Integrating Real Estate Market Conditions into Home Price Forecasting Systems

Draft: March 26, 2012

Norm Miller, PhD, Professor, University of San Diego

Contact: Nmiller@sandiego.edu

Michael Sklarz, PhD, CEO and President, Collateral Analytics

Contact: Msklarz@collateralanalytics.com

**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 requires 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 get a better handle on 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.

Integrating Real Estate Market Conditions into Home Price Forecasting Systems

## I. Introduction

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 better and better 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", he 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.[2] 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 myriads of exotic functional forms there is a greater likelihood that spurious results can occur.[3] 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 we suggest papers by Kaboudan (2008, 2011), Kaboudan and Sarkor (2008), Crawford and Fratanoni (2003), Conway (2001), Dua, Miller and Smyth (1999), Dua and Miller (1996) among others.

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

---

[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 and 1990) focused on the autoregressive nature of housing prices and market momentums.

[2] See M. Kaboudan (2011)

[3] 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 UK 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.

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 terms price trends and these must also be monitored.[4]

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 on 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.[5]

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.[6] See for example, papers by Goodman (1993), Kuo (1996), Kaplanski and Levy (2009).

## II. 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

[4] For example, a moratorium on foreclosures will delay the normal pattern towards equilibrium, which we have seen occur at the state and Federal level.

[5] 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.

[6] See “Seasonality in Home Prices: Evidence from the CBSA’s” by N. Miller, V. Sah, M. Sklarz and S. Pampulov, Working Paper, Collateral Analytics and University of San Diego, 2011.

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).[7] 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.[8] One might argue that housing markets suffer from greater heterogeneity than apartments but they still provide some substitution at the margin and have been shown to interact with home prices, Yong (2009), and Gallin (2012). The point is that the indicators of rental market affordability should be included in most models that forecast short to intermediate term housing prices.

In Exhibit 1 we show one of these fundamental demand drivers, quarterly employment, versus housing real sales price percent 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 historical averages. The ease of getting a loan approved was also quite high. Duca, Muellbauer and Murphy (2009) incorporated the loan-to-value ratio for first-time home buyers, as a proxy for credit ease, with excellent results in terms of explaining changes home prices. Duca et al show that the loan-to-value (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 established, which we will provide further evidence of here. See for example Reichert (1990), or Harris (1989) or Miller, Sklarz and Thibodeau (2005). In Exhibit 2 we show one example of real fixed-rate mortgages (inflation is subtracted using the percent change in the CPI) versus home prices for San Diego. Except for the very

[7] One huge issue in forecasting is how small a geographic market can we get reasonable data estimates for?

[8] 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 is 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 but these are readily available.

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 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) where they focus on the issue of affordability.

One way to factor in supply is to bring into the model an index which measures the difficulty of adding new supply. This supply difficulty is a function of only two categories, one natural and one human induced.[9] 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 jumped through prior to gaining entitlement.[10] 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

[9] Two recent papers that deal with these issues are worth reading. “A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index” by Joseph Gyourko, Albert Saiz, and Anita A. Summers The Wharton School, University of Pennsylvania, Final Version: March 29, 2007 published in Urban Studies; also “The Geographic Determinants of Housing Supply” by Albert Saiz forthcoming in the Quarterly Journal of Economics, written January 5, 2010.

[10] Louis A. Rose wrote one of the first papers on this topic, “Urban land supply: Natural and contrived restrictions”, Journal of Urban Economics, Vol. 25, #3, 1989, pp. 325-345.

inventory in a given year. See HUD Cinch data as an example of such estimates.[11] 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.[12]

## III. 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 and 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:

- ✓ Volume of Sales
- ✓ Turnover Ratio (Percent of Total Inventory Sold)
- ✓ Days on Market for Sold Properties
- ✓ Months Remaining Inventory (Existing units for sale divided by recent sales rate)
- ✓ Sold to List Price Ratio
- ✓ Percent of all units (inventory stock) for Sale
- ✓ Percent of Units for Sale with Price Revisions (generally down but in some exceptional cases, upward)
- ✓ Prices of new listings adjusted for size and quality
- ✓ Changes in the affordability of housing based on changes in LTV, capital access or interest rates based on an affordable index or corresponding affordable price.

---

[11] See http://www.huduser.org/portal/datasets/cinch.html

[12] Miller, N. , M. Sklarz and T. Thibodeau "The Impact of Interest Rates and Employment on Housing Prices" International Real Estate Review, Vol.8, No. 1: pp. 26-42. 2005

- ✓ 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.

**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 and we 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.[13]

Forecast models using traditional fundamentals or market condition variables would not have done a good job of capturing the ease of credit impact which we observed in in 2000 through 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) and had we had a variable to capture the extent of credit ease we might have better understand the impact of credit tightening now observed. What might be described as changing market credit conditions are not easy to measure but loan to value ratios, and the percent 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 period of 1987 to 2007. 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

[13] See N. Miller, M. Sklarz and N. Ordway "Exchange Rates and Speculation in Real Estate Markets," Journal of Real Estate Research, Vol. 3, No. 3, Fall 1988.

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, a fairly small set of major markets.

More recently, Miller, Sah, Sklarz and Pampulov have 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 United States and a hierarchical regression to tease out the seasonality impact. For example, in Exhibit 3a we see price seasonality for all CBSA's using data from 1999 or earlier through 2010 for Months January through December. 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 we compare Cook County (Chicago) versus 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 Exhibits 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 4a 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 which works quite well. The **turnover rate** is measured via the percent of total stock sold. Rather than measure the percent of listings sold, we measure the percent 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 percent 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. In Exhibit 5 we show 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 can measure days on market for existing listings or for homes which have actually sold, and we do so in Exhibit 6 below. Here 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 days on market is dropping rapidly we see more rapid appreciation, and that when graphed on a monthly basis, we see a several period lead between days on market and prices.

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.[14] 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 days-on-market 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.[15] Thus, the days on market 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 days on market 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 build up a significant inventory of shadow inventory (owners who would like to sell but are waiting for better market conditions) which has been pulled from the market but will return as soon as prices stabilize, start to head up or when sellers accept

[14] We understand that some MLS organizations now have rules to prevent gaming the system.

[15] 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.

the inevitable declines. So the actual MRI when the shadow inventory is considered can sometimes appear to be lower than the true inventory available once sellers see an opportunity to sell with less pain or an actual gain. Here 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 and in fact we can characterize most markets in this fashion, where MRI less than 3 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 3 to 6 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 months or more |

**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, ARMs (adjustable rate mortgages) seem to be the dominant choice of mortgages while in most other markets, FRMs (fixed-rate mortgages) 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.

**Ease of capital access** is a challenge to pin down but after experimenting with various measures including the percent of loans that are subprime mortgages and loans above 80% loan-to-value, (LTV), we settled upon the percent 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 et al (2009) when using national data on LTVs for first-time home buyers. In Exhibit 10 we provide the correlation matrix between real home prices and various lags of the proportion of mortgages with LTV 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 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 which also works equally as well is to use the percent 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. In Exhibit 12a we show the general inverse indicator provided by withdrawn listings. In Exhibit 12b we show the listing expired without selling as a percent 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. Anthony 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) which suggested a 23% discount on distressed sales. In our own research 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 below.

**The Impact of REO and Foreclosure Sales On Single Family Homes**

| Study Title | Authors | Study Period | Geography | Typical Discount Found Versus Non-distressed |
|---|---|---|---|---|
| REO Properties, Housing Markets, and the Shadow Inventory | Alan 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 | Dan 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 | Claudia Coulton, Michael Schramm, and April 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 | Kai-yan Lee, Federal Reserve Bank of Boston | 2007-09 | Mass. | -19.9% |
| Optimal Choice for Lenders Facing Defaults: Short Sale, Foreclose, or REO | Terrence M. Clauretie & Nasser 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 | Nasser Daneshvary, Terrence M. Clauretie, and Ahmad Kader | 1990-2008 | U.S.; Nevada | -13.5% for REO sales |
| The Contagion Effect of Foreclosed Properties | Harding, Rosenblatt, 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% |
| 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 | Anthony Pennington-Cross | 1990-2006 | U.S. | -15 to -22% depending on condition and timing |

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 13a we show distressed sales as a percent of total sales versus price per square foot. The inverse relationship is clear. In Exhibit 13b we show a simple estimate of the discount from regular sales versus this same distress percent. 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 simply 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.

**IV. 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 single 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.

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 which 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 below (Exhibit 4) we see the best fit between sales volume and changes in home prices at 6 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 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.

| **Demand Drivers** | **Hypothesized Relationship On Housing Prices** |
|---|---|
| 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 and 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 | Hypothesized Relationship On Housing Prices |
|---|---|
| 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** | **Hypothesized Relationship On Housing Prices** |
| 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 Percent 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 |
| Percent 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 Percent Change Trend | Positive |
| Time on the Market to Sell (DOM) and the Percent Change Trend in DOM | Inverse |

## An Illustrated Home Price Forecast Model

Quarterly data from 1981 through the first quarter of 2011 is 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 shown below for San Diego. For DOM, MRI and foreclosures the data starts in 1988 and runs through Quarter 1 of 2011. Specifically, we use the following variables in the first set of models, with the correlation matrix shown below:

| Variable | **Mean** | **Standard Deviation** |
|---|---|---|
| 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** | **22.78** |
| San Diego MRI (Months Remaining Inventory) | **8.29** | **4.28** |
| San Diego Foreclosure Percent of Regular and REO Sales | **11.48** | **14.37** |

In Exhibit 14 we show 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 below along with the statistical results. Note that in examining the variables included the highest t values are generally when using a two quarter lead. We include affordability, sales volume turnover, affordability, foreclosure percentages and months remaining inventory along with employment. The employment and interest rate forecasts included are those of Economy.com and we did not reflect the uncertainty behind the Economy.com forecasts for those particular variables.[16]

With respect to the actual outlooks, our models are less sanguine that those of Kaboudan. 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

[16] 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.

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, but 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.

We could further improve our model results by using some of the more sophisticated techniques of combining neural networks and genetic programming suggested by Mak 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 $R^2$ of .87 compared to .89 for our own work. His best work for San Diego was $R^2$ 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.

## V. 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 which 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 remaining inventory, or regular sale turnover rates, or the percent 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 is 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 United States.

## References


Brueckner, Jan K., Paul S. Calem, and Leonard I. Nakamura (2011) “Subprime Mortgages and the Housing Market” working paper, the University of California at Irvine, Federal Reserve Board of Governors and the Federal Reserve Bank of Philadelphia, presented at the Homer Hoyt Institute, May 14, 2011.

Case, Karl E. and Robert J. Shiller, (1989) “The Efficiency of the Market for Single-Family Homes,” The American Economic Review, Vol. 79, No. 1, March, pp. 125-137.

Case, Karl E., and Robert J. Shiller. (1990) "Forecasting Prices and Excess Returns in the Housing Market." *American Real Estate and Urban Economics Association Journal* 18, no. 3: 253-273.

Conway, Richard S., Jr. (2001) "The Puget Sound Forecasting Model: A Structural Time-Series Analysis of Ron Miller's Home Town." In *Input-output analysis: Frontiers and extensions*, 431-450. Houndmills, U.K. and New York: 2001.

Crawford, Gordon W., and Michael C. Fratantoni.(2003) "Assessing the Forecasting Performance of Regime-Switching, ARIMA and GARCH Models of House Prices." *Real Estate Economics* 31, no. 2: 223-243.

Dua, Pami, and Stephen M. Miller. (1996) "Forecasting Connecticut Home Sales in a BVAR Framework Using Coincident and Leading Indexes." *Journal of Real Estate Finance and Economics* 13, no. 3: 219-235.

Dua, Pami, Stephen M. Miller, and David J. Smyth. (1999) "Using Leading Indicators to Forecast U.S. Home Sales in a Bayesian Vector Autoregressive Framework." *Journal of Real Estate Finance and Economics* 18, no. 2: 191-205.

Family Mortgage Foreclosures on Property Values”. Fannie Mae Foundation. *Housing Policy Debate*, 17:1, 57–79.

Follain, James R. and Seth H. Giertz, 2011, “A Look at U.S. House Price Bubbles from 1980-2010 and the Role of Local Market Conditions” The Nelson A. Rockefeller institute of Government. See http://www.rockinst.org/in_print/follainj/2011-07-LILP-house_price_bubbles.aspx

Forgey, Fred A., Ronald C. Rutherford and Michael L. Van Buskirk, (1994) “Effect of Foreclosure Status on Residential Selling Price,” *Journal of Real Estate Research*, Vol. 9, No. 3; 313-318.

Gallin, Joshua, (forthcoming 2012), “The Long Run Relationship Between Home Prices and Rents” *Real Estate Economics.*

Glaeser, Edward L. and Joseph Gyourko, Rethinking Federal Housing Policy, The AEI Press, Washington D.C., 2008.

Glaeser, Edward L., Triumph of the City, The Penguin Press, NY, 2011.

Goodman, J., (1993) A Housing Market Matching Model of the Seasonality in Geographic Mobility. The Journal of Real Estate Research, 8:1, 117-138.

Harding, J.P., E. Rosenblatt, and V.W. Yao. "The Contagion Effect of Foreclosed Properties" *Journal of Urban Economics*, 2009, 66:3, 164–78.

Harris, Jack C. (1989) "The Effect of Real Rates of Interest on Housing Prices" *Journal of Real Estate Finance and Economics*, Vol. 2, No. 1, 47-60.

Hodrick, R. and E. Prescott, Post-War U.S. Business Cycles: An Empirical Investigation, Carnegie Mellon University, 1980.

Immergluck, D. and G. Smith. (2006) "The External Costs of Foreclosure: The Impact of Single-
Kaboudan, M. (2011) "Forecasting the S&P/Case Shiller Home Price Index for Los Angeles & San Diego by Use of Agent-Based Modeling" March 1, 2011 University of the Redlands, Working Paper presented at ARES, April 14, 2011.

Kaboudan, Mak, and Avijit Sarkar. (2008) "Forecasting Prices of Single Family Homes Using GIS-Defined Neighborhoods." *Journal of Geographical Systems* 10, no. 1: 23-45.

Kaboudan, Mak. (2008) "Genetic Programming Forecasting of Real Estate Prices of Residential Single-Family Homes in Southern California." *Journal of Real Estate Literature* 16, no. 2: 219-239.

Kaplanski G and Levy H. (2009) Real Estate Prices: Seasonality's Sentiment Effect. Working Paper. Available at SSRN: http://ssrn.com/abstract=1438826

Kuo, C.L., (1996) "Serial Correlation and Seasonality in the Real Estate Market", *Journal of Real Estate Finance and Economics*, 12, 139-162.

Lambson V, G McQueen and B Slade, (2004) "Do Out-of-State Buyers Pay More for Real Estate? An Examination of Anchoring-Induced Bias and Search Costs". *Real Estate Economics*, 2004, 32, 1, 85–126.

Leonard, T. and J.C. Murdock. (2009) "The Neighborhood Effects of Foreclosure", *Journal of Geographical Systems*, 11:4, 317–32.

Lin, Z., E. Rosenblatt, and V.W. Yao. (2009) "Spillover Effects of Foreclosures on Neighborhood Property Values". *Journal of Real Estate Finance and Economics*, 38:4, 387–407.

Mcgough, T. and Tsolacos, S., (1995) "Property cycles in the UK: an empirical investigation of the stylized facts", Journal of Property Finance, 6:4, 45-62.

Miles, W. 2008. "Boom-Bust Cycles and the Forecasting Performance of Linear and Non-linear Models of House Prices." *Journal of Real Estate Finance and Economics* 36, no. 3: 249-264.

Miles, William. 2011. "Long-Range Dependence in U.S. Home Price Volatility." *Journal of Real Estate Finance and Economics* 42, no. 3: 329-347.

Miller, N. and M. Sklarz, (1986) "A Note on Leading Indicators of Housing Market Price Trends," *The Journal of Real Estate Research*, Vol. 1, No. 1, 99-109.

Miller, N., M. Sklarz and N. Ordway, (1988) "Exchange Rates and Speculation in Real Estate Markets," Journal of Real Estate Research, Vol. 3, No. 3.

Miller, N., M. Sklarz, and T. Thibodeau (2005) "The Impact of Interest Rates and Employment on Nominal Housing Prices," *International Real Estate Review*, Vol. 8, No. 1, 26-42.

Miller, N., V. Sah, M. Sklarz and S. Pampulov (2011) "Seasonality in Home Prices: Evidence from the CBSAs" Working Paper, Collateral Analytics and University of San Diego.

Ngai, L. Rachel and Tenreyro, S., (2009) "Hot and Cold Seasons in the Housing Market", CEP Discussion Papers, 922. Centre for Economic Performance, London School of Economics and Political Science, London, UK.

Pennington-Cross, A. (2010) "The Duration of Foreclosures in the Subprime Mortgage Market: A Competing Risk Model with Mixing", *Journal of Real Estate Finance and Economics*, 40:2,109–29.

Pennington-Cross, Anthony (2006), "The Value of Foreclosed Property," *Journal of Real Estate Research*, Vol. 28, No. 2; 193-214.

Reichert, Alan K. (1990), "The Impact of Interest Rates, Income, and Employment Upon Regional Housing Prices," *Journal of Real Estate Finance and Economics*, Vol. 3, No. 4; 373-391.

Rogers, W.H. and W. Winters. (2009) "The Impact of Foreclosures on Neighboring Housing Sales", *Journal of Real Estate Research*, 31:4, 455–79.

Schuetz, J., V. Been, and I.G. Ellen. (2008) "Neighboring Effects of Concentrated Mortgage Foreclosures". *Journal of Housing Economics*, 17:4, 306–19.

Shilling, J.D., J.D. Benjamin, and C.F. Sirmans. (1990) "Estimating Net Realizable Value for Distressed Real Estate". *Journal of Real Estate Research*, 5:1, 129–39.

Yong (2009), "Rent-Price Ratios and the Earnings Yield on Housing" University of Southern California, Lusk Center paper, http://www.usc.edu/schools/sppd/lusk/research/pdf/kim-2009.pdf

Exhibit 1: Quarterly Employment Versus Changes in Home Prices for San Diego

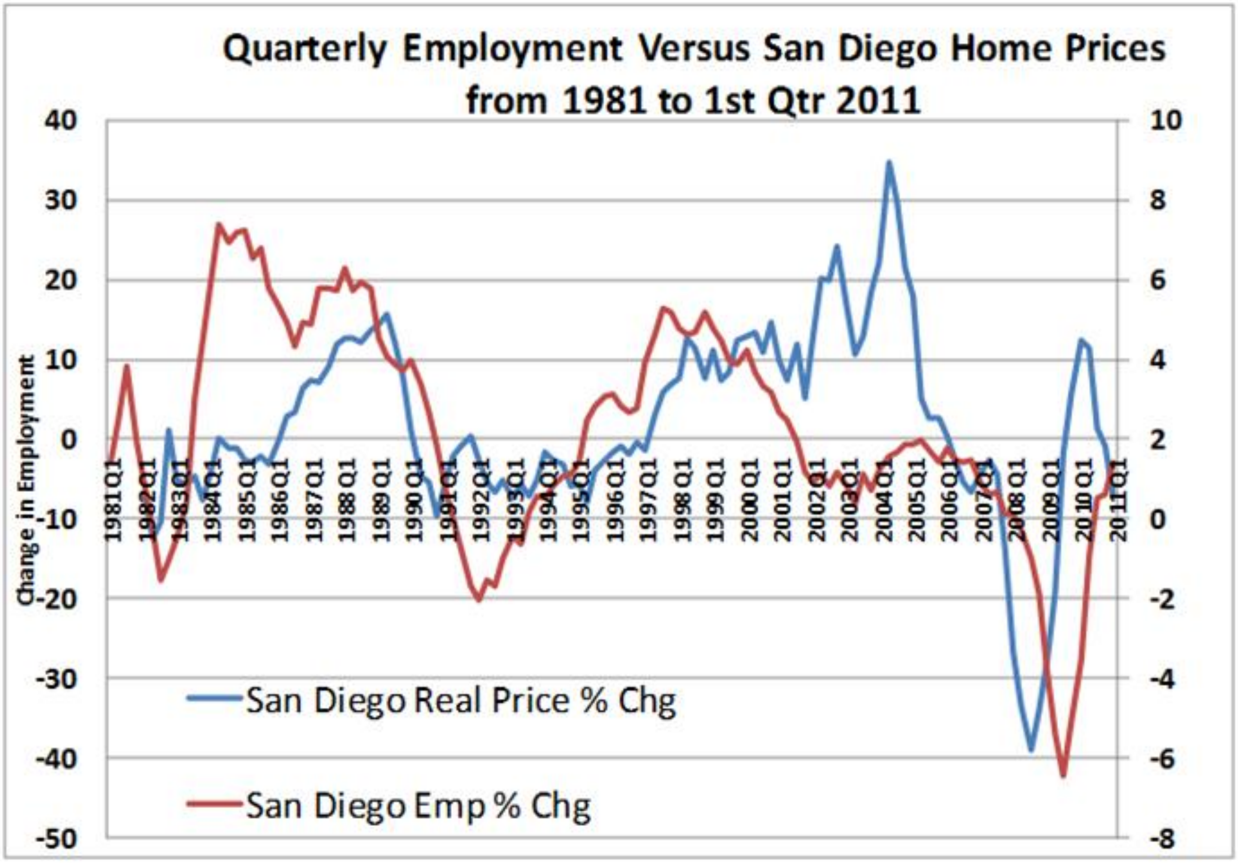


Exhibit 2: FRM Mortgage Rates Versus Home Prices

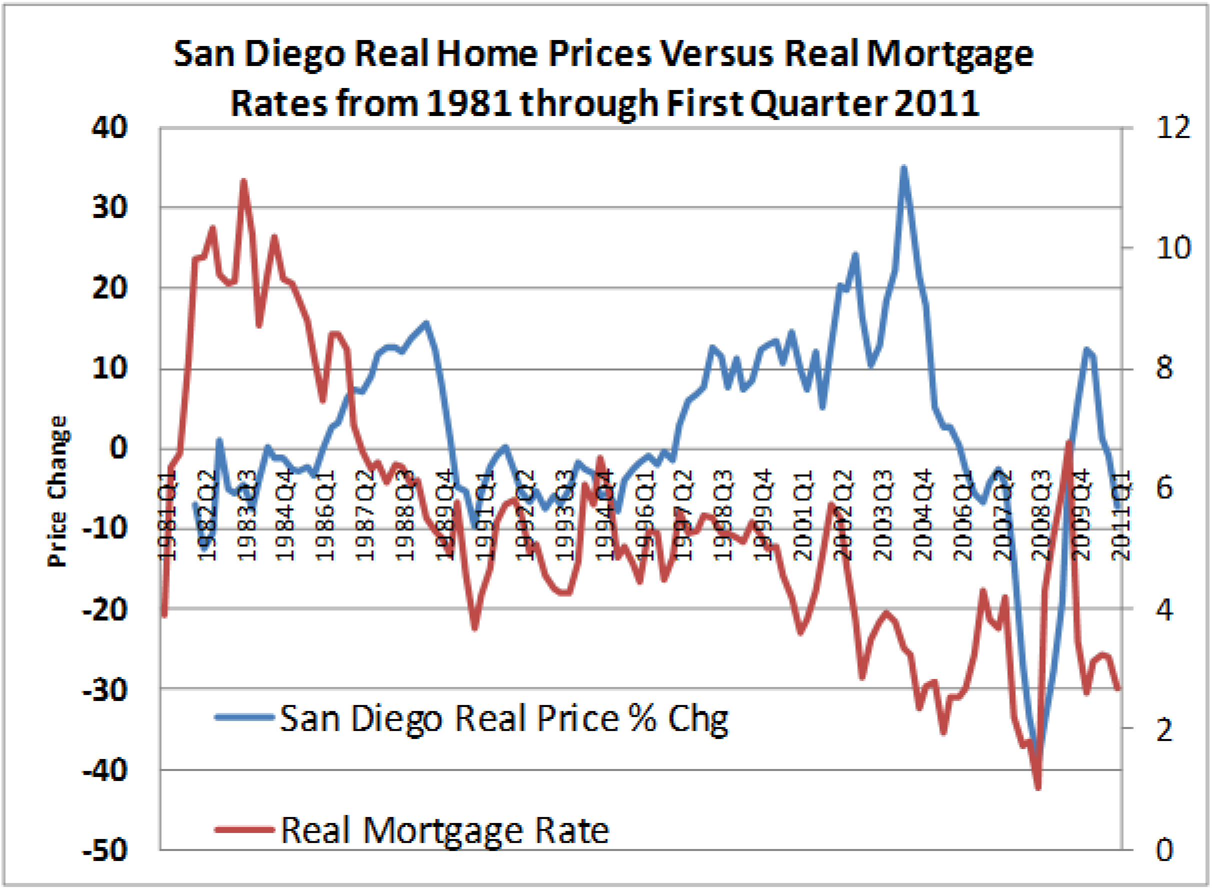


Exhibit 3a: Monthly Price Seasonality in All CBSA's as of data from 2000 to 2011

Source of data: Collateral Analytics

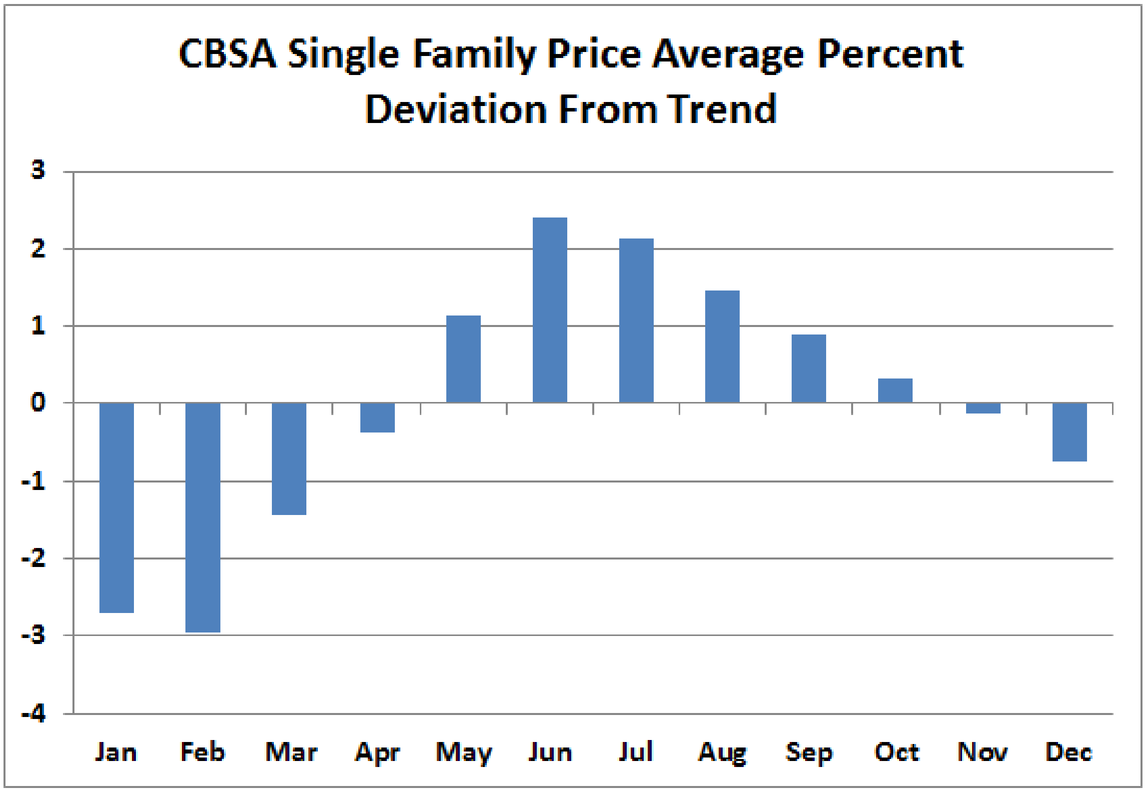


Exhibit 3b: Price Seasonality Illustrated for Cook County (Chicago) versus Los Angeles County

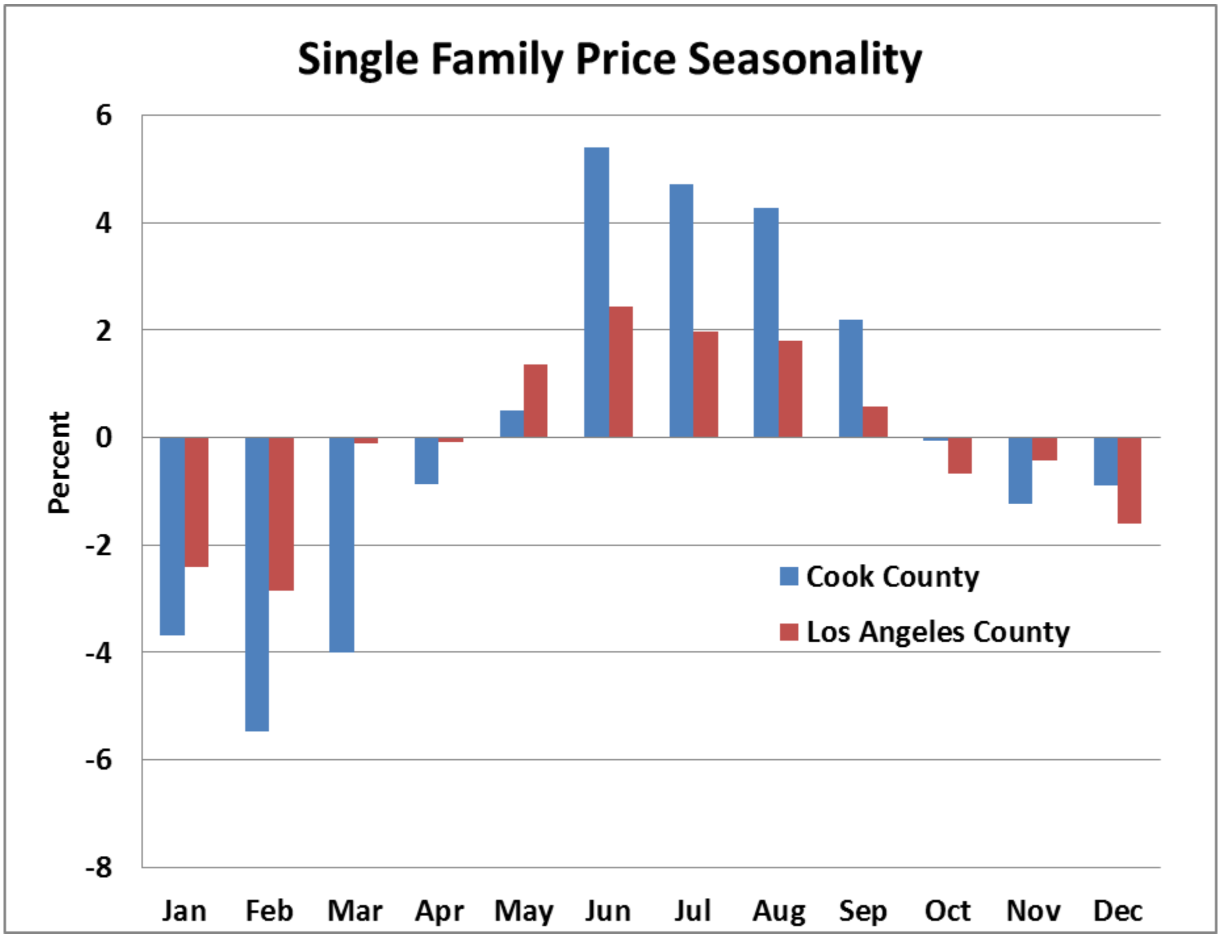
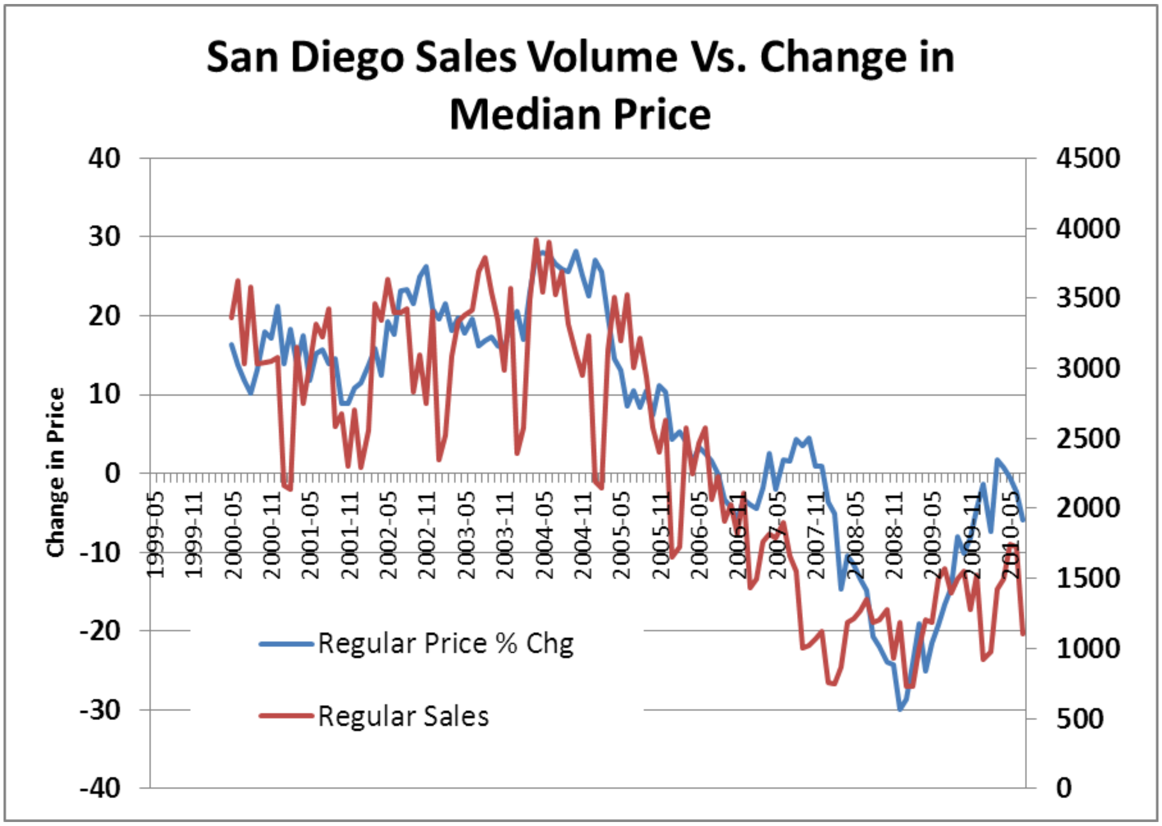


Exhibit 4: Sales Volume (not seasonally adjusted) in San Diego Metro Versus the Change In Median Price Using Monthly data Using Regular Non-Distressed Sales




The correlation matrix behind this graph is as follows:

| *Lead Time shown below in ( )* | *San Diego Regular Price % Change* |
|---|---|
| San Diego Regular Sales | 0.832919 |
| San Diego Regular Sales(-1) | 0.837357 |
| San Diego Regular Sales(-2) | 0.839841 |
| San Diego Regular Sales(-3) | 0.844485 |
| San Diego Regular Sales(-4) | 0.849545 |
| San Diego Regular Sales(-5) | 0.847036 |
| San Diego Regular Sales(-6) | **0.850599** |
| San Diego Regular Sales(-7) | 0.838841 |
| San Diego Regular Sales(-8) | 0.832730 |
| San Diego Regular Sales(-9) | 0.822250 |
| San Diego Regular Sales(-10) | 0.808278 |
| San Diego Regular Sales(-11) | 0.793572 |
| San Diego Regular Sales(-12) | 0.773712 |

Exhibit 5: Turnover Rate Versus Real Home Prices for San Diego

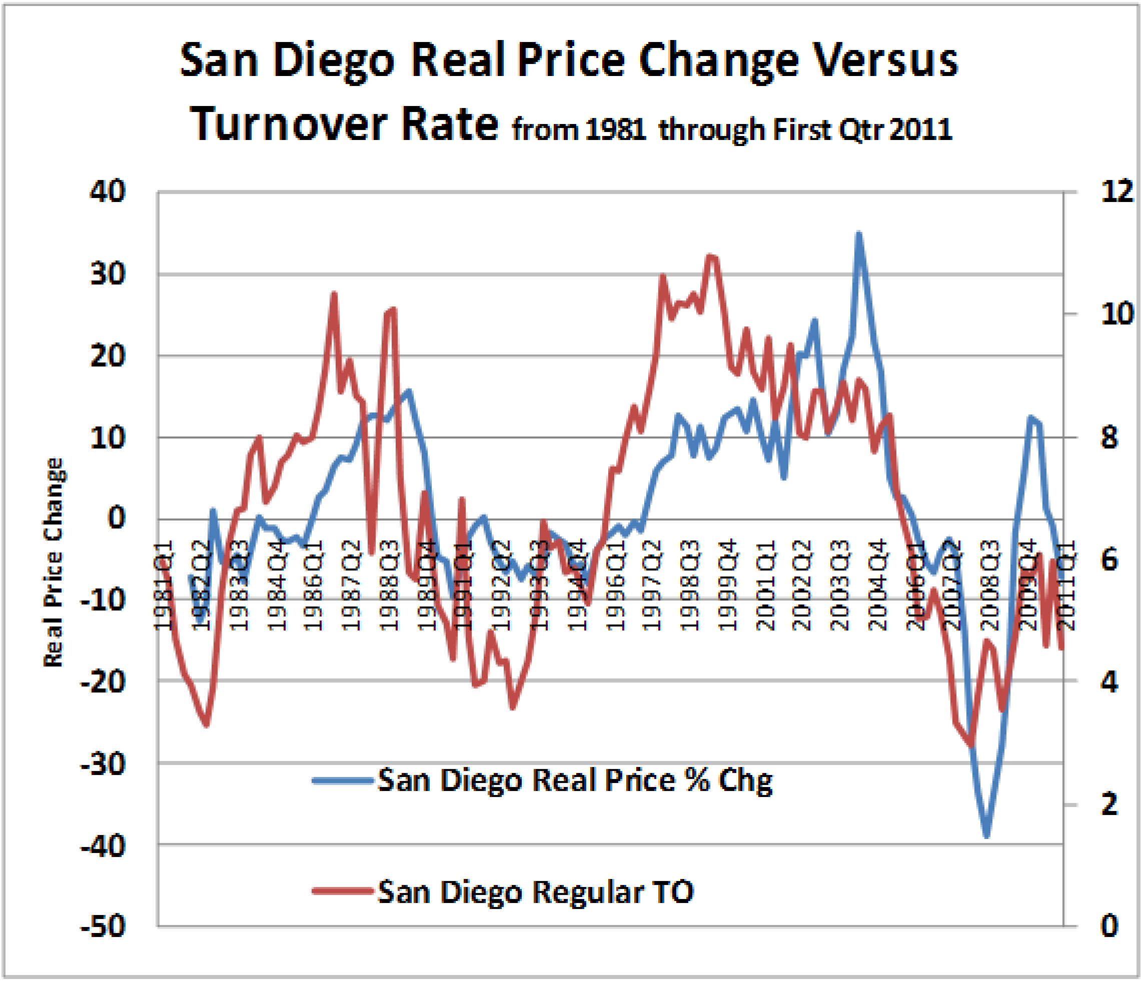


Exhibit 6: Days on Market (Sold Market Time) Versus Median Single Family Price

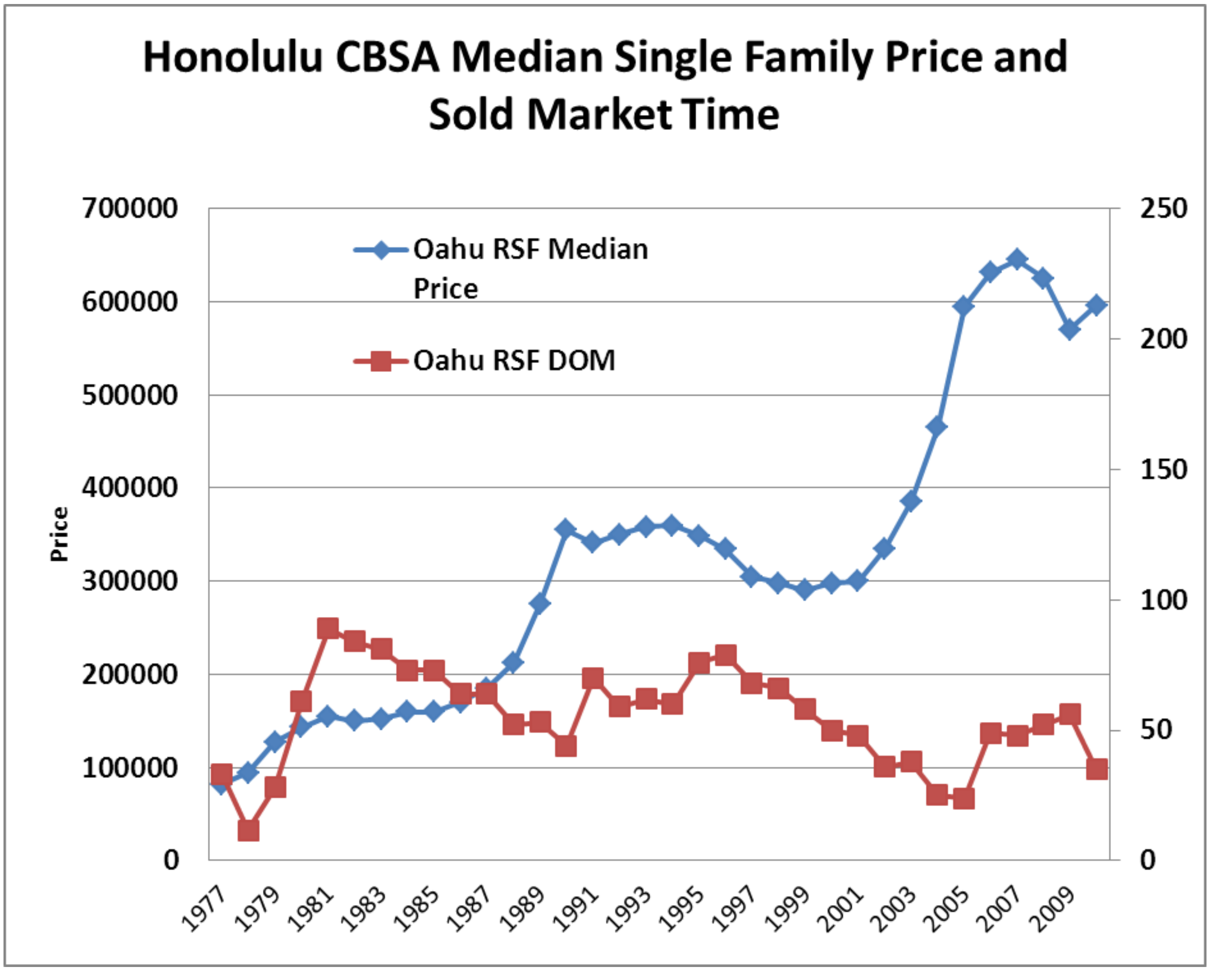


Exhibit 7: Months Remaining Inventory Versus Honolulu Median Single Family Prices from 1977 through 2009
Data: Collateral Analytics

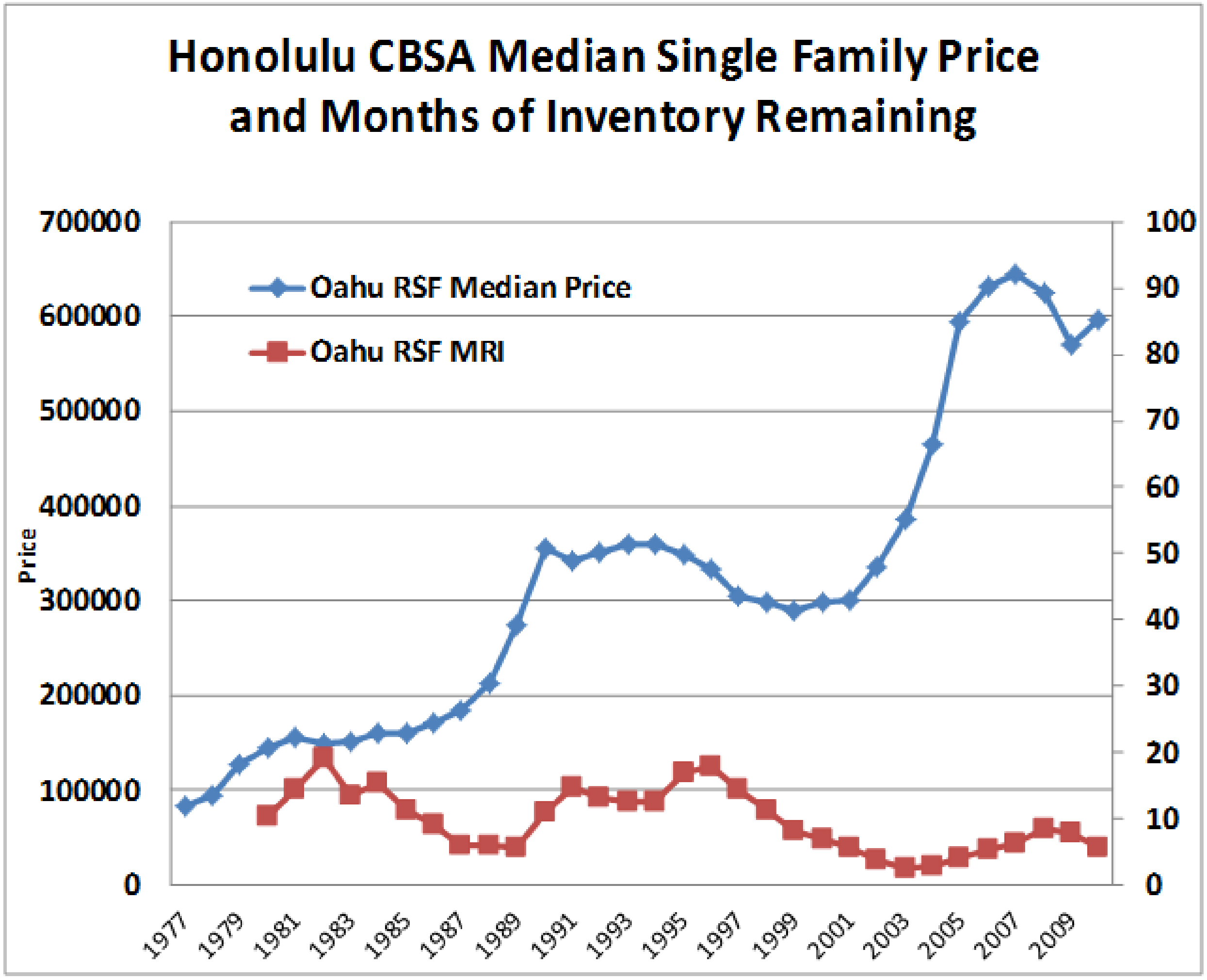


Exhibit 8: ARM Rates Versus San Diego Real Home Prices

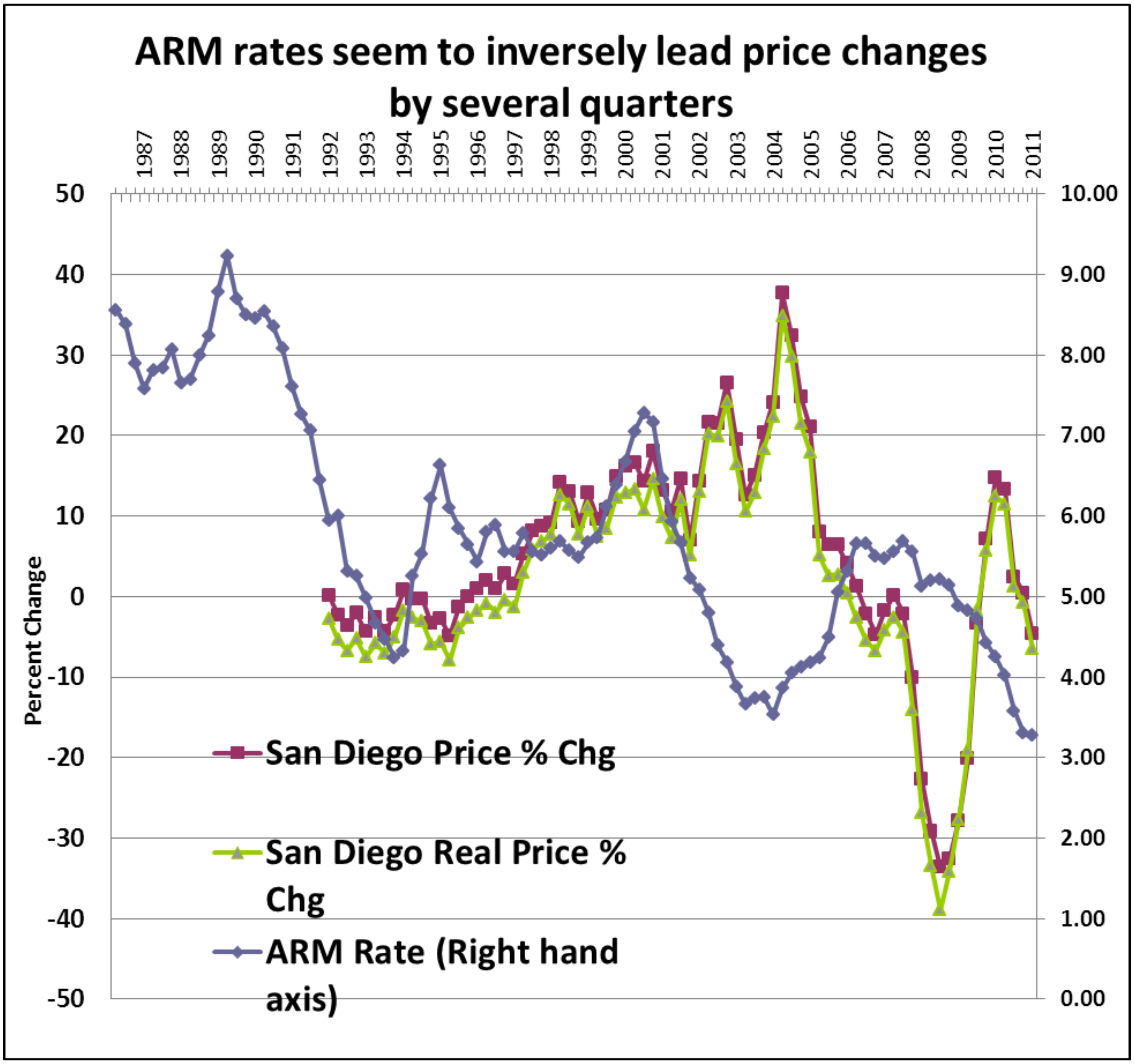


Exhibit 9:  Percent of Loans Over 90% LTV Versus Home Prices

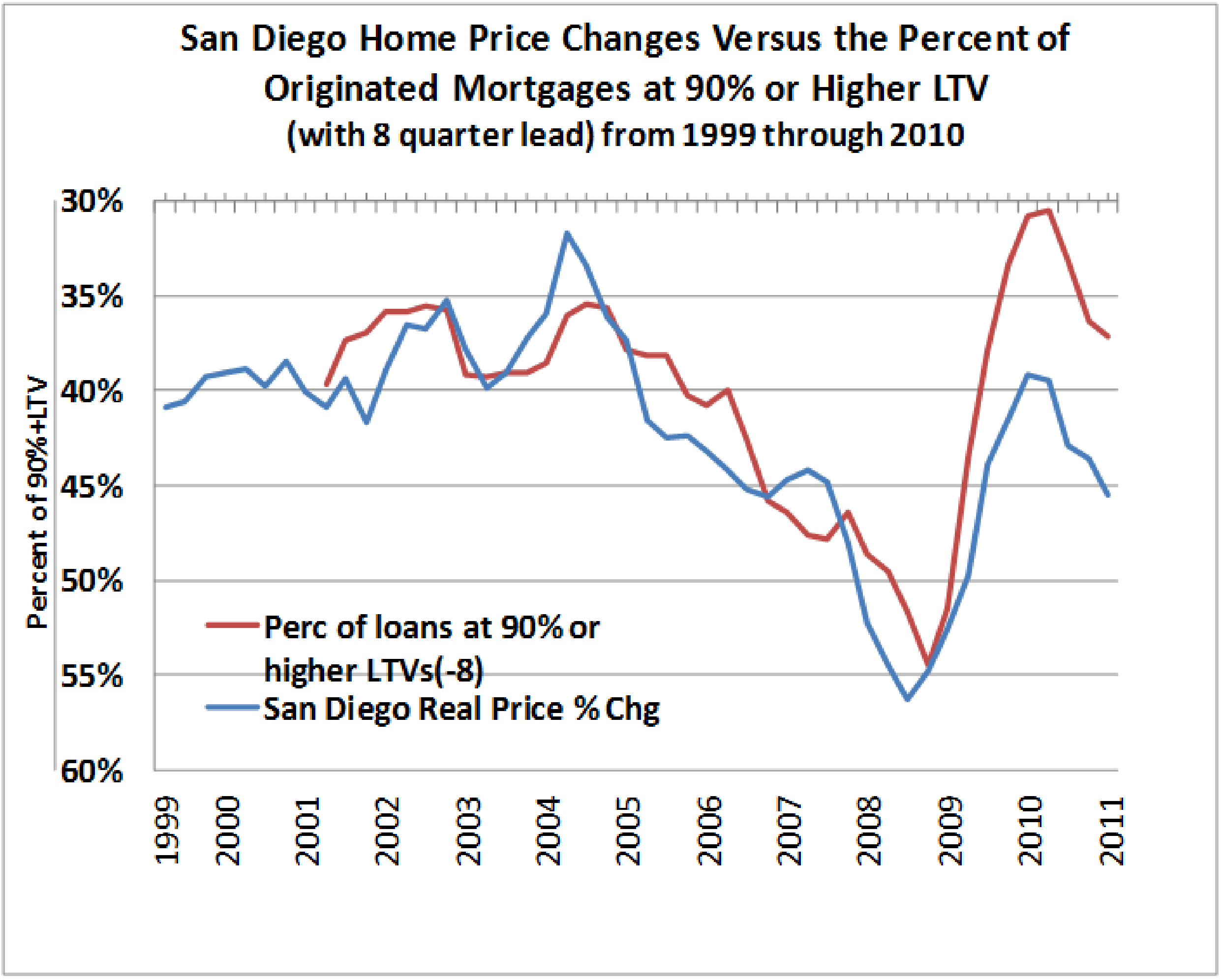


Exhibit 10: Correlation Matrix of 90% Plus LTV Versus Home Prices at Various Leads

| | *San Diego Real Price % Chg* | *Perc of loans at 90% or higher LTVs* | *Perc of loans at 90% or higher LTVs(-1)* | *Perc of loans at 90% or higher LTVs(-2)* | *Perc of loans at 90% or higher LTVs(-3)* | *Perc of loans at 90% or higher LTVs(-4)* | *Perc of loans at 90% or higher LTVs(-5)* | *Perc of loans at 90% or higher LTVs(-6)* | *Perc of loans at 90% or higher LTVs(-7)* | *Perc of loans at 90% or higher LTVs(-8)* | *Perc of loans at 90% or higher LTVs(-9)* | *Perc of loans at 90% or higher LTVs(-10)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| San Diego Real Price % Chg | 1 | | | | | | | | | | | |
| Perc of loans at 90% or higher LTVs | 0.218087799 | 1 | | | | | | | | | | |
| Perc of loans at (-1) | 0.189298722 | 0.924215 | 1 | | | | | | | | | |
| Perc of loans at (-2) | 0.135993758 | 0.766554 | 0.922741 | 1 | | | | | | | | |
| Perc of loans at (-3) | 0.025587498 | 0.581425 | 0.761861 | 0.921281 | 1 | | | | | | | |
| Perc of loans at (-4) | -0.1417175 | 0.400341 | 0.567928 | 0.753019 | 0.915979 | 1 | | | | | | |
| Perc of loans at (-5) | -0.364473984 | 0.254645 | 0.376788 | 0.553099 | 0.74462 | 0.915638 | 1 | | | | | |
| Perc of loans at (-6) | -0.578100003 | 0.173725 | 0.237656 | 0.364803 | 0.545088 | 0.744282 | 0.91687 | 1 | | | | |
| Perc of loans at (-7) | -0.736994147 | 0.0977 | 0.144805 | 0.216964 | 0.350507 | 0.540731 | 0.740417 | 0.91771 | 1 | | | |
| Perc of loans at (-8) | -0.801265511 | 0.022769 | 0.077384 | 0.130056 | 0.206097 | 0.347064 | 0.537509 | 0.739555 | 0.918079 | 1 | | |
| Perc of loans at (-9) | -0.767682546 | -0.07118 | 0.006201 | 0.06572 | 0.121453 | 0.2042 | 0.344816 | 0.537226 | 0.740268 | 0.91818 | 1 | |
| Perc of loans at (-10) | -0.667117813 | -0.17724 | -0.09662 | -0.01146 | 0.051854 | 0.108821 | 0.189536 | 0.336008 | 0.527655 | 0.735358 | 0.915856 | 1 |

Exhibit 11: Sales Price Per Square Foot Versus Sale Price to List Price Ratio

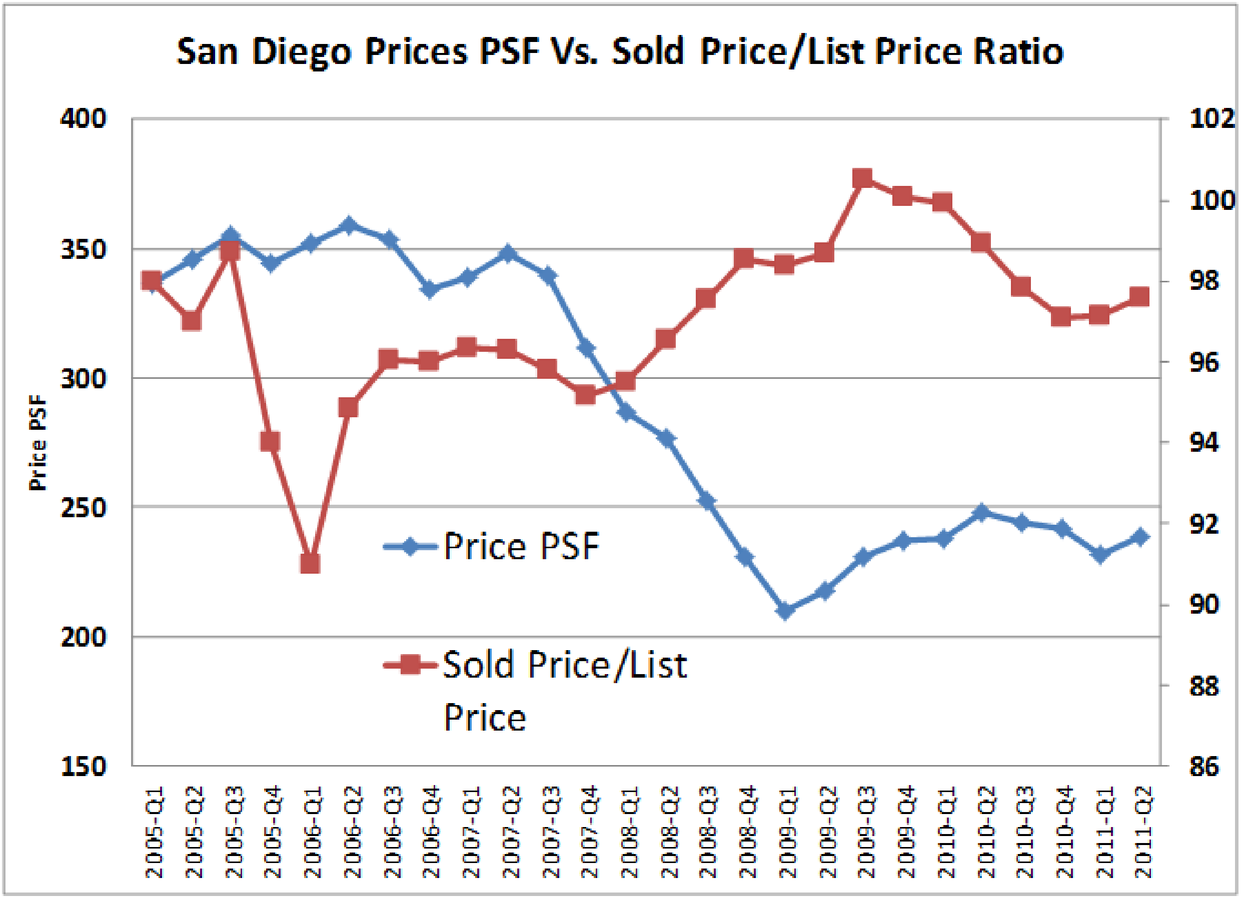


Exhibit 12a Percent of Listings Withdrawn as a % of those Sold for San Diego

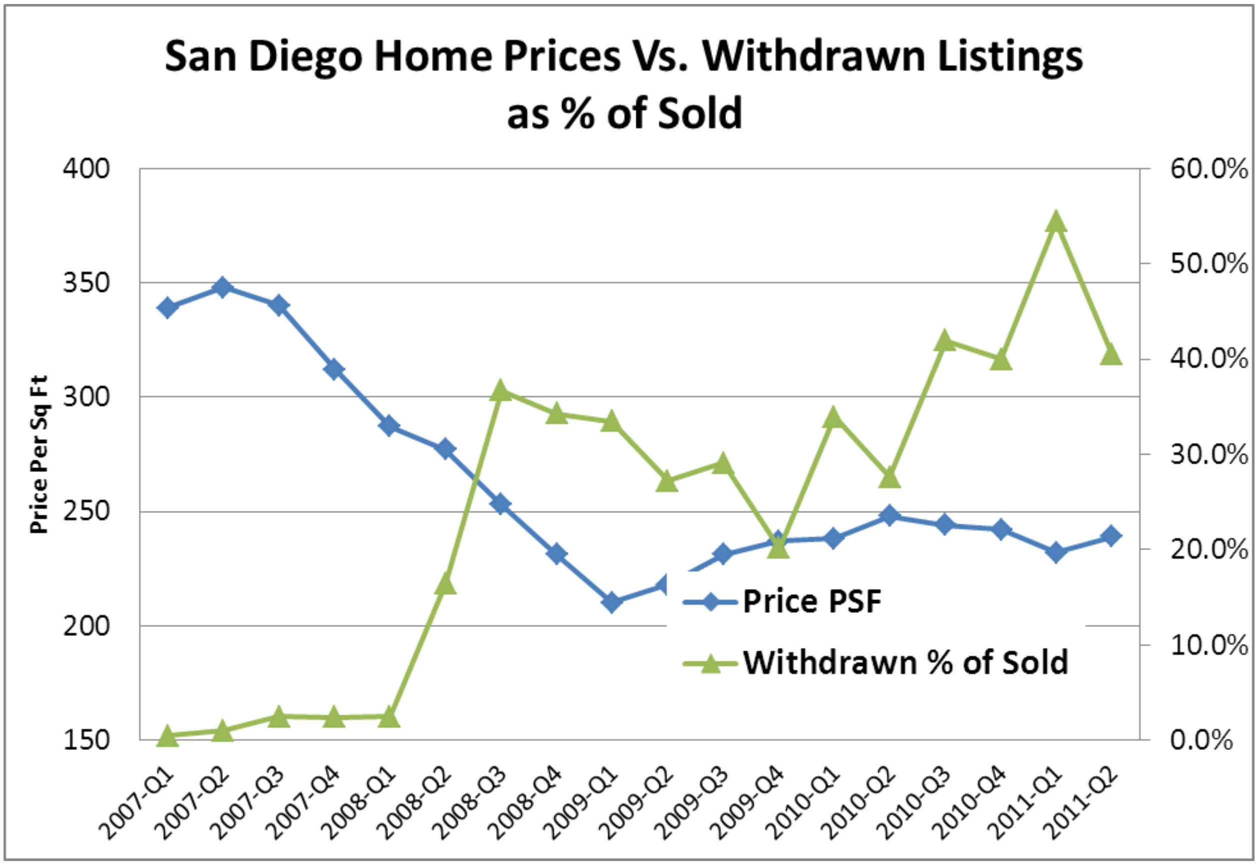


Exhibit 12b: Expired Listings as Percent of those Sold Versus Price

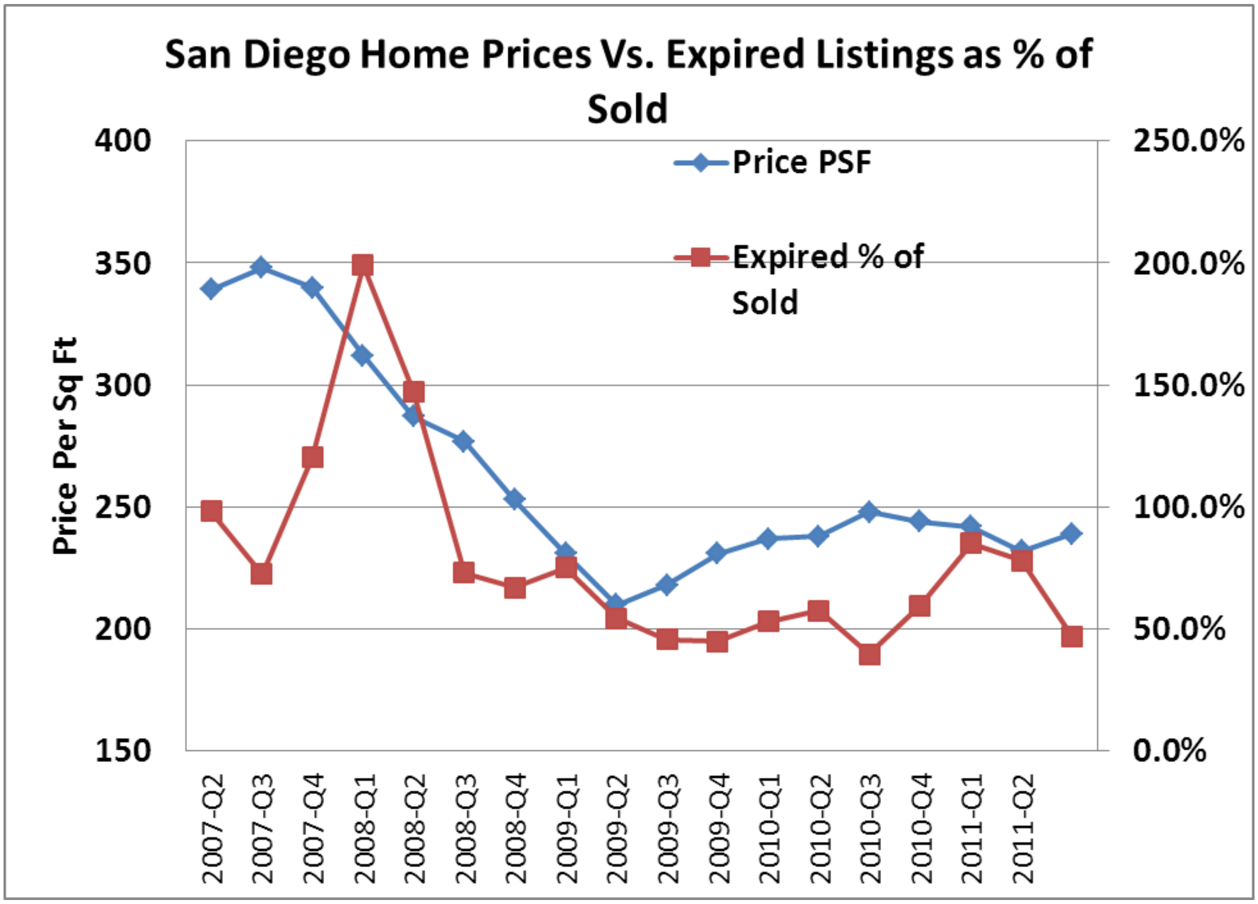


Exhibit 13a Distressed Sales as a Percent of Total Sales Versus Price Per Square Foot for all Sales

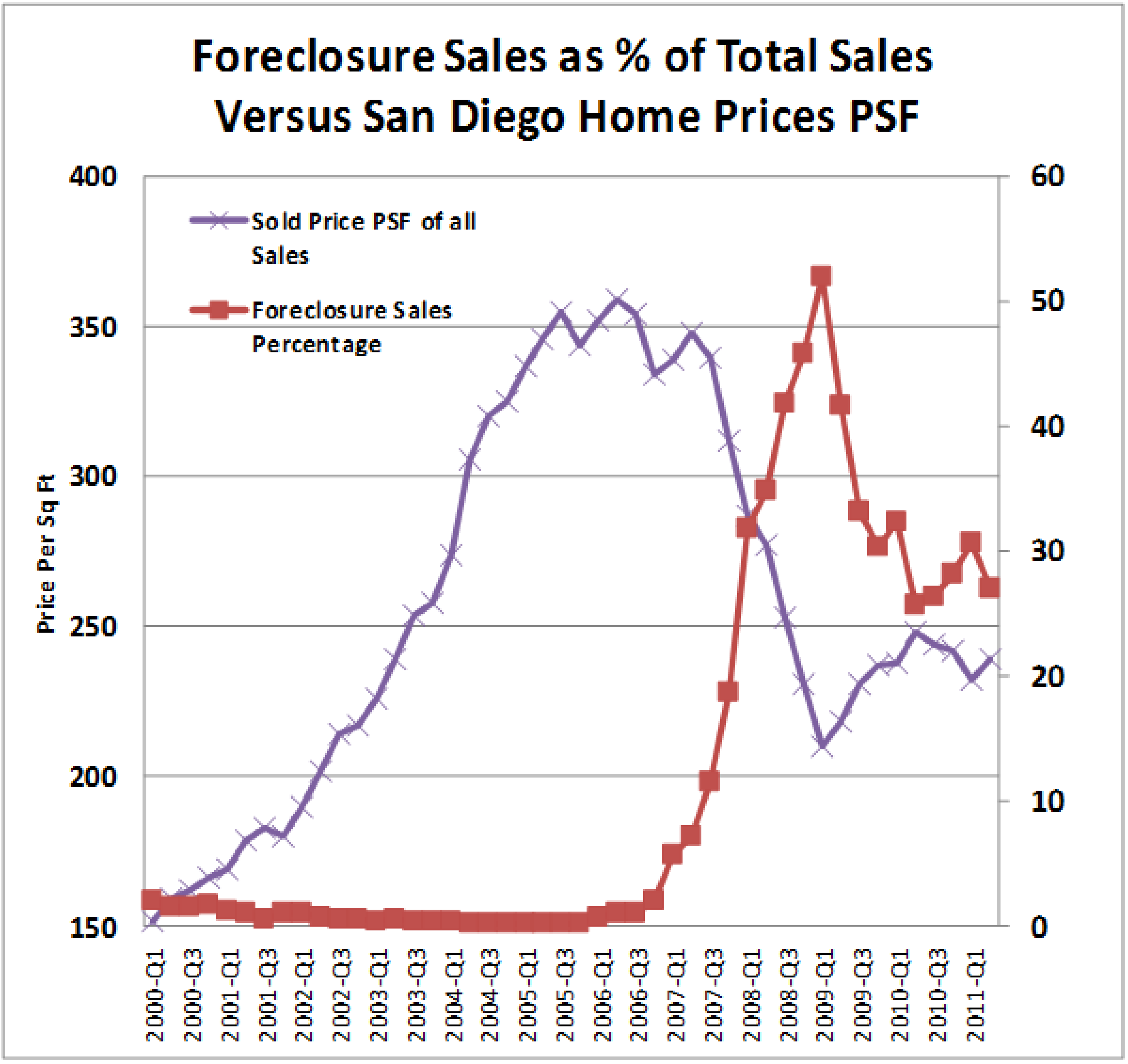


Exhibit 13b: Distressed Sales as a Percent of Total Sales Versus the Discount Estimate From Non-Distressed Sales Shown With Trend Line

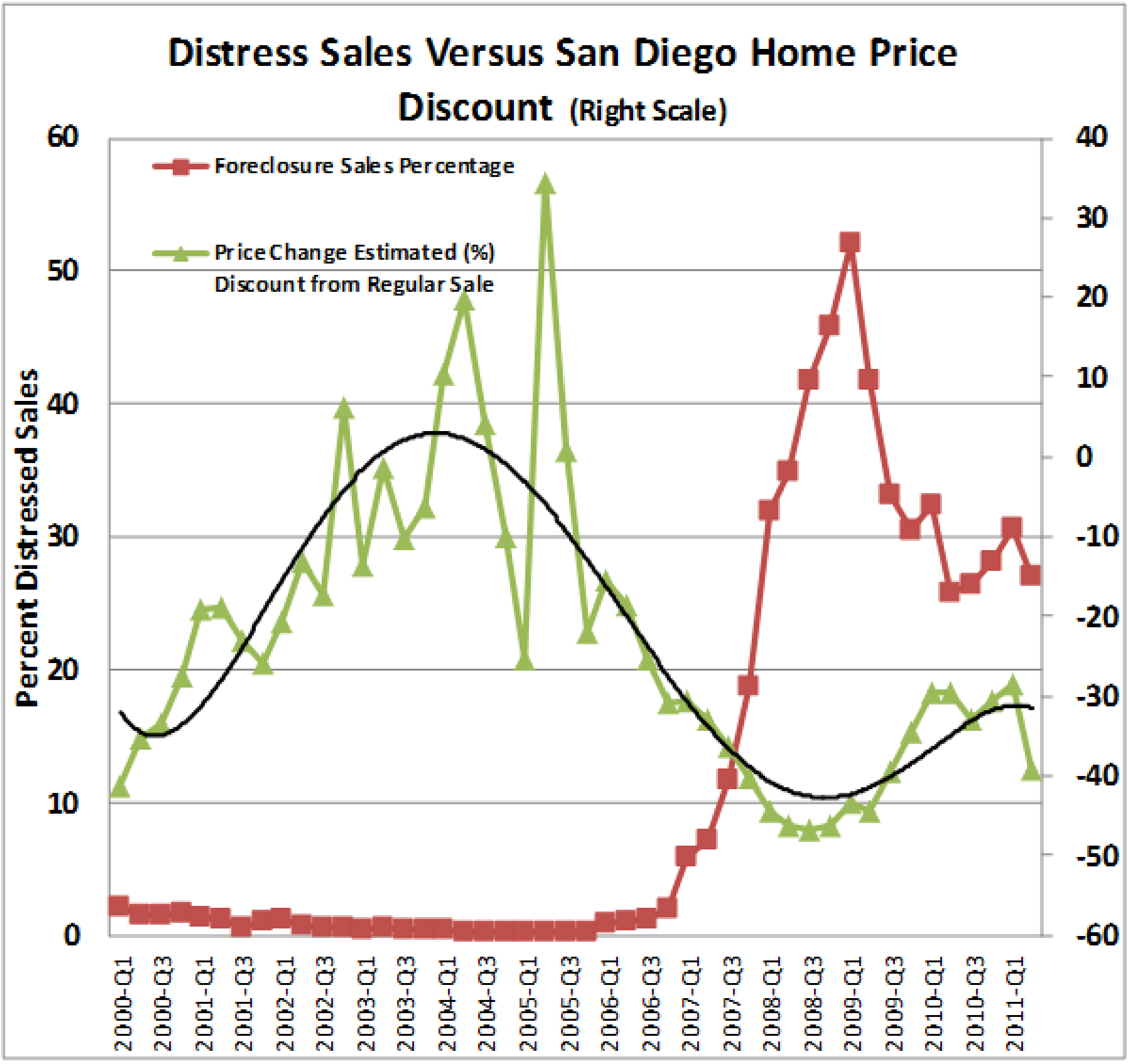


Exhibit 13c: Distressed Sales Volume (Right Scale) Versus San Diego Home Prices Per Square Foot

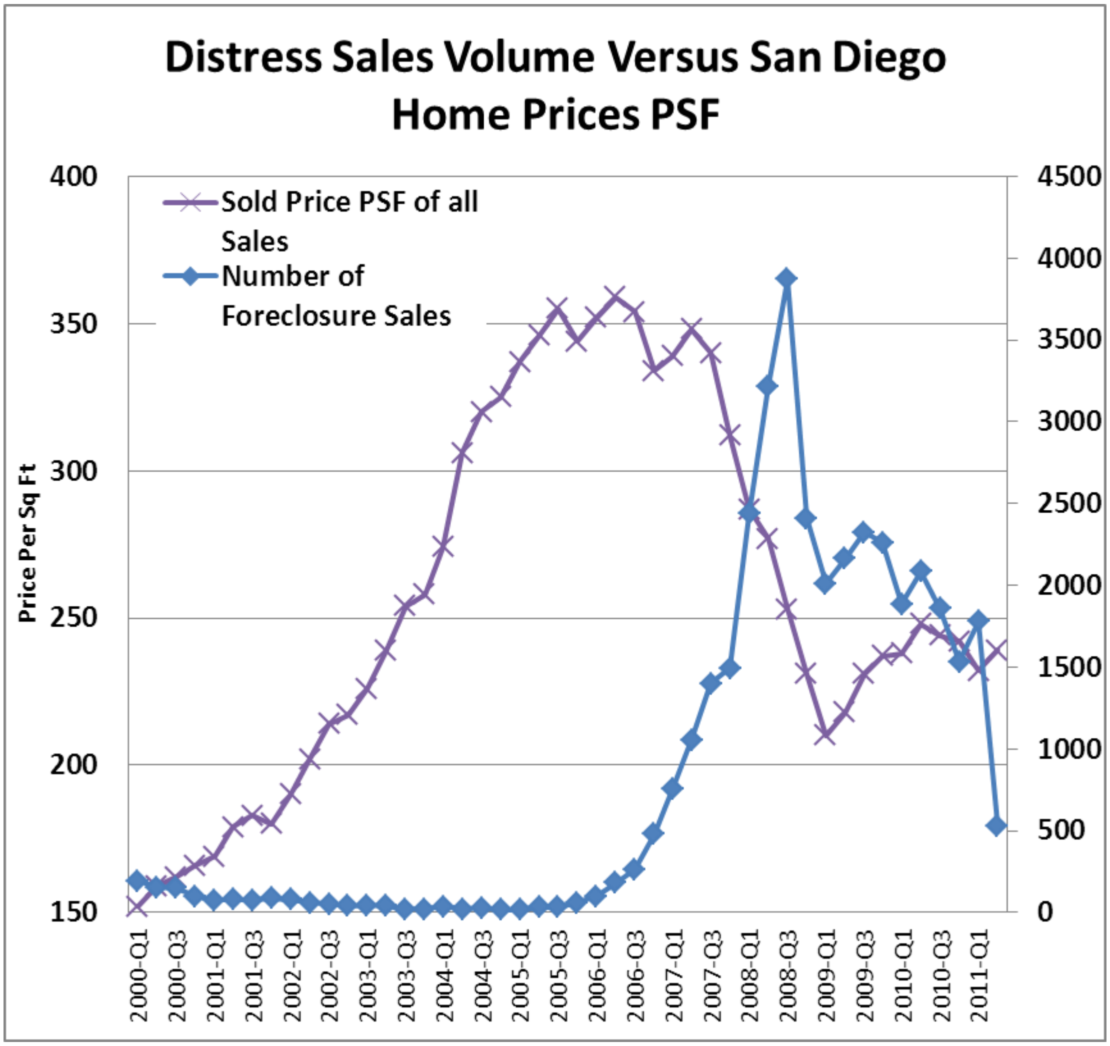
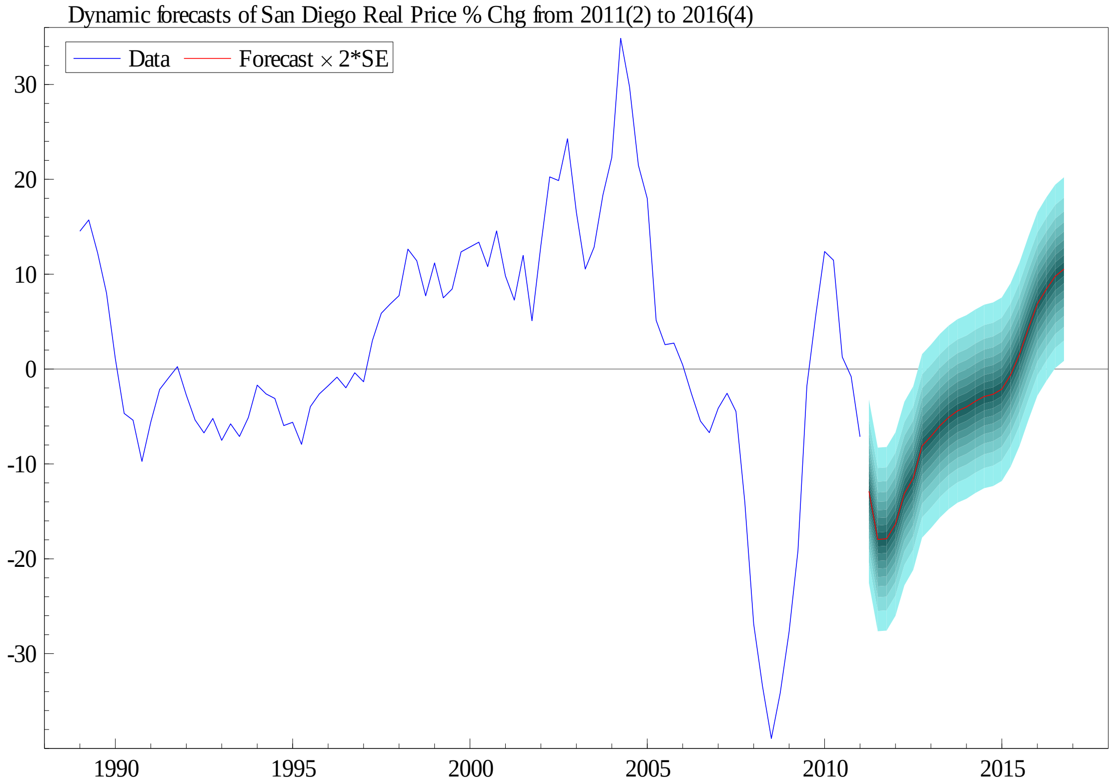


Exhibit 14: San Diego  Median Home Price Forecast With the Percent Change on the Y1 Axis



**GUM( 1) Modelling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988 (3) - 1995 (1)**

| | Coeff | StdError | t-value | t-prob |
|---|---|---|---|---|
| Constant | 6.40813 | 6.89756 | 0.929 | 0.3728 |
| San Diego Regular Sale TO Rate | 0.07725 | 0.50621 | 0.153 | 0.8815 |
| San Diego Regular Sale TO Rate_1 | 0.40399 | 0.50107 | 0.806 | 0.4372 |
| San Diego Regular Sale TO Rate_2 | 0.62689 | 0.62297 | 1.006 | 0.3359 |
| San Diego Emp % Chg | -.39981 | 1.32800 | -.301 | 0.7690 |
| San Diego Emp % Chg_1 | -4.55963 | 1.51734 | -3.005 | 0.0120 |
| San Diego Emp % Chg_2 | 5.27433 | 0.95389 | 5.529 | 0.0002 |
| San Diego Real Aff Price % Chg | .43387 | 0.10746 | 4.038 | 0.0020 |
| San Diego Real Aff Price % Chg_1 | .01967 | 0.10772 | 0.183 | 0.8584 |
| San Diego Real Aff Price % Chg_2 | -.11278 | 0.11198 | -1.007 | 0.3355 |
| San Diego MRI | -.26886 | 0.15187 | -1.770 | 0.1044 |
| San Diego MRI_1 | -.40890 | 0.21618 | -1.891 | 0.0852 |
| San Diego MRI_2 | -.48108 | 0.14697 | -3.273 | 0.0074 |
| San Diego FC % of Regular & REO Sales | -.56912 | 0.31060 | -1.832 | 0.0941 |
| San Diego FC % of Regular & REO Sales_1 | .35628 | 0.47263 | 0.754 | 0.4668 |
| San Diego FC % of Regular & REO Sales_2 | .10185 | 0.40517 | 0.251 | 0.8061 |

RSS 30.54020 sigma 1.66625 R^2 0.98017 Radj^2 0.95312

LogLik -1.66330 AIC 1.30839 HQ 1.53673 SC 2.07630

| | 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 |

**GUM( 2) Modelling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988 (3) - 2000 (1)**

| | Coeff | StdError | t-value | t-prob |
|---|---|---|---|---|
| Constant | 7.57860 | 3.91144 | 1.938 | 0.0618 |
| San Diego Regular Sale TO Rate | 0.16662 | 0.41215 | 0.404 | 0.6888 |
| San Diego Regular Sale TO Rate_1 | 0.22815 | 0.55205 | 0.413 | 0.6823 |
| San Diego Regular Sale TO Rate_2 | 0.93100 | 0.41748 | 2.230 | 0.0331 |
| San Diego Emp % Chg | -.94494 | 0.94633 | -0.999 | 0.3258 |
| San Diego Emp % Chg_1 | -1.9645 | 1.42955 | -1.374 | 0.1792 |
| San Diego Emp % Chg_2 | 2.97565 | 0.85654 | 3.474 | 0.0015 |
| San Diego Real Aff Price % Chg | 0.19595 | 0.07289 | 2.688 | 0.0115 |
| San Diego Real Aff Price % Chg_1 | 0.08921 | 0.10074 | 0.886 | 0.3827 |
| San Diego Real Aff Price % Chg_2 | -.18836 | 0.07377 | -2.553 | 0.0158 |
| San Diego MRI | -.34464 | 0.16964 | -2.032 | 0.0508 |
| San Diego MRI_1 | -.48135 | 0.18714 | -2.572 | 0.0151 |
| San Diego MRI_2 | -.34638 | 0.15885 | -2.181 | 0.0369 |
| San Diego FC % of Regular & REO Sales | -.62796 | 0.36718 | -1.710 | 0.0972 |
| San Diego FC % of Regular & REO Sales_1 | .14915 | 0.53877 | 0.277 | 0.7837 |
| San Diego FC % of Regular & REO Sales_2 | -.1522 | 0.35601 | -0.428 | 0.6718 |

RSS 162.58960 sigma 2.29016 R^2 0.93762 Radj^2 0.90744

LogLik -29.16542 AIC 1.92193 HQ 2.15894 SC 2.55177

| | 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 |

**GUM( 3) Modelling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988 (3) - 2005 (1)**

| | Coeff | StdError | t-value | t-prob |
|---|---|---|---|---|
| Constant | 12.42325 | 7.63543 | 1.627 | 0.1099 |
| San Diego Regular Sale TO Rate | 0.37758 | 0.79944 | 0.472 | 0.6387 |
| San Diego Regular Sale TO Rate_1 | 0.59436 | 1.01418 | 0.586 | 0.5604 |
| San Diego Regular Sale TO Rate_2 | 0.39462 | 0.79058 | 0.499 | 0.6198 |
| San Diego Emp % Chg | 0.78795 | 1.59371 | 0.494 | 0.6231 |
| San Diego Emp % Chg_1 | -.52410 | 2.36389 | -0.222 | 0.8254 |
| San Diego Emp % Chg_2 | -.53015 | 1.49417 | -0.355 | 0.7242 |
| San Diego Real Aff Price % Chg | 0.00116 | 0.12043 | 0.010 | 0.9924 |
| San Diego Real Aff Price % Chg_1 | 0.02988 | 0.16466 | 0.181 | 0.8567 |
| San Diego Real Aff Price % Chg_2 | -.11819 | 0.12352 | -0.957 | 0.3431 |
| San Diego MRI | -.18457 | 0.33381 | -0.553 | 0.5827 |
| San Diego MRI_1 | -.58805 | 0.38107 | -1.543 | 0.1290 |
| San Diego MRI_2 | -.50050 | 0.30120 | -1.662 | 0.1027 |
| San Diego FC % of Regular & REO Sales | -1.03210 | 0.76124 | -1.356 | 0.1811 |
| San Diego FC % of Regular & REO Sales_1 | -0.01903 | 1.09503 | -0.017 | 0.9862 |
| San Diego FC % of Regular & REO Sales_2 | -0.14586 | 0.73527 | -0.198 | 0.8435 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| RSS | 1267.55772 | sigma | 4.98539 | R^2 | 0.81654 | Radj^2 | 0.76258 |
| LogLik | -98.49518 | AIC | 3.41777 | HQ | 3.62610 | SC | 3.94426 |

| | 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) Modelling San Diego Real Price % Chg by OLS (using San Diego Data for Home Price Model.xls), 1988 (3) - 2011 (1)**

| | Coeff | StdError | t-value | t-prob |
|---|---|---|---|---|
| Constant | -10.32707 | 6.28351 | -1.644 | 0.1045 |
| San Diego Regular Sale TO Rate | 1.07328 | 0.79476 | 1.350 | 0.1809 |
| San Diego Regular Sale TO Rate_1 | 1.37813 | 1.05948 | 1.301 | 0.1973 |
| San Diego Regular Sale TO Rate_2 | 1.45592 | 0.81707 | 1.782 | 0.0788 |
| San Diego Emp % Chg | 2.09417 | 1.31255 | 1.595 | 0.1148 |
| San Diego Emp % Chg_1 | -2.98000 | 2.13874 | -1.393 | 0.1676 |
| San Diego Emp % Chg_2 | -1.18125 | 1.21533 | -0.972 | 0.3342 |
| San Diego Real Aff Price % Chg | -.00742 | 0.12945 | -0.057 | 0.9544 |
| San Diego Real Aff Price % Chg_1 | 0.16076 | 0.17335 | 0.927 | 0.3567 |
| San Diego Real Aff Price % Chg_2 | -.17697 | 0.13436 | -1.317 | 0.1918 |
| San Diego MRI | 0.51496 | 0.33719 | 1.527 | 0.1309 |
| San Diego MRI_1 | -.46174 | 0.39723 | -1.162 | 0.2488 |
| San Diego MRI_2 | -.76614 | 0.30224 | -2.535 | 0.0133 |
| San Diego FC % of Regular & REO Sales | 0.00124 | 0.13898 | 0.009 | 0.9929 |
| San Diego FC % of Regular & REO Sales_1 | -.15488 | 0.18393 | -0.842 | 0.4024 |
| San Diego FC % of Regular & REO Sales_2 | -.30165 | 0.14437 | -2.089 | 0.0401 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| RSS | 2652.06138 | sigma | 5.94650 | R^2 | 0.82600 | Radj^2 | 0.79120 |
| LogLik | -153.43660 | AIC | 3.72388 | HQ | 3.90199 | SC | 4.16535 |

| | 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 | 16.690 | 0.0000 |
| ARCH 1-4 test | 5.5985 | 0.0006 |
| hetero test | 29.125 | 0.5110 |