−0.1522	0.3560	−0.428	0.6718

Notes: RSS = 162.5896; σ = 2.2902; R^2 = 0.9376; adj. R^2 = 0.9074; log-likelihood = −29.1654; AIC = 1.9219; HQ = 2.1589; SC = 2.5518.

	Value	Prob.
Chow (1994:2)	2.2870	0.1138
Chow (1999:1)	1.6198	0.1980
Normality test	0.6559	0.7204
AR 1-4 test	0.4193	0.7932
ARCH 1-4 test	0.3055	0.8713
Hetero test	27.5977	0.5917

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GUM(3) Modeling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988:Q3 – 2005:Q1

	Coeff.	Std. Error	*t*-Value	*t*-Prob.
Constant	12.4233	7.6354	1.627	0.1099
San Diego Regular Sale TO Rate	0.3776	0.7994	0.472	0.6387
San Diego Regular Sale TO Rate_1	0.5944	1.0142	0.586	0.5604
San Diego Regular Sale TO Rate_2	0.3946	0.7906	0.499	0.6198
San Diego Emp % Chg	0.7880	1.5937	0.494	0.6231
San Diego Emp % Chg_1	−0.5241	2.3639	−0.222	0.8254
San Diego Emp % Chg_2	−0.5302	1.4942	−0.355	0.7242
San Diego Real Aff Price % Chg	0.0012	0.1204	0.010	0.9924
San Diego Real Aff Price % Chg_1	0.0299	0.1647	0.181	0.8567
San Diego Real Aff Price % Chg_2	−0.1182	0.1235	−0.957	0.3431
San Diego MRI	−0.1846	0.3338	−0.553	0.5827
San Diego MRI_1	−0.5881	0.3811	−1.543	0.1290
San Diego MRI_2	−0.5005	0.3012	−1.662	0.1027
San Diego FC % of Regular & REO Sales	−1.0321	0.7612	−1.356	0.1811
San Diego FC % of Regular & REO Sales_1	−0.0190	1.0950	−0.017	0.9862
San Diego FC % of Regular & REO Sales_2	−0.1459	0.7353	−0.198	0.8435

Notes: RSS = 1,267.5577; σ = 4.9854; R^2 = 0.9376; adj. R^2 = 0.7626; log-likelihood = −98.4952; AIC = 3.4178; HQ = 3.6261; SC = 3.9443.

	Value	Prob.
Chow (1996:4)	9.0326	0.0000
Chow (2003:3)	11.2261	0.0000
Normality test	10.9513	0.0042
AR 1-4 test	11.4569	0.0000
ARCH 1-4 test	2.5278	0.0543
Hetero test	20.9319	0.8900

GUM(4) Modeling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988:Q3 – 2011:Q1

	Coeff.	Std. Error	*t*-Value	*t*-Prob.
Constant	−10.3271	6.2835	−1.644	0.1045
San Diego Regular Sale TO Rate	1.0733	0.7948	1.350	0.1809
San Diego Regular Sale TO Rate_1	1.3781	1.0595	1.301	0.1973
San Diego Regular Sale TO Rate_2	1.4559	0.8171	1.782	0.0788
San Diego Emp % Chg	2.0942	1.3126	1.595	0.1148
San Diego Emp % Chg_1	−2.9800	2.1387	−1.393	0.1676
San Diego Emp % Chg_2	−1.1813	1.2153	−0.972	0.3342
San Diego Real Aff Price % Chg	−0.0074	0.1295	−0.057	0.9544
San Diego Real Aff Price % Chg_1	0.1608	0.1734	0.927	0.3567
San Diego Real Aff Price % Chg_2	−0.1770	0.1344	−1.317	0.1918
San Diego MRI	0.5150	0.3372	1.527	0.1309
San Diego MRI_1	−0.4617	0.3972	−1.162	0.2488
San Diego MRI_2	−0.7661	0.3022	−2.535	0.0133
San Diego FC % of Regular & REO Sales	0.0012	0.1390	0.009	0.9929
San Diego FC % of Regular & REO Sales_1	−0.1549	0.1839	−0.842	0.4024
San Diego FC % of Regular & REO Sales_2	−0.3017	0.14437	−2.089	0.0401

Notes: RSS = 2,652.0614; σ = 5.9465; R^2 = 0.8260; adj. R^2 = 2 0.7912; log-likelihood = −153.4366; AIC = 3.7239; HQ = 3.9020; SC = 4.1654.

	Value	Prob.
Chow (1999:4)	10.4041	0.000
Chow (2008:4)	2.1224	0.0396
Normality test	7.1256	0.0284
AR 1-4 test	16.6900	0.0000
ARCH 1-4 test	5.5985	0.0006
Hetero test	29.1250	0.5110

Conclusions

As we suggested in 1986, housing prices are predictable and the high transactions costs and stickiness (serial autocorrelation) of price trends suggests that they will continue to be one of the more predictable markets. The selection of variables to use in modeling home prices is both an art and a science. We can develop predictive models housing prices driven by well-known and established fundamentals such as employment and household demographic trends, the movement of interest rates or affordability measures. Factors that have mattered more in recent years include credit access and ease. There are a large variety of market condition factors, reflecting the interaction of supply and demand and the behavior of buyers and sellers such as months of remaining inventory, regular sale turnover rates, the percentage of distress sales or the proportion of listings with price revisions, all of which provide various leading indicators of price trends. These market conditions have proved essential for more precise prediction of turning points that are probably more relevant to the market than overall price trend accuracy.

We suggest that such market condition factors, albeit many of which are highly correlated, have seldom been used to the extent possible for short- to intermediate-term home price forecasting. Most economists prefer to utilize fundamental data, which are often available less frequently and less accurately in the short run (subject to multiple revisions), and dwell instead on long-term trends. Such approaches will miss the ability to nail short-to intermediate-term housing price trends, which are readily predictable if market condition factors are available. Today, such market condition factors are available for most local markets across the U.S.

Endnotes

1. This work builds upon the early work on leading indicators by Miller and Sklarz (1986) where multiple listing service variables such as sales volume and time on the market were used to predict subsequent home price trends. Later work by Case and Shiller (1989, 1990) focused on the autoregressive nature of housing prices and market momentums.
2. There are millions of variables in the Economy.com data set. If for example, one finds that a variable like industrial sales of heavy equipment in Japan fits with housing prices in Kansas and only Kansas, should you trust the variable as having validity? Or if Karaoke sales in the U.K. leads New York condo prices by 24 months should we include the variable? By ''exotic functional'' forms, we mean the purely curve-fitting-model types that are generated by GP models or neural networks.
3. For example, a moratorium on foreclosures will delay the normal pattern towards equilibrium, which we have seen occur at the state and federal levels.
4. Today if you type ''housing bubbles'' into Google Scholar you will see 67,700 articles. If you type ''housing behavioral price trends'' you will get 57,300 results.
5. One huge issue in forecasting is how small a geographic market can we get reasonable data estimates for?
6. One can solve for the break-even price that equates the after-tax costs of owning to renting similar quality and sized housing, where such rental data are available. Then, if you factor in rising rents, you can use an adjusted and higher level of rent that equates with a growing stream of future payments and solve for what might be a similar after-tax costs to own. One must consider property taxes, insurance, and maintenance data but these are readily available.
7. Two recent papers that deal with these issues are worth reading; Gyourko, Saiz, and Summers (2008) and Saiz (2010).
8. Rose (1989) wrote one of the first papers on this topic.
9. See http://www.huduser.org/portal/datasets/cinch.html.
10. We understand that some MLS organizations now have rules to prevent gaming the system.
11. The off-market date refers to the date when the listing is in contract and no longer available. However, in some cases the contract does not result in a closing and so using the closing date is a more conservative measure of DOM.
12. This results in a smaller flare over time in the forecast range than would normally be the case. The other variable forecasts are our own.

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