# California Housing Markets: A Tale Twice Told

Nathan Gallatin and Daniel Hill

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Department of Economics

Pomona College

Claremont, California

## Abstract

This paper aims to examine the current health of the California residential real estate market through an analysis that is threefold. In the first portion of our analysis, we observe the relationship between home price and real estate specific measures that are widely considered predictive of home price appreciation. We conduct this analysis on both the county and state level. Using a cross-covariance analysis with varying lag lengths, we find that the majority of our "leading indicators" most closely vary with price contemporaneously. In the subsequent two sections, we focus our analysis on the state level and do not consider local county level real estate markets. The second section identifies confounding economic factors that may also influence price movements in real estate markets. Collectively, the selected confounding factors appear highly predictive of future price movements and yield an inauspicious outlook for California home prices. Finally, we employ a vector autoregressive model to quantify future home price movements in California. We project home prices, as measured by House Price Index for California (HPI), to fall roughly 30 percent in the median case over the next four years.

**Introduction:**

The mention of housing markets often elicits memories of the 2008 housing collapse that crippled domestic and international economies. Over a decade later, while economists and financial analysts alike have tried to predict the next housing bubble, speculation still runs rampant—at least that is our contention. *How is it that something so engrained in the fabric of every economy is so misunderstood?* Maybe we have learned our lesson over the past 11 years, but this paper will elucidate real housing trends and debunk the housing fallacies that often lead to a dislocation between price and value. Our method of review and analysis of data include the rigorous employment of a cross-covariance model, which establishes relationships between key market indicators and housing prices, as well as with commentary on historical price movements with the aforementioned indicators.

**Literature Review:**

A primary source of inspiration for the modelling that we use in this paper is the work conducted by Follain and Giertz following the housing market crash of 2008. James Follain and Seth Giertz first published their inquiries about establishing a new house price stress test in 2011. By evaluating the effectiveness of the house price stress test (termed ALMO), they sought to determine whether or not the ALMO stress test sufficiently represented the riskiness of the housing market prior to the Great Recession of 2008. Essentially, they use Monte Carlo simulations to quantify the effects of low probability events, such as the remarkable price declines seen during the housing market crash of 2008. Significantly, the authors determined that the relationships between housing price appreciation and established explanatory variables have changed over time and that momentum increasingly plays a role in house price outcomes. Follain and Giertz build upon their research in a particularly interesting working paper from 2012. They analyze data over a 20-year period from 1990-2010 to establish relationships between housing prices and relevant explanatory variables. By employing a vector error correction model (VECM) and running Monte Carlo simulations, the authors are able to analyze projections on many house price paths. These tests are run with the intent of accurately modelling the house price changes that occurred from 2008-2010. Additionally, Follain and Giertz find, again, that increased momentum plays a significant role and seems to sensitize the housing market to the exogenous negative shocks which ultimately led to the monumental crash of 2008. In our paper, we similarly adopt an autoregressive model whereby we use the generated empirical relationships to forecast an out-of-sample period for house prices.

Robert Shiller and Karl Case grabbed national attention for their seminal research on bubbles in relation to the housing market when housing markets finally collapsed in 2008. As early as 2003, in their paper *Is There a Bubble in the Housing Market?*, they posited that there was significant bubble sentiment in three of the four large metropolitan areas in which they focused. These suspected bubble regions were Los Angeles, San Francisco, and Boston, which were all characterized by consumer notions of excess demand and upward rigidity in asking prices. Further, Shiller and Case noted that three relevant components of a speculative bubble already existed in some cities: strong investment motive, high expectations of future prices increases, and strong influence of word-of-mouth discussion. While the authors did not anticipate a massive bursting of the bubble in 2003, they correctly identified the growing speculative nature of United States housing market and provided a framework for understanding the fundamentals of a housing bubble. We rely on these findings in our preliminary analysis of current housing market conditions.

Finally, the initial portion of our analysis closely mirrors the statistical methods that Norman Miller and Michael Sklarz use in their 1986 paper *A Note On Leading Indicators of Housing Market Price Trends*. Similar to Miller and Sklarz, our study investigates the relationship between various real estate specific supply and demand factors and housing prices. Our analysis includes a few of the same determinants of house prices that are regarded as leading indicators, such as “Time (days) on Market” and “Unsold Inventory.” Additionally, we implement Miller and Sklarz cross covariance analysis between our selected variables and real housing price appreciation using various time staggers. Employment of this model sheds light on how changes in market indicators today may inform us about housing prices at different time points in the future. However, unlike Miller and Sklarz, our study also includes metrics outside of measures of housing supply in the real estate market that we contend are deterministic of future housing prices. Such indicators not investigated by Miller and Sklarz include the “Housing Affordability Index”, the 10-Year Treasury Rate, and volume of building permits approved.

# *Part 1: A Cross-Covariance Analysis*

**Data:**

We delineate below our five explanatory variables, which we believe to be paramount to discerning housing price behavior in real estate markets. The historical data for these five explanatory variables are largely pulled from the California Association of Realtors (CAR). The CAR also provides the monthly median sales price for single-family detached homes in California dating back to January 1990. Monthly median sales prices are given for each of the 58 counties in California as well as for the state as a whole. Such data allow our study to analyze differences in housing markets between individual counties in California. The scope of this study includes the state of California as a whole, as well as the following five representative counties individually, selected to be geographically and demographically diverse: Ventura, Los Angeles, Sacramento, San Francisco, and Santa Clara. We believe that a comprehensive analysis of California coupled with these five diverse counties will accurately depict current housing market conditions and provide an outlook for future price movements.

A well-known issue with using median home price data is that it does not control for the size of the houses being sold. Higher median home prices may simply be the product of larger homes on average. To control for this key issue, we use data from two indices as our selected measure of real home price appreciation. For our county analyses, we employ the *Zillow Home Value Index* (ZHVI), which seeks to avoid mischaracterizing the composition of properties sold in one period versus another—a bias to which many aggregate indices are vulnerable. Zillow utilizes their extensive valuation data to form estimates of potential sale prices on every home. They also note that while there is estimation error involved with estimated sales price, the likelihood that this error is above or below the actual sale price is equal. Thus, the distributions of estimated and actual sale prices are very similar. To construct the ZHVI, Zillow first takes aggregate value estimates and calculates the raw median estimates, called "Zestimates." Then, after adjusting for any residual systematic error, they apply the Henderson Moving Average Filter. Lastly, Zillow applies a seasonal adjustment to produce the completed index. For the purpose of this study, we use monthly median index data at the county level from the Single-Family market segment.

For our analysis focused on the state of California, we utilize quarterly House Price Index (HPI) data from the U.S. Federal Housing Finance Agency as a component of our responding variable, which is real price appreciation. All California state analysis is conducted on a quarterly basis, while county analysis is completed on a monthly basis. We adjust both ZHVI and HPI by CPI less shelter from the Bureau of Economic Analysis to account for inflation and determine real price appreciation. We make the distinction of using CPI less shelter because we want to eliminate the effect of non-housing related inflation to capture real price appreciation. *In brief, we use ZHVI and HPI data instead of median home price as an estimate for real price appreciation to control for fundamental changes in properties sold.*

For both our county and state level analyses we run regressions with the same five explanatory variables. These five variables are: The Traditional Housing Affordability Index (HAI), Unsold Inventory Index (UII), Median Time on Market (TOM), Building Permits, and Ten-Year Treasury Note yield. We employ the traditional HAI from the California Association of Realtors (CAR), which is calculated as the proportion of people that can afford a median priced home. The traditional HAI assumes a 20% down-payment and uses, "[the] national average effective mortgage interest rate on all fixed and adjustable rate mortgages closed for the purchase of previously occupied homes as reported monthly by the Federal Housing Finance

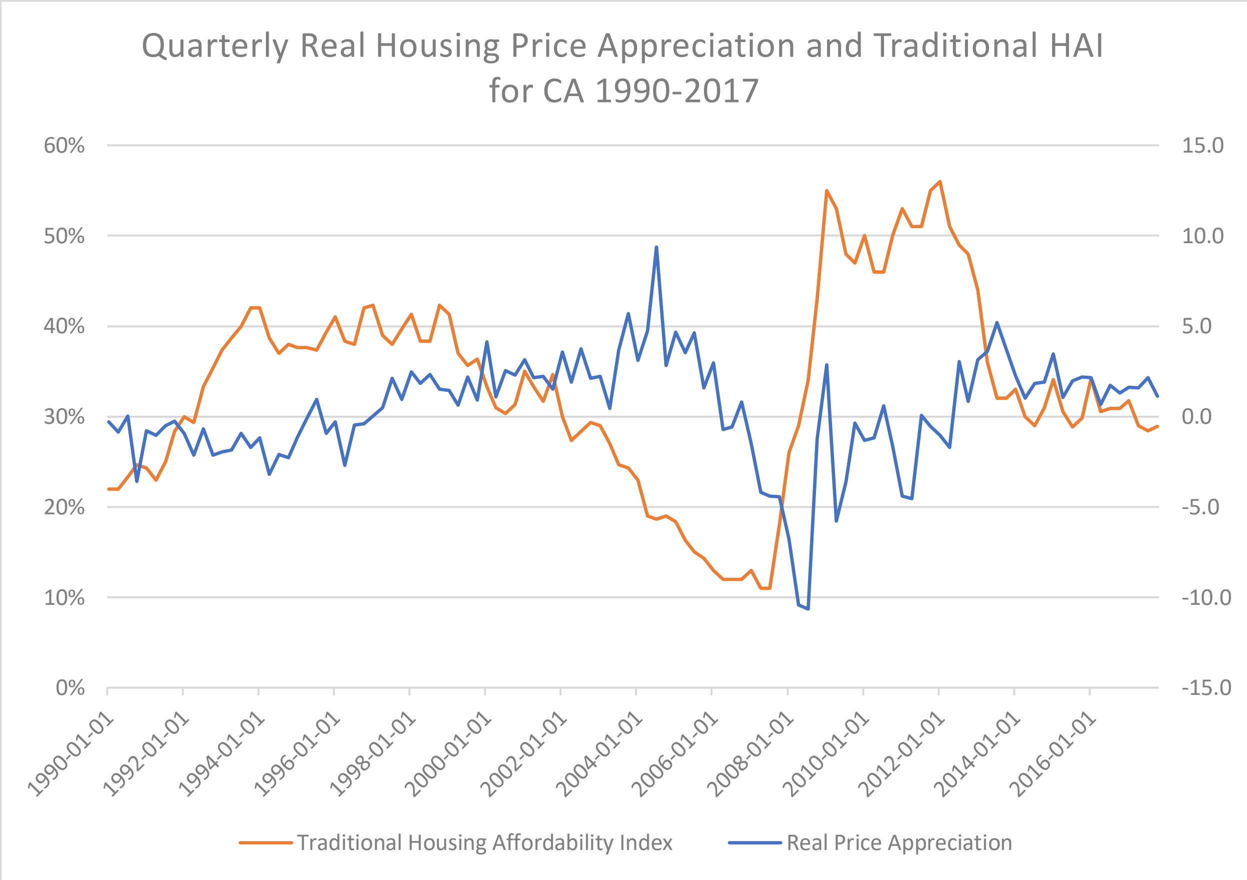
Board" (CAR 2019). Because CAR only supplies quarterly data for the traditional HAI, we must interpolate monthly values to conduct our county-based analysis. We do so via cubic spline interpolation, which essentially fits a cubic function to the quarterly data and provides insight as to the monthly values in between. While a cubic spline model introduces autocorrelation to our data, we can control for this in our analysis which we expound upon later in our methodology section. The Unsold Inventory Index data are also gathered from CAR and are simply the number of homes for sale divided by the number of homes sold in the most recent month. Our Median Time on Market variable represents the median time spent on the market between list and sale in a given month for a given county, or a given quarter for the state of California. Building Permits are defined as the number of approved building permits for new housing units. Data for new building permits are gathered monthly from the Federal Reserve Economic Data (FRED) and are adjusted to quarterly data for our California analysis. Lastly, we utilize FRED data for ten-year Treasury note yields.

**Hypotheses:**

In any statistical model it is possible to find a relationship between entirely unrelated variables. Thus, in the interest of good practice, we must explain the relevance of the variables in our analysis and their expected influence on housing prices before executing statistical tests. Specifically, our statistical approach considers the relationship between real appreciation in housing price and five variables: The Traditional Housing Affordability Index, Unsold Inventory Index, Median Time on Market, number of approved Building Permits, and the 10-year United States Treasury rate. The degree to which these variables exhibit a sensible and statistically significant relationship with real appreciation in housing price will serve as the basis for our outlook on the near-term health of the housing market. In the following paragraphs, we delineate our hypotheses regarding the relationship between these five variable and future housing prices before delving into our statistical methods.

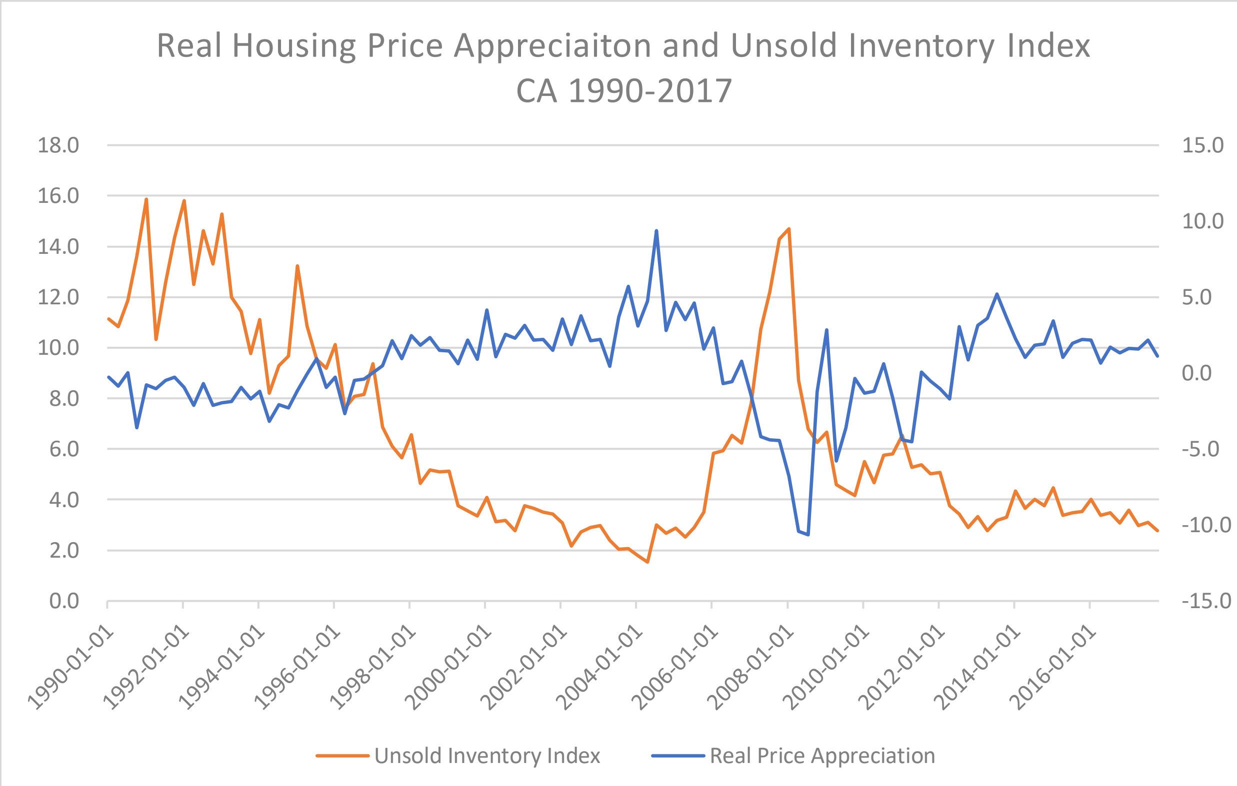
Similar to all markets, prices in the real estate market are partially determined by the magnitudes of supply and demand. The HAI is included in our model because it serves as a proxy for housing demand. When HAI values are relatively high, a greater number of individuals can afford a mortgage on a home signifying greater demand in the market. As home prices rise, mortgages become more expensive. Fewer people can afford these mortgages so the Traditional Housing Affordability Index falls, reflecting shrinking demand in the housing market. While HAI is logically correlated with price *levels*, it is contemporaneously related to percent change in price. By definition, any instantaneous positive change in price would be matched by a decrease in HAI. *Ergo*, we expect HAI and price appreciation to express an inverse relationship. As HAI falls, housing prices should rise until demand reaches such low levels that prices must collapse to correct for the lack of demand. *Exhibit 1.1* below shows the historical relationship between HAI and real house appreciation in California and depicts consistently low levels of HAI prior to the 2007 housing collapse.

Exhibit 1.1:



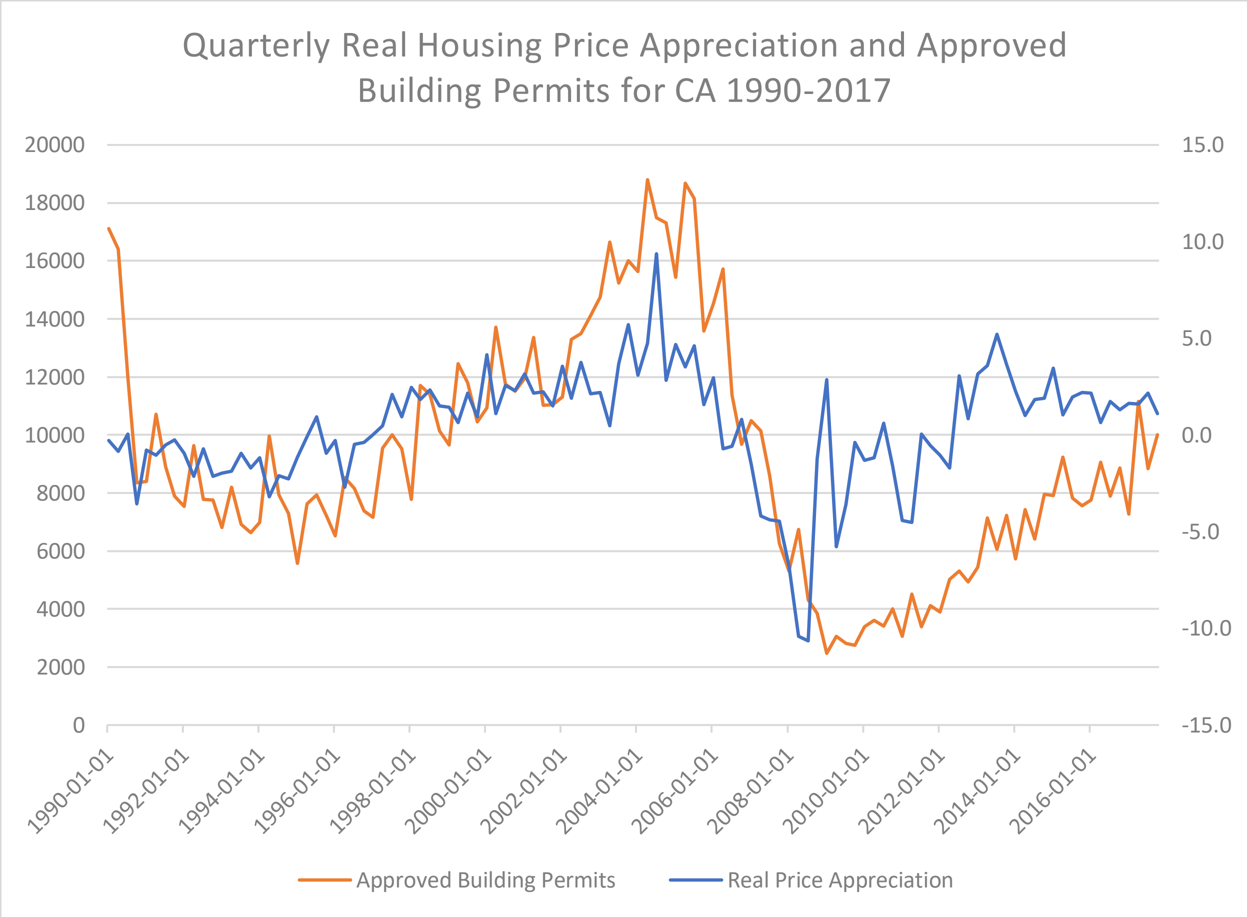

Conversely, tracking the Unsold Inventory Index serves as a gauge for market supply. As the Unsold Inventory Index rises, either the number of non-purchased units is rising, or the rate at which units are selling is falling. High Unsold Inventory Index scores can be interpreted as an oversupply of available housing in the market. Thus, like HAI we expect UII scores to be negatively related to housing prices and for real prices to fall in periods following high UII scores. The historical relationship between UII and real housing price appreciation is shown below in *Exhibit 1.2.*

Exhibit 1.2:



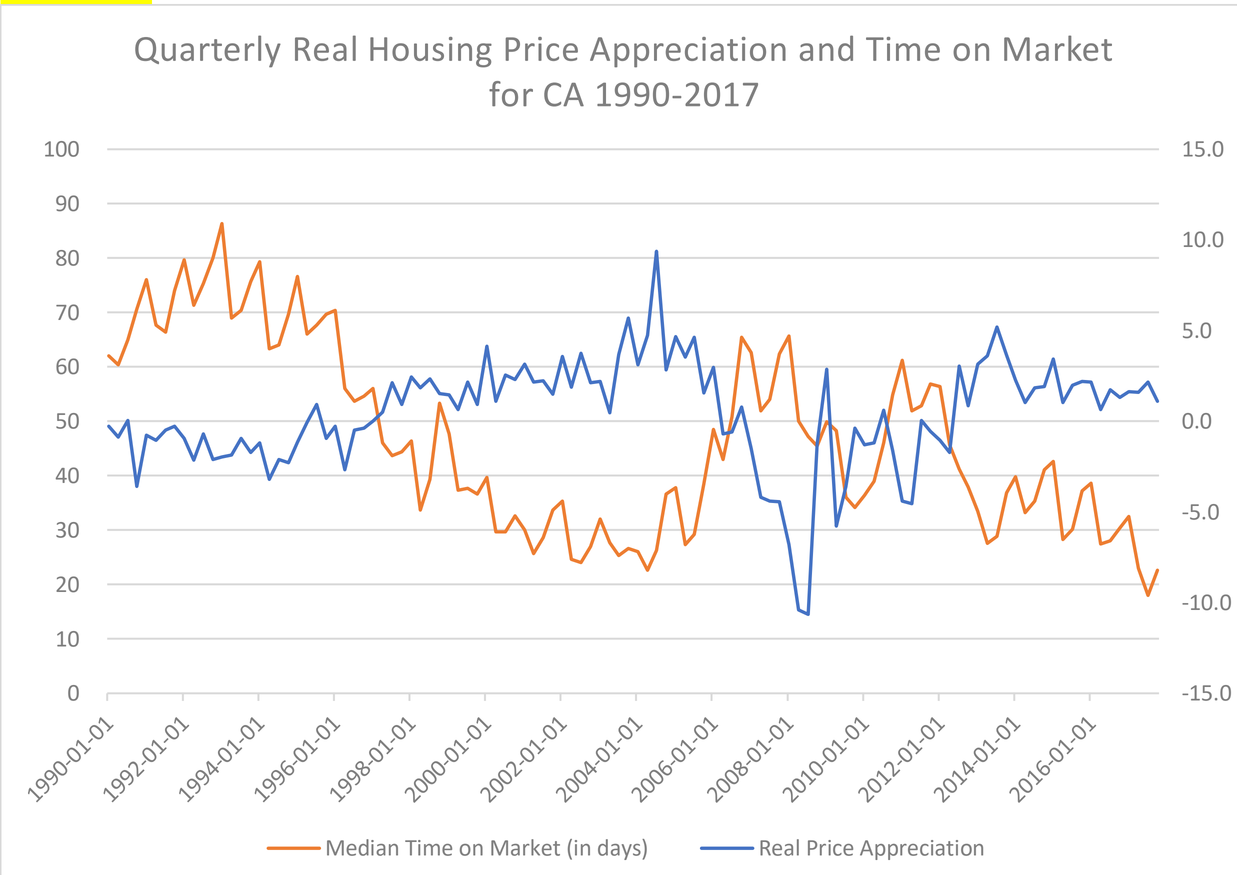

The number of approved building permits also serves as a measure of supply in the housing market and should therefore influence price. In no dissimilar fashion to the Unsold Inventory Index, an increasing volume of approved housing permits represents an increase in market supply. However, after obtaining a building permit a house must still be built before it is listed on the market. Because of the construction period, or lag, between the approval of a permit and the house's actual listing on the market, we do not expect a contemporaneous negative relationship between real housing price appreciation and the number of approved building permits. Rather, we expect a considerable time lag between the number of building permits and its impact on housing prices. In short, we contend that building permits will be negatively correlated with real housing prices, however, this effect should only be observed after a greater period of time when compared to supply indicators that exclusively recognize houses currently listed on the market. *Exhibit 1.3* details the historical relationship between approved building permits and real house appreciation in California.

Exhibit 1.3:



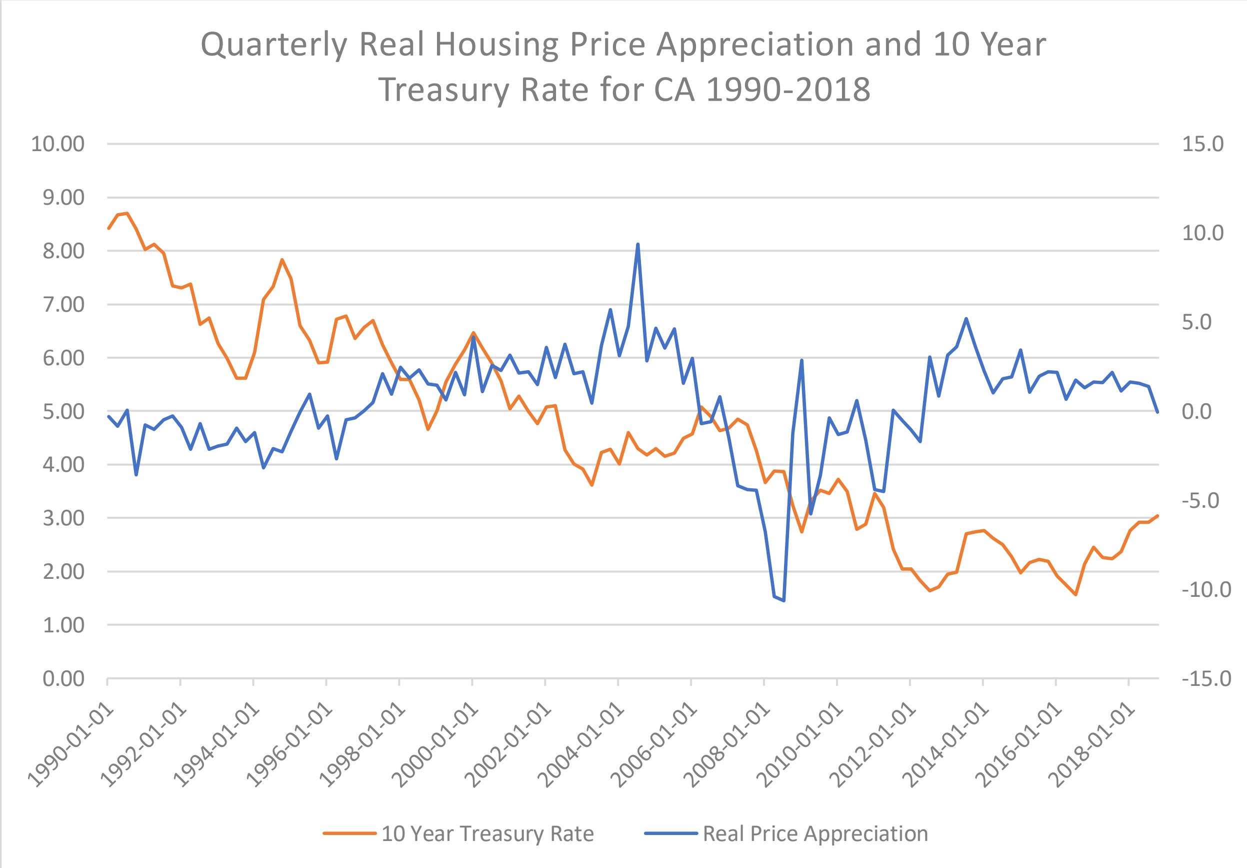

We regard our fourth variable "Median time on market" as relevant to future housing prices for two key reasons. First, median time on market is a barometer for demand in the housing market. The intuition here is that periods where the median time on market for listings is low represent high levels of demand, while periods with high median time on market represent a period with significantly more sellers than buyers. Secondly, median time on market also characterizes levels of liquidity in the housing market. Real estate is widely viewed as an illiquid asset class and investors may be averse to home purchases due to significant liquidity risk. A shorter median time on market indicates greater ability to turnover a house and thus dampens the liquidity risk perceived by any homebuyer. Because we stipulate that lower median time on market values indicate stronger market demand, and lower levels of liquidity risk for investors, we anticipate an inverse relationship between median time on market and real housing price appreciation. An overview of the past relationship between median time on market and housing price appreciation is shown below in *Exhibit 1.4.*

Exhibit 1.4:




The fifth and final variable we consider in our study is the 10-year Treasury rate. The 10-year Treasury rate can be viewed as yet another measure of supply in the housing market. Our assumption that Treasury rates are tied to real estate market supply is based on the notion that the vast majority of homes are purchased with some form of mortgage rather than with upfront cash. The U.S. 10-year Treasury rate is paramount in determining borrowing rates disseminated by major liquidity providers, in the housing markets, such as the Federal National Mortgage Association (Fannie Mae). Therefore, a higher 10-year Treasury rate coincides with higher interest rates on mortgages granted by lenders such as Fannie Mae and homes become more expensive for the typical investor attempting to buy into the housing market. In light of this relationship, we expect the 10-year Treasury rate to be negatively correlated with real home price appreciation. *Exhibit 1.5* depicts the historical context of the aforementioned relationship.

Exhibit 1.5:

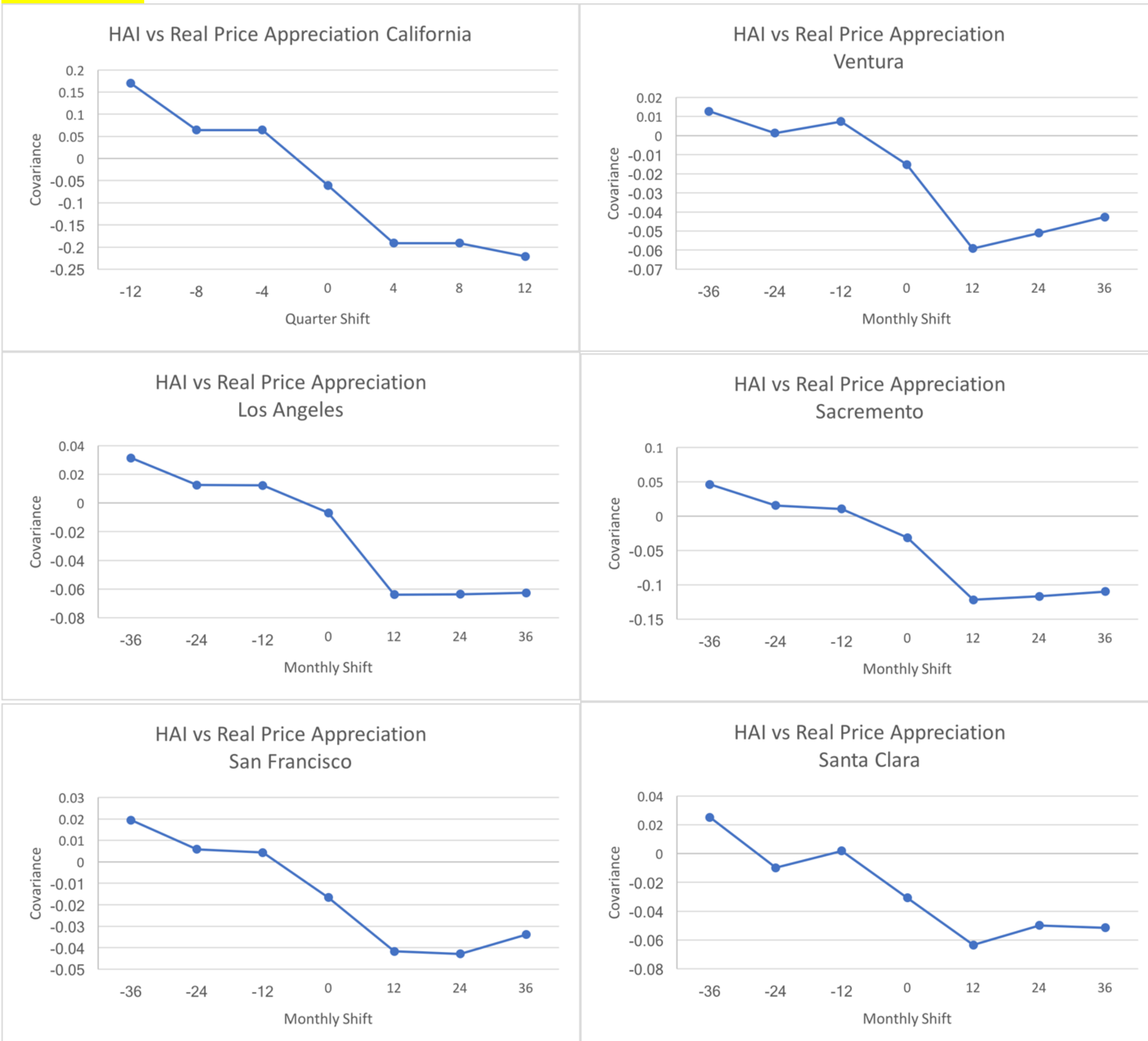


**Cross-Covariance Results:**

The following cross-covariance analysis indicates the extent that each variable has covaried with changes in real home price between 2008-2017. Results are listed by variable, detailing relationships in each of the six regions analyzed (i.e. California state analysis and the five county analyses). The graphs track cross-covariance on the Y-axis and time-lag on the X-axis. Negative values along the X-axis represent the selected variable shifted in time relative to real price appreciation. In other words, a value of "-12" calculates covariance between the given variable with changes in real price 12 months later. Contrarily, a value of "12" calculates covariance between price appreciation (percent change in price) and the selected variable 12 months later. Thus, calculated covariance values for negative values along the X-axis highlight the degree that the selected variable is a "leading indicator" or varies with future price appreciation. On the other hand, positive values along the X-axis reveal the extent to which price appreciation relates with future values of the selected variable. It should be noted that X-axis values for the California graphs are in quarters while X-axis values for the counties are in months. A "-12" shift for the California analysis equates to a "-36" time shift in our county analyses. Consistent throughout both state and county analysis is the exploration of one, two, and three-year time lags/leads (negative/positive X-axis values). In this analysis, we are seeking to establish which time lags have the highest absolute values of covariance. The time lag with the highest absolute covariance is indicative of the strongest relationship between the given variable and real price appreciation and informs us on which time shifts should be used in our regressions. The results detailed in *Exhibit 1*.6 below examine region results by variable.

Traditional Housing Affordability Index:

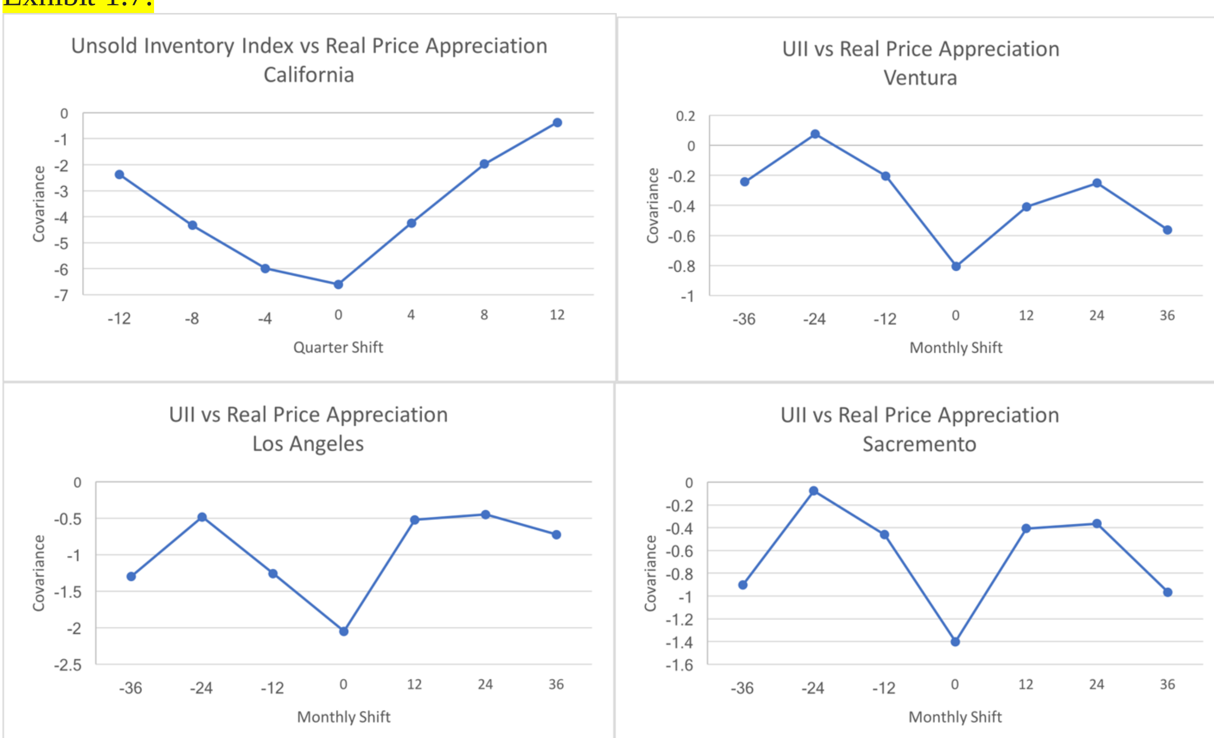
Exhibit 1.6:

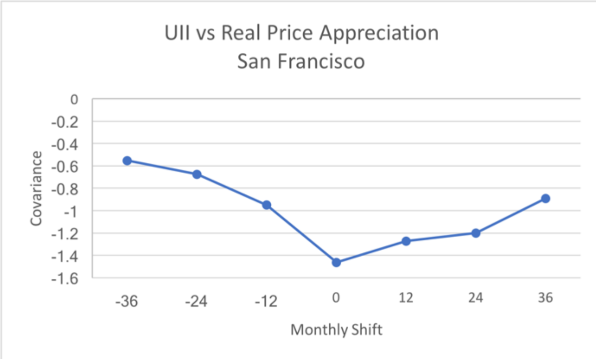


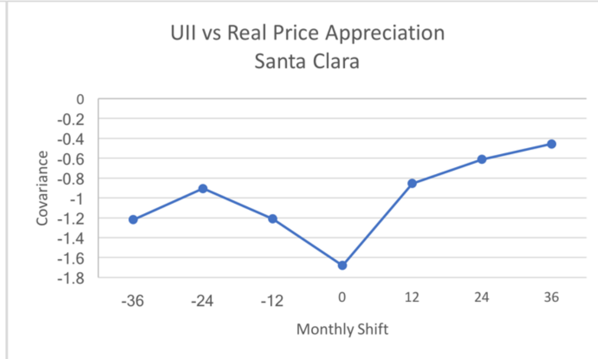

Our cross-covariance analysis for HAI and change in real housing price yielded consistent but surprising results. Intuitively, we hypothesize that the relationship between HAI and housing price should be negative: as prices rise, HAI drops. In all five counties and for the entire state we find a weekly negative contemporaneous relationship (covariance at x=0). However, what is unanticipated, and contradicts our hypothesis for HAI is that in all six of our tests the most extreme negative relationship between HAI and housing price appreciation occurred with a positive time shift of roughly twelve months. This undermines our notion of viewing HAI as a leading indicator for price appreciation. In all six of our results, the relationship between HAI and price appreciation is not negative until price appreciation is compared to a future HAI (X>0). With the exception of San Francisco, the most extreme negative relationship between HAI and real housing price appreciation exists when real price appreciation is compared to HAI one year in the future. Given the consistency in our cross-covariance analysis across counties and the state as a whole, it seems that price appreciation leads HAI, rather than the converse. The lack of a strongly negative relationship between HAI and real housing price appreciation when HAI leads implies that the notion of HAI as a leading indicator for home prices is largely unfounded.

<u>Unsold Inventory Index</u>:

Exhibit 1.7:






Here, we find that the highest covariance absolute value for the Unsold Inventory Index occurs with zero shift in all regions. Across the six regions there is a similar shape of the curve for the varying staggers of UII over time. Further, with the exception of Ventura County, covariance values for all staggers are negative, implying an inverse relationship between real price appreciation and the UII. When observing the entire state of California, UII is similarly negatively correlated with zero time shift as with a shift of -4 quarters. This indicates that the UII may be useful as a one-year leading indicator of housing prices. In other words, high values of UII correspond with decreasing home prices one year out. If we were to extrapolate with this predictive power, *Exhibit 1.2* indicates that for the subsequent year we can anticipate price appreciation in home values. However, it is worth nothing that while we forecast this trend for the next year, the curvature of UII versus time looks remarkably similar to UII just before it bottomed out in 2006 and price depreciation began in the housing market.

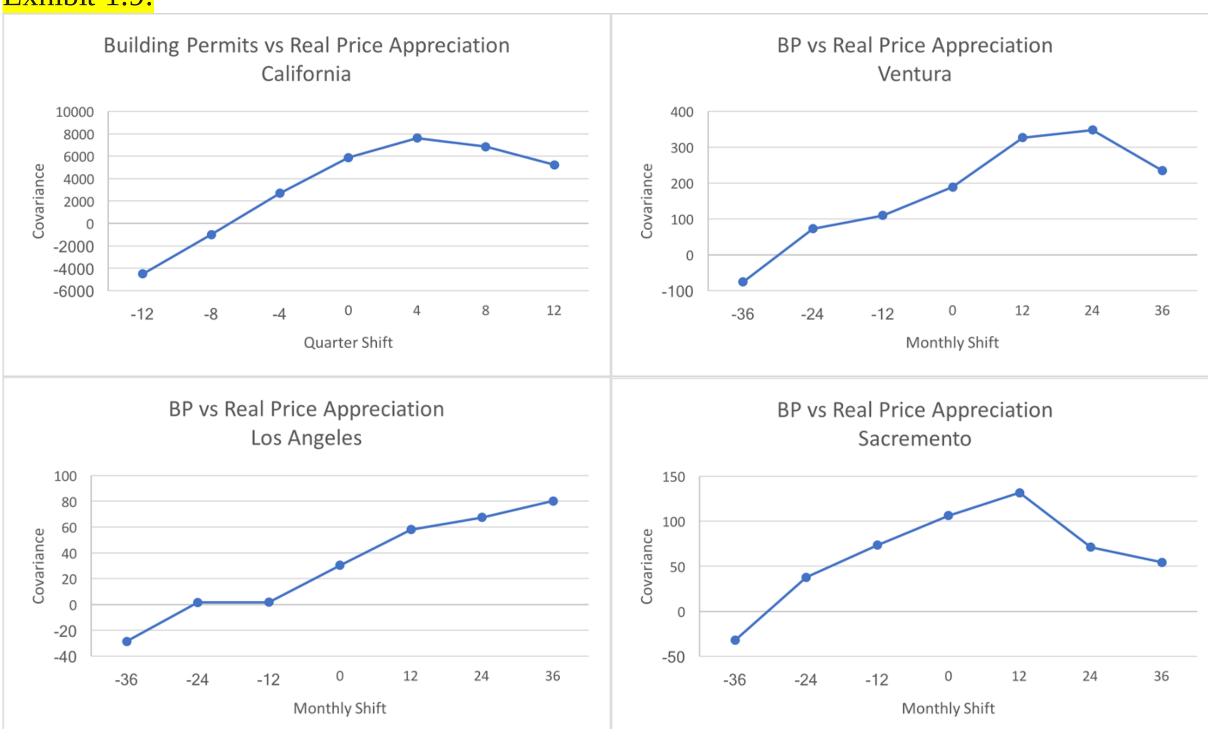
Median Time on Market:

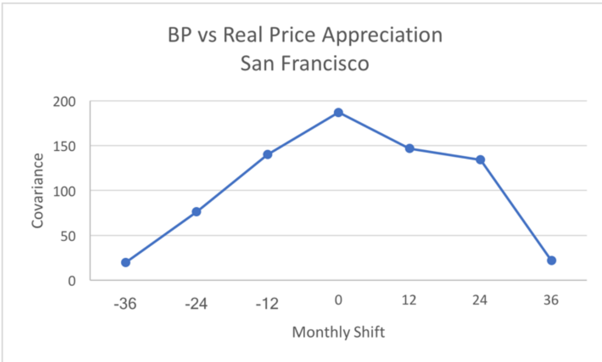
Exhibit 1.8:

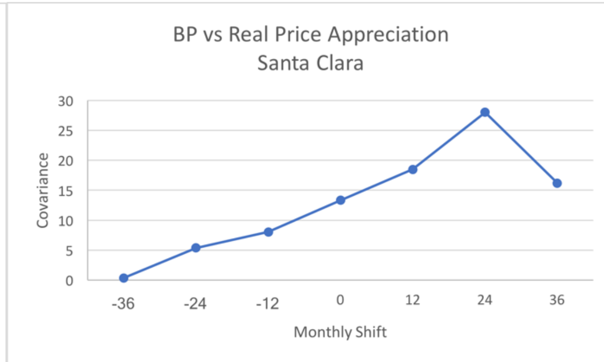

With the exception of Ventura County, there is a clear relationship of negative covariance between median time on market and real price appreciation across all staggers. In the California data, it is evident that the strongest covaried relationship between median time on market and real price appreciation occurs with zero lag or lead. In every county except for Santa Clara, however, the largest covariance value occurs with a lag of 12-36 months for median time on market. In all of these cases, though, the covariance without any time lag is a close second. The tentative theory that we propose, is that real price changes precede movements in median time on market because of changes in consumer confidence that these price changes induce. For instance, a recession may subdue consumer confidence for up to three years before confidence is restored and median time on market decreases. Looking back at *Exhibit 1.4* it is interesting to note that median time on market has approached historical lows. Current median time on market levels closely mirror levels seen immediately before the collapse of the 2008 housing bubble. Such extraordinarily low median time on market levels indicate exceptionally high levels of consumer confidence and may allude to overly aggressive speculation in the current housing market. Should current consumer confidence not be grounded in a rise in the intrinsic value of homes, we can expect an impending market correction.

Building Permits:

Exhibit 1.9:






The results of our building permits cross covariance tests are highly insightful as they enable us to more precisely quantify the length of the time lag between the approval of building permits and their impact on housing prices. As stated in our hypothesis, we expected building permits to exhibit a delayed inverse relationship to housing price as a rise in approved building permits today will result in an increase in the supply of future housing. In four of our six cross covariance tests, the largest negative covariance value was calculated when building permits were compared to housing prices three years later. Only Santa Clara and San Francisco exhibited a positive covariance with a three-year time lag. However, even these two counties experienced their least positive covariance values with a three-year time lag and were approaching negative values. Such a finding supports our hypothesis of a delayed negative relationship between the number of building permits and housing prices and also suggests that perhaps the most significant negative relationship lies in a time shift greater than three years. Yet another insightful finding from our building permits covariance analysis is the positive relationship expressed in all six counties when prices are compared to the number of building permits in the future. The consistent positive relationship that exists between building permits and housing price appreciation when price is considered as the leading indicator is likely explained by market momentum. When housing prices begin to rise, builders scramble to get their own piece of the wealth. Thus, we see the number of building permits increase concurrently with and after an increase in real home prices. Currently the data do not allow us to make a sound prediction about the effect of building permits on near term housing prices. While the number of building permits has been on the rise for the last eight years, they have been climbing from historical lows seen after the collapse of the last housing bubble. Therefore, it is difficult to discern if the rise in building permits in the recent past will actually result in an oversupply of homes in three years.

Ten-Year Treasury Yield:

Exhibit 1.10:

For all of the counties included in our covariance analysis, a zero time shift of the ten-year Treasury yield corresponded with the greatest covariance value. However, for the state of California as a whole, the shift with greatest covariance was a lead of four quarters. Additionally, the covariance for a shift of eight quarters in that same direction was also greater than the covariance for no shift at all. Across the six regions all staggers were negatively correlated with real price appreciation. We correctly anticipated this relationship due to the correlation between ten-year Treasury yields and mortgage rates that we discussed previously. While Treasury yields have been subdued as a result of monetary policy such as quantitative easing in lieu of the global financial crisis, yields have been rising and at some point may pressure housing markets via rising mortgage rates.

Regression Analysis:

Exhibit 1.11:

| | Housing Affordability Index | | Unsold Inventory Index | | Building Permits | | Time on Market | | Ten Year Treasury | | 36-month BP Lag | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Coefficient* | *P-Value* | *Coefficient* | *P-Value* | *Coefficient* | *P-Value* | *Coefficient* | *P-Value* | *Coefficient* | *P-Value* | *Coefficient* | *P-Value* |
| **California** | -5.25 | 0.061 | -0.45 | 0.00 | 0.00037 | 0.00 | -0.010 | 0.00 | -0.32 | 0.00 | -0.00027 | 0.003 |
| **Ventura** | -1.17 | 0.47 | -0.45 | 0.00 | 0.00043 | 0.00 | -0.031 | 0.00 | -0.88 | 0.00 | -0.00053 | 0.00 |
| **Sacramento** | -2.38 | 0.071 | -0.64 | 0.00 | 0.0017 | 0.007 | -0.092 | 0.00 | -1.38 | 0.00 | -0.00016 | 0.72 |
| **Los Angeles** | -1.09 | 0.54 | -0.28 | 0.00 | 0.0019 | 0.033 | -0.05 | 0.00 | -0.96 | 0.00 | -0.0031 | 0.00 |
| **San Francisco** | -5.41 | 0.02 | -0.34 | 0.00 | 0.0013 | 0 | -0.049 | 0.00 | -0.88 | 0.00 | -0.000094 | 0.68 |
| **Santa Clara** | -4.34 | 0.012 | -0.32 | 0.00 | 0.0024 | 0.014 | -0.11 | 0.00 | -0.96 | 0.00 | -0.0036 | 0.00 |

From the outset of our study, the aim was to uncover the relationship between the selected variables above and real housing prices. While the cross-covariance analysis enables us to better understand how and when our selected variables interacted with housing prices, it does not provide information on *how much* they influence price. The objective of our linear regression analysis is to discern the magnitude of influence of our selected variables on housing price and how much variability in home prices can be explained by the variables used in our study. We maximize the significance of our regression analysis by employing the findings in our cross-covariance analysis and time shifting individual variables with their respective highest levels of covariance with price appreciation.

Because of the autocorrelation introduced to the Traditional HAI county data from the cubic spline interpolation process described in the data section, all bivariate regressions run for Traditional HAI are Newey-West regressions. Newey-West standard errors do not rely on the same set of assumptions that most regression models use, and thus aim to overcome issues of autocorrelation and heteroskedasticity in time series data. Additionally, all of our bivariate regressions utilize robust standard errors. Our adoption of robust standard errors is based on the logical assumption that some of our data could be heteroskedastic and obtain non-constant variance over time. For example, quantitative easing undoubtedly dampened variance of interest rates in the years immediately following the crisis. In the Appendix, we include all 36 bivariate regressions that we ran. For the Unsold Inventory Index, Median Time on Market, Building Permits, and the Ten-Year Treasury Rates, we considered the results of our cross-covariance analysis and regressed zero time lags of these variables against real price appreciation. For the Traditional HAI, we looked at 3-year leads of HAI versus real price appreciation as well as a base case with zero shift. All regression results can be referenced in the Appendix.

Assuming a significance level of $\alpha$=.05 our regression results for California as a whole show that four of our five variables had a statistically significant influence on price appreciation with no time shift. The only variable that did not yield a statistically significant result was HAI. UII and median time on market appeared to have the largest impact on housing price as measured by “R-squared” values with “R-squareds” of .33 and .32 respectively. Additionally, building permits yielded an R-squared of .24 while the Ten-Year Treasury rate produced an R-squared of only .04. Finally, building permits with a three-year time shift also had a statistically significant influence on price, but yielded a lower R-squared of .13 when compared to the R-squared of building permits with no time shift. Interestingly, unlike the concurrent regression for building permits, employing a three-year time shift yielded a negative beta coefficient for building permits. This difference between the two building permit regressions reinforces the finding of our cross-covariance analysis that building permits are positively correlated with prices today but negatively correlated with prices in the future.

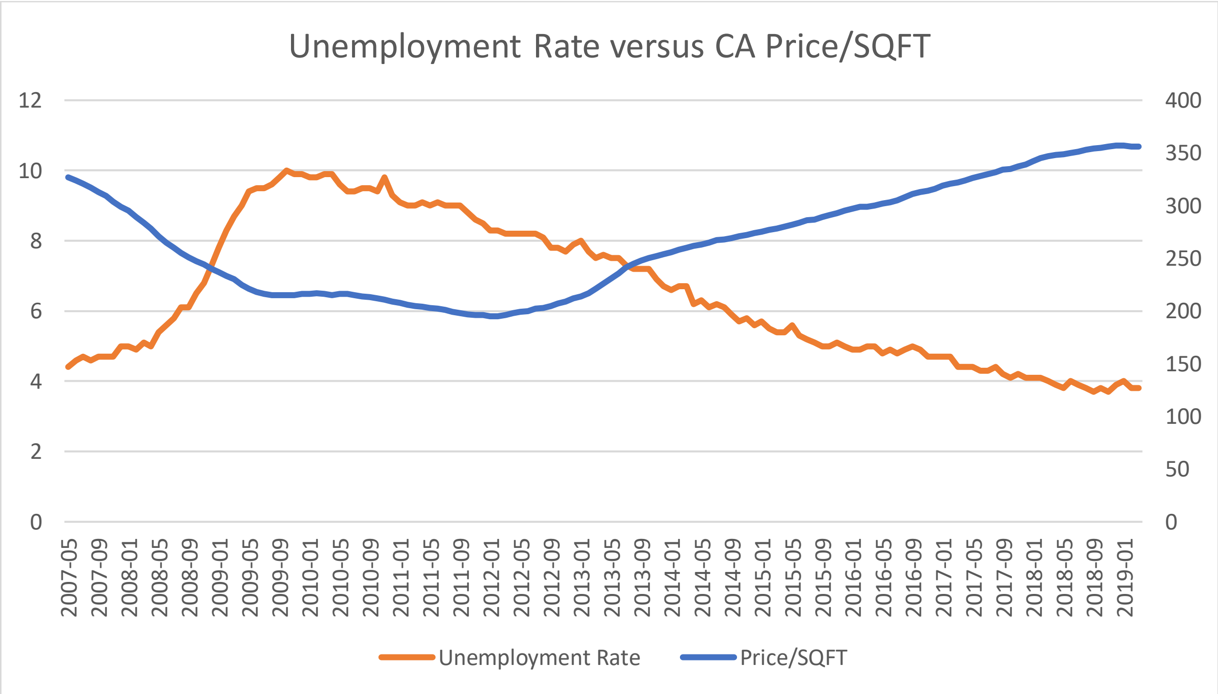
The analysis for the five counties can be largely generalized, as they demonstrated very similar relationships between regressors and real price appreciation. For instance, in all five counties the Unsold Inventory Index, Median Time on Market, and the Ten-Year Treasury were all statistically significant at the 95% confidence level. There were, however, varying results between counties for HAI and building permits. We attribute the lack of significance of HAI to the conclusions in our cross-covariance analysis that HAI adjusts to change in home price and does not hold predictive power over future housing prices. Variability in home price explains variability in HAI and not vice-versa. Because the regressions conducted for HAI only consider the relationship between HAI and real home price in the same period it is not surprising that HAI failed to hold a statistically significant relationship with home prices. In light of our cross-covariance analysis it seems more probable that there exists a statistically significant relationship between real home prices today and HAI in the future. In regard to building permits, we believe that the inconsistencies in significance across counties is simply due to our use of the nominal number of building permits across months instead of looking at percent changes in building permits across periods. We believe that an expansion of our study that looks at building permit growth rather than number would find significance in all counties when regressed against real price appreciation.

# *Part 2: Confounding Economic Factors: A Macroeconomic View*

In Part 1 of our study, we analyzed the relationship between housing prices and real estate specific factors such as traditional HAI, unsold inventory, building permits, and time on market. While such an analysis is informative, it would be myopic to assume that only factors within the real estate sector determine housing prices. An astute analysis of housing prices must not evaluate the real estate market in isolation, rather it must also consider a broader scope of economic factors that may impact home prices. In this portion of our paper we take a more general approach and examine the relationship between home prices and macroeconomic factors not exclusively confined to the real estate sector. The macroeconomic measures we believe to be especially relevant to home prices are: the current unemployment rate, S&P 500 performance, the 10-2 Treasury spread, and the health of the construction industry.

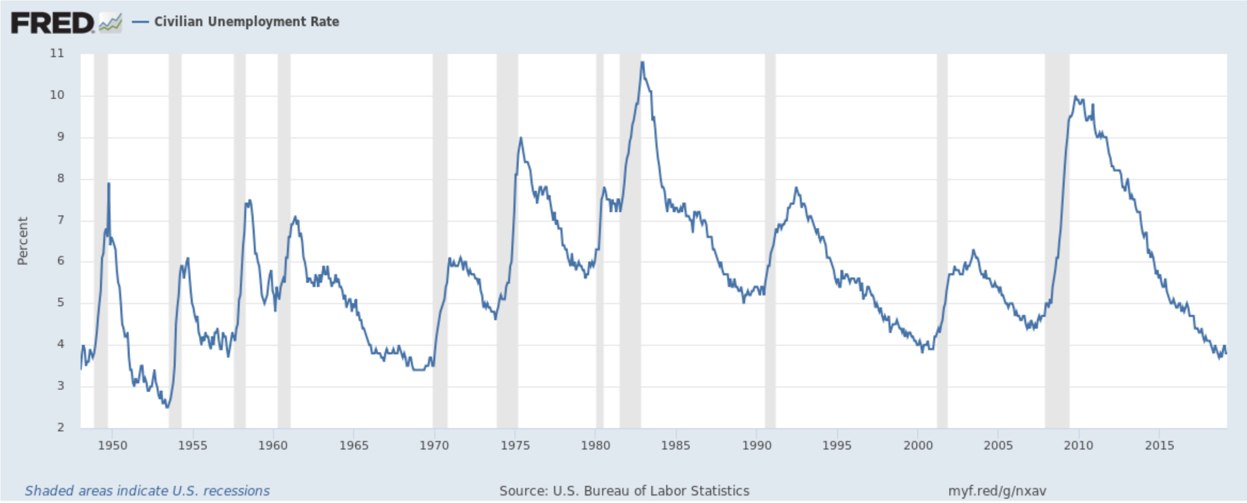
The first macroeconomic metric we chose to consider in our analysis is the unemployment rate. We expect unemployment to exhibit a negative relationship with home prices. An increase in the unemployment rate can be interpreted as a decrease in housing demand. Fewer people employed results in less wealth among consumers and thus less capital among potential homebuyers. Additionally, lower rates of unemployment coincide with less employer flexibility to suppress wages. When unemployment rates are low, labor is in high demand and employers must compete for workers by offering higher wages. The aforementioned relationship between the unemployment rate and growth in wages is well known phenomena that is referred to within the field of macroeconomics as the *Phillips Curve*. Such economic theory further suggests that periods of falling unemployment should correspond with greater consumer purchasing power and precipitate higher home prices. It should be noted that we do not expect this negative relationship to be contemporaneous. Similar to the time lag between the implementation of an economic policy and realized effects on the economy, changes in the unemployment rate should affect housing prices in the future. Consumers need time to accrue greater wealth and consumer confidence associated with falling unemployment rates before they can act differently within real estate markets. *Figure 2.1* below provides an overview of the relationship between the U.S. unemployment rate and California housing prices since April 2007 and largely confirms our expectations that the unemployment rate is an inverse leading indicator of home prices.

Exhibit 2.1*:*




In addition to solidifying our expectation of a lagged inverse relationship between the unemployment rate and home prices, the most compelling trend in this graph is the long period of falling unemployment since the Great Recession. It appears that this trend has finally begun to slow with unemployment stabilizing around 4% in 2018. The lengthy period of falling unemployment that appears to have reached its conclusion is especially pertinent because unemployment is cyclical in nature. The historical cyclicality of unemployment is highlighted in *Exhibit 2.2* below.

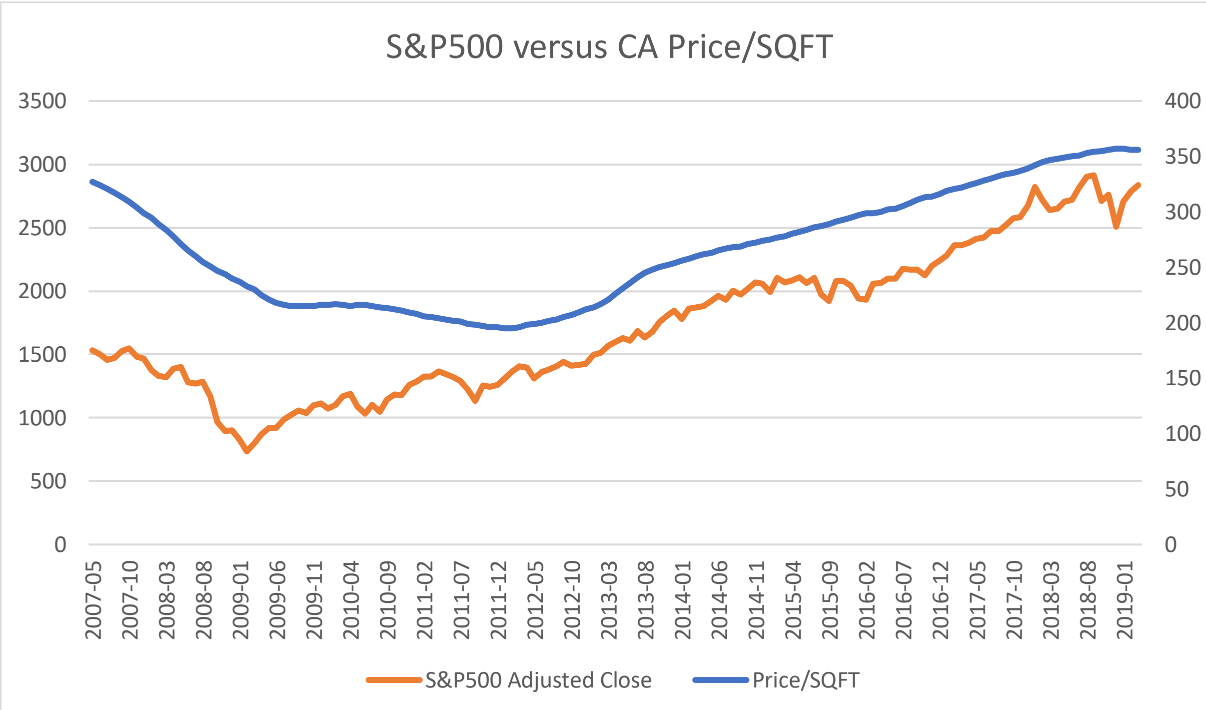
Exhibit 2.2:




This graphic provided by the FRED suggests that the United States is reaching the end of an economic cycle and should anticipate rising unemployment rates in the near future. During and after a recession, it has become common for the Federal Reserve to restore economic activity with a period of quantitative easing that ensures a low interest rate environment. However, after the economy has recovered, inflation rates become the Federal Reserve's primary concern. In an effort to avoid periods of stagflation or a serious future correction, the Federal Reserve slowly inches interest rates up. This contraction in monetary policy makes it more expensive for corporations to borrow or pay off pre-existing adjustable rate debt and places pressure on corporate profit margins. The inevitable result is that the unemployment rate begins to creep back up as heightened costs render companies more hesitant to expand and take on new employees. Given the depicted cyclicality of unemployment and the established relationship between the unemployment rate and housing prices, the current U.S. interest rate environment spells trouble for the future of the housing market. Since its meeting in December 2015, the Federal Reserve has initiated its plan of slowly raising interest rates, typically in 25 basis point increments. As rates rise we can expect unemployment rates to steadily increase and future home prices to steadily fall.

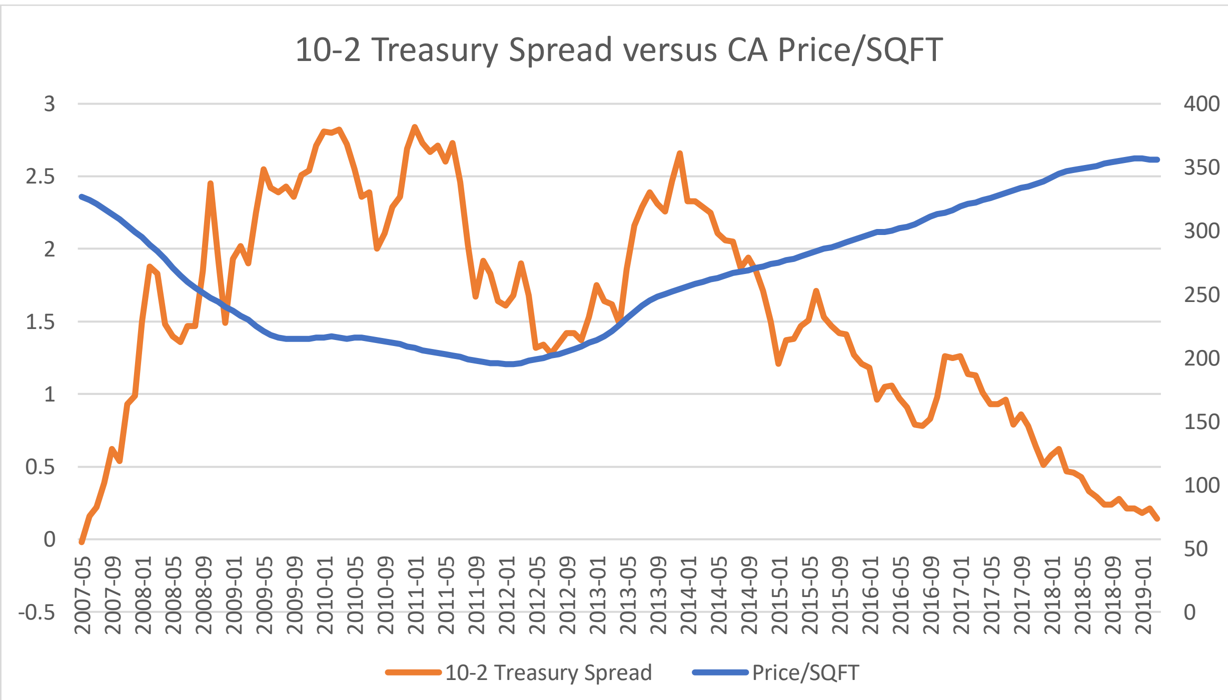
The second broader economic factor considered in this portion of our analysis is the S&P 500. The S&P 500 is an index comprised of the largest 500 U.S. companies by market capitalization. Given its composition, S&P 500 performance is widely considered to be a benchmark for the health of the U.S. economy. During a bull market, or sustained period where the S&P 500 appreciates in value, consumer confidence is high. Conversely, during a bear market, market participants are more apprehensive about investing as they fear buying in before the economy bottoms out. Because a home purchase represents most individuals' most substantial investment, the proclivity of consumers to purchase a home is likely influenced by changes in economic sentiment tied to S&P 500 performance. Furthermore, the enormous amount of wealth tied to the index suggests that the number of people capable of purchasing a home fluctuates with S&P 500 performance. For instance, three of the largest exchange traded funds (ETFs) tracking the S&P 500 are SPY, IVV, and VOO. These three ETFs alone collectively hold nearly a trillion dollars in assets. Considering the immense amount of investment assets tied to the S&P 500, a downward turn in the index yields a substantial financial blow and loss in purchasing power to the American people. In consideration of the above, we expect housing prices to move in concert with S&P 500 performance. The relationship between housing prices and the S&P 500 are delineated below in Exhibit 2.3.

Exhibit 2.3:




A preeminent concern among investors in real estate is liquidity. The closure of any real estate transaction is a laborious process that requires agents, escrows, and finding the appropriate buyer. For this reason, real estate investments are extraordinarily illiquid in comparison to stocks and other financial derivatives that can be quickly turned over to realize profits. Liquidity, or lack thereof, is paramount in encouraging or deterring investments in real estate and thus a measure of housing market liquidity must be included in our analysis. While imperfect, our measure for liquidity in the housing market is the 10-2 Year Treasury spread. Banks and other credit lending financial institutions often borrow short term from the Treasury at the federal funds rate and then lend to long-term borrowers such as homebuyers at a higher interest rate. Although the 10-2 spread is not an exact representation of the margin between banks borrowing and lending rates, it serves as a proxy for the profitability of these institutions as they must remain competitive with long-term lending rates. *Ergo*, as the spread shrinks, institutional lenders face smaller profit margins and are less willing to provide credit. The result is that only borrowers with near zero default risk are granted loans. Given the majority of homebuyers must take out a mortgage to afford a home, a tighter Treasury spread significantly curbs liquidity in the housing market as few investors are granted the needed credit to purchase a home. Thus, we expect the 10-2 Treasury spread to exhibit a positive relationship with price. However, like the relationship between the unemployment rate and home price, we expect the inverse relationship to be lagged. We do not expect credit spreads to have an instantaneous effect on home prices because only after a substantial amount of home buyers are rejected by lenders will housing market demand and liquidity be noticeably impacted. The relationship between the 10-2 Year Treasury spread is shown below in Exhibit 2.4.

Exhibit 2.4:




While the relationship between the Treasury spread does not reflect our hypothesized relationship, it does not fully reject our intuition. The graph is contradictory to what we expected in that since early 2014, the 10-2 Treasury Spread has expressed a clearly inverse relationship with home prices. However, the focus of this graph should be that the spread is once again approaching zero. As shown by *Figure Z*, the last time similar spread values were observed was in 2007 and housing prices plummeted in the following months. The takeaway here is that although *the spread does not express a positive linear relationship with home prices* as we anticipated, shrinking spreads *do create significant issues for the real estate market at a certain critical level.* This is likely because financial institutions can still make profits as long as a positive spread exists, and thus their credit lending behavior does not change substantially enough to hamper home prices as the spread shrinks. However, once the spread between short-term and long-term rates is near zero, or disappears entirely, lending profits are too minimal to risk borrower default. At this point net interest margins are so small or nonexistent that lending becomes unenticing and uninsurable through the purchase of credit default swaps. Naturally, profit seeking financial institutions step away from lending and credit falls into deep shortage. Credit is no longer able to prop up demand in the housing market and a liquidity crisis ensues driving home prices down. In short, current home buyers should be seriously alarmed by current spread levels. Though the 10-2 spread does not exhibit the linear relationship with home prices we expected, it seems that current spread levels near zero still pose a significant threat to the housing market.

The fourth and final variable considered in our broader analysis is an ETF sponsored by *State Street Global Advisors* known as the *SPDR S&P Homebuilders* (XHB). XHB seeks to provide “exposure to the homebuilders segment of the S&P 500” (State Street 2019). Including XHB in our analysis provides a barometer for the health of the housing market as high demand for home construction today suggests a positive outlook on future demand for homes. Thus we expect a lagged positive relationship between XHB and home prices. Additionally, because XHB consists entirely of homebuilding companies, we expect the value of the ETF to be closely correlated with building permits. As the number of building permits increases so should the amount of construction contracts and earnings secured by companies held in XHB. Such a suspected correlation bolsters our hypothesis that XHB (like building permits) acts as a leading indicator for home prices. As mentioned before, we do not expect the relationship between either XHB or building permits to contemporaneous with home prices because of the lag between construction of a house and its actual listing on the market. The relationship between XHB and building permits is illustrated below in Exhibit 2.5. Further, the relationship between XHB and home price is highlighted by Exhibit 2.6.

Exhibit 2.5:

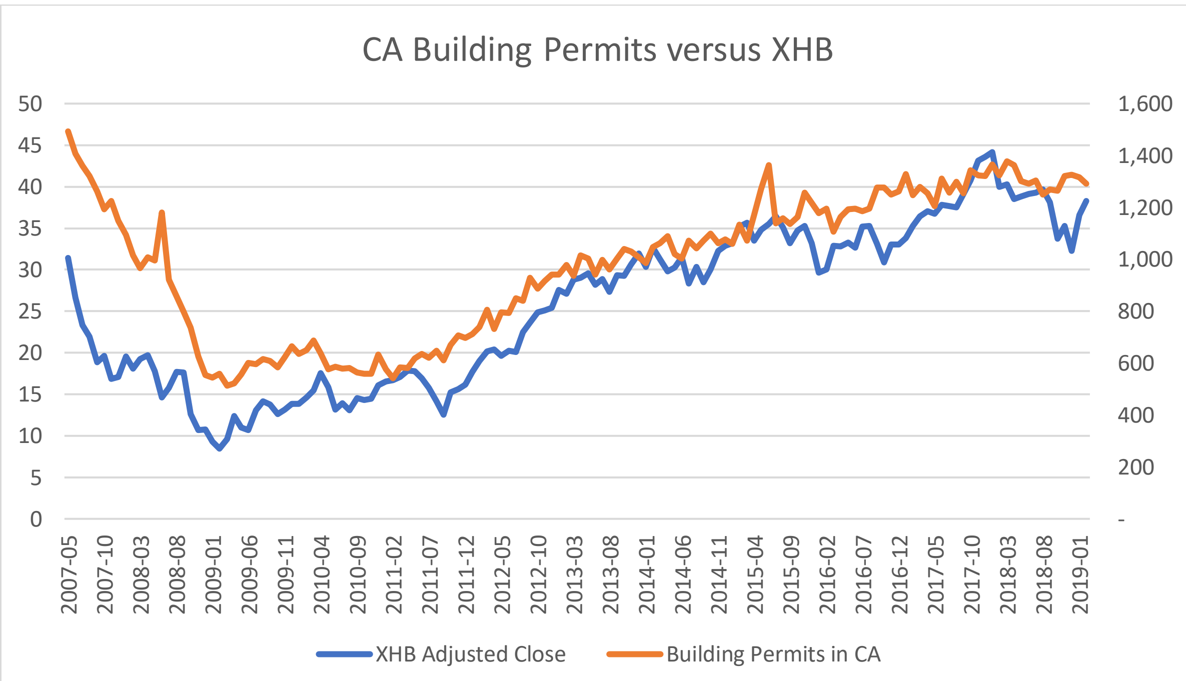
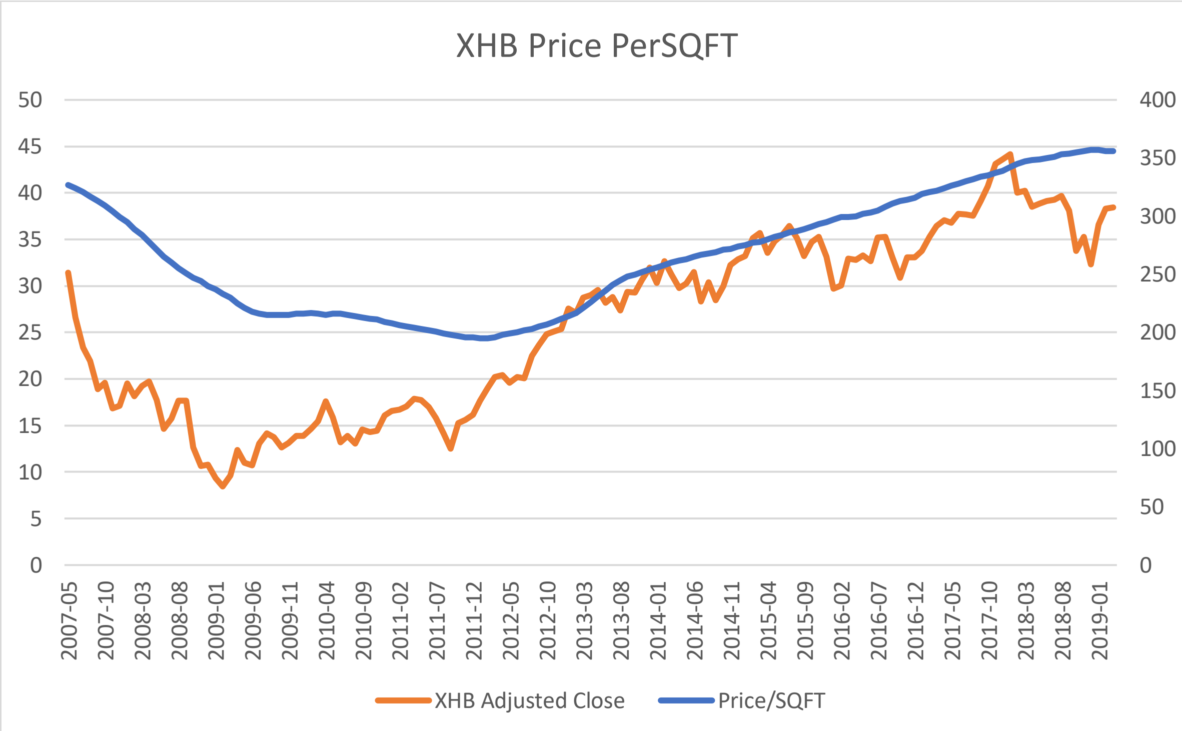


Exhibit 2.6:




In light of the two graphs above, it appears that both our contentions about XHB were confirmed. A simple glance at *Exhibit 2.5* shows that XHB and building permits practically move in unison and demonstrate near one-to-one correlation. Moreover, Exhibit 2.6 shows in the years following the onset of the Great Recession XHB begins recovering well before housing prices. More interestingly, in the most proximal months we see XHB fall from its peak value in the beginning of 2018. Similar to the current 10-2 Treasury spread levels near zero and the historically cyclical nature of unemployment, it seems that XHB could be alluding to an impending fall in home prices in the near future.

Now that we have outlined the factors considered in our broader analysis, it is time to consolidate these components into a single analysis. Depicted in Exhibit 2.7 below are the results of an ordinary least squares regression analyzing the relationship between the aforementioned four factors and housing price defined by the Zillow price per square foot data. For three of our four variables in our regression, a lag of one year has been implemented. In other words, any value for these three variables is compared with square foot prices one year in the future. The only variable that is not lagged is the S&P 500 closing value because this is the only factor that we expect to have a contemporaneous relationship with price.

Exhibit 2.7:

| Source | SS | df | MS | | | |
|---|---|---|---|---|---|---|
| Model | 343385.73 | 4 | 85846.4326 | Number of obs | = | 131 |
| Residual | 10221.9338 | 126 | 81.1264583 | F(4, 126) | = | 1058.18 |
| | | | | Prob > F | = | 0.0000 |
| | | | | R-squared | = | 0.9711 |
| | | | | Adj R-squared | = | 0.9702 |
| Total | 353607.664 | 130 | 2720.05895 | Root MSE | = | 9.007 |

| pricesqft | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| SP500 | .0523869 | .0034943 | 14.99 | 0.000 | .0454718 | .0593021 |
| lag2Tspread | -3.533105 | 1.972792 | -1.79 | 0.076 | -7.437202 | .3709924 |
| lag2XHB | .5408519 | .2747378 | 1.97 | 0.051 | -.0028461 | 1.08455 |
| lag2UE | -10.0624 | .9376911 | -10.73 | 0.000 | -11.91807 | -8.206741 |
| _cons | 231.3895 | 7.392995 | 31.30 | 0.000 | 216.759 | 246.02 |

Our regression analysis yields a tremendously high R-squared and adjusted R-squared of .97. This result emphasizes the relevance of our selected factors in determining future home prices as an estimated 97% of the variance in value per square foot can be explained by changes in the variables in our model. Additionally, the coefficients of all our regressors (selected variables) were significant at the 10% level with the S&P500 and lagged unemployment rate holding significance at the 1% level. Lastly, the signs associated with our regression coefficients (except lagged treasury spread) further legitimize our hypothesized relationships and are therefore logically grounded. Both the S&P 500 and lagged XHB exhibited an expected positive relationship with price while lagged unemployment exhibited an anticipated negative relationship with price.

To conclude, the results of our regression analysis suggest that the relationship between our selected variables and home prices is fairly strong. In retrospect, this analysis yields a decidedly inauspicious outlook for the housing markets as three of our four variables allude to the possibility of an imminent collapse. The negative relationship between unemployment rates and home prices a year in the future is statistically significant. The cyclical nature of unemployment points to a rise in the unemployment rate in the coming years and thus we can expect a fall in home prices soon after. Further, the 10-2 spread is trending towards zero and matching rates during the last housing meltdown. Finally, XHB’s close correlation with building permits advocates for its reputation as a leading indicator for home prices. When lagged one year, the ETF demonstrates a positive relationship with home prices that is statistically significant. The recent decline in the ETF’s value yet again suggests that we may see a correction in home prices in the near future.

# *Part 3: Vector Autoregressive Model: A Forecast for Future House Prices*

The final element of our three-pronged approach to studying house price behavior is the implementation of a vector autoregressive (VAR) model. The inspiration for this analysis stems from Follain and Giertz and their use of a similar vector error correction (VEC) model. Follain and Giertz identify employment, income, the 10-1 Treasury spread, and the 10-year treasury yield as important predictors of house price. While Follain and Giertz cite Estrella and Hardouvelis (1991) who determine that the 10-1 Treasury spread is a good predictor of economic activity, we find the 10-2 Treasury spread to be as useful and more broadly cited. We adopt these variables and make a single addition of a generalized rent variable as well. Given that the data are time series and multivariate, it is appropriate to consider a VAR model. VAR models employ a stochastic process to recognize the linear interdependencies that may exist among the multiple time series. VAR is the generalization of the univariate autoregressive (AR) model and is better able to depict the relationship between multiple variables, which is advantageous in creating forecasts. Ultimately, implementation of the VAR model enables us to quantify and predict house price paths following the rigorous study of statistically significant determinants (i.e. employment).

**Data**

The scope of this analysis will be the state of California and all data are quarterly beginning in the first quarter of 2004 and ending in the fourth quarter of 2018. As mentioned above, the determinants of house price that we use in our VAR model are employment, income, the 2-10 Treasury spread, the 10 year treasury yield, and a generalized variable for rent. Employment data are from the Federal Reserve Economic Data (FRED) and are measured in persons and are not seasonally adjusted. Income data are gathered from the Bureau of Economic Analysis (BEA) and are defined as aggregate personal income (in millions) for the state of California and are seasonally adjusted. The 10-2 Treasury spread data are from the FRED and represent the difference between the 10 Year Treasury (constant maturity) yield and the 2 Year Treasury (constant maturity) yield. Similarly, the 10 Year Treasury yield data are also from the FRED and calculated as the 10-Year Treasury (constant maturity) rate. Lastly, the generalized rent variable that we have alluded to is generated from the FRED and the data are defined as real estate, rental, and leasing earnings in California (in thousands of dollars) and are seasonally adjusted. The responding price variable is the all-transactions House Price Index (HPI) for California where 1980:Q1 is indexed as equaling 100—these data are not seasonally adjusted.

**Methodology and Results**

To correctly employ a VAR model analysis one must first determine the optimal number of lags and then ensure that all data used is stationary. The processes for discerning optimal lags and stationarity are outlined in the following paragraphs.

As mentioned above, we first address the time series data and use a criterion for finding the optimum number of lags. Generally, researchers use a maximum lag of 4 for quarterly data. We find (below) by using the Akaike Information Criterion that 3 lags will be the appropriate number of lags to use:

Exhibit 3.1:

Selection-order criteria
Sample: 2005q1 - 2018q4 Number of obs = 56

| lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | -2855.71 | | | | 9.8e+36 | 102.204 | 102.288 | 102.421 |
| 1 | -2401.6 | 908.23 | 36 | 0.000 | 3.2e+30 | 87.2714 | 87.8603 | 88.7904 |
| 2 | -2297.55 | 208.1 | 36 | 0.000 | 3.0e+29 | 84.8411 | 85.9348 | 87.6621* |
| 3 | -2246.78 | 101.54 | 36 | 0.000 | 2.0e+29* | 84.3135* | 85.912* | 88.4366 |
| 4 | -2215.96 | 61.633* | 36 | 0.005 | 3.0e+29 | 84.4987 | 86.602 | 89.9237 |

Endogenous: HPI Emp Inc T10Y2Y T10Y Rent
Exogenous: _cons

This optimal lag is identified by the asterisk next to 84.31 under the AIC column. Also notice that Hannan and Quinn information criterion (HQIC) and final prediction error (FPE) make the same recommendation.

Next, we use the specified optimal lag number for our model to help with testing stationarity for our data. We choose the Augmented Dickey-Fuller test as our test for stationarity. Here, the null hypothesis is that the data follow a unit root process (i.e. the data is nonstationary), and rejection of the null would indicate that the data is stationary—a necessary condition for using a vector autoregressive model. We find that levels of HPI are stationary, but the other variables are not, initially. A common way to address the issue of nonstationary data is to look at first and second differences of the nonstationary variables. If one fails to take a difference when the process is deemed nonstationary, regressions will often yield a spuriously significant trend, which is not desirable. We find that we can reject the null hypothesis and demonstrate stationarity for employment at the second difference, and for all other variables at the first difference. We can then say HPI is I(0), employment is I(2), and all other variables are I(1). The results of the Augmented Dickey-Fuller test are detailed below with rejection of the null hypothesis satisfied at the 10% level for all variables:

Exhibit 3.2:

```
. dfuller HPI, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        56

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.255            -3.572            -2.925            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0170
```

```
. dfuller d2.Emp, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        54

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.945            -3.574            -2.927            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfuller d.Inc, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        55

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -2.783            -3.573            -2.926            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0608
```

```
. dfuller d.T10Y2Y, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        55

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.305            -3.573            -2.926            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0146
```

```
. dfuller d.T10Y, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        55

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -3.364            -3.573            -2.926            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0122

. dfuller d.Rent, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        55

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
------------------------------------------------------------------------------
 Z(t)             -2.614            -3.573            -2.926            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0901

. varbasic HPI d2.Emp d.Inc d.T10Y2Y d.T10Y d.Rent, lags(1/3) step(8) nograph
```

Now that the assumptions of stationarity have been met, we can specify our VAR model. Using the results from the above Augmented Dickey-Fuller tests, we use the level data for HPI, first difference data for income, 2-10 Treasury spread, 10 Year Treasury yield, and Rent, and second difference data for employment. The aforementioned specification yields the following results:

Exhibit 3.3:

| | | | | | |
|---|---|---|---|---|---|
| Sample: 2005q2 - 2018q4 | | | Number of obs | = | 55 |
| Log likelihood = | -2249.26 | | AIC | = | 85.93673 |
| FPE | = | 1.01e+30 | HQIC | = | 87.54568 |
| Det(Sigma_ml) | = | 1.34e+28 | SBIC | = | 90.09738 |

| Equation | Parms | RMSE | R-sq | chi2 | P>chi2 |
|---|---|---|---|---|---|
| HPI | 19 | 5.20083 | 0.9981 | 28216.1 | 0.0000 |
| D2_Emp | 19 | 37512.2 | 0.5134 | 58.03288 | 0.0000 |
| D_Inc | 19 | 24076.4 | 0.4061 | 37.60503 | 0.0044 |
| D_T10Y2Y | 19 | .232386 | 0.5000 | 55.00882 | 0.0000 |
| D_T10Y | 19 | .247539 | 0.6060 | 84.58272 | 0.0000 |
| D_Rent | 19 | 2.4e+06 | 0.2499 | 18.32205 | 0.4346 |

After executing a VAR model it is important to run diagnostic tests to investigate the prevalence of common statistical issues that undermine the validity of a model. We first test the model for autocorrelation using the Lagrange Multiplier test. The results are detailed below:

Exhibit 3.4:

Lagrange-multiplier test

| lag | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 69.6366 | 36 | 0.00065 |
| 2 | 46.4293 | 36 | 0.11428 |
| 3 | 46.3283 | 36 | 0.11623 |

H0: no autocorrelation at lag order

As mentioned in our optimal lag analysis, we used three lags in our VAR model and thus accept the null hypothesis that there is no autocorrelation. The next diagnostic is testing for normality in the distribution of residuals for all variables. Our test of choice is the Jarque-Bera test which has the null hypothesis of normally distributed residuals. The results are provided below:

Exhibit 3.5:

Jarque-Bera test

| Equation | chi2 | df | Prob > chi2 |
|---|---|---|---|
| HPI | 0.788 | 2 | 0.67452 |
| D2_Emp | 2.885 | 2 | 0.23630 |
| D_Inc | 86.002 | 2 | 0.00000 |
| D_T10Y2Y | 1.307 | 2 | 0.52017 |
| D_T10Y | 30.039 | 2 | 0.00000 |
| D_Rent | 1.856 | 2 | 0.39532 |
| ALL | 122.877 | 12 | 0.00000 |

Notice that we accept the null hypothesis for four of our six variables, concluding that for those four variables the residuals are normally distributed. Because we are unable to reject the null for the majority of our variables, our model sufficiently satisfies the diagnostic test for normality. Lastly, we use the Granger-Causality test to investigate causality among our time series data. We find that four of five variables are granger-causal of HPI in our model at the 10% level, with the exception being income. Further, the variables are jointly granger-causal at the 1% level. These findings are reported below:

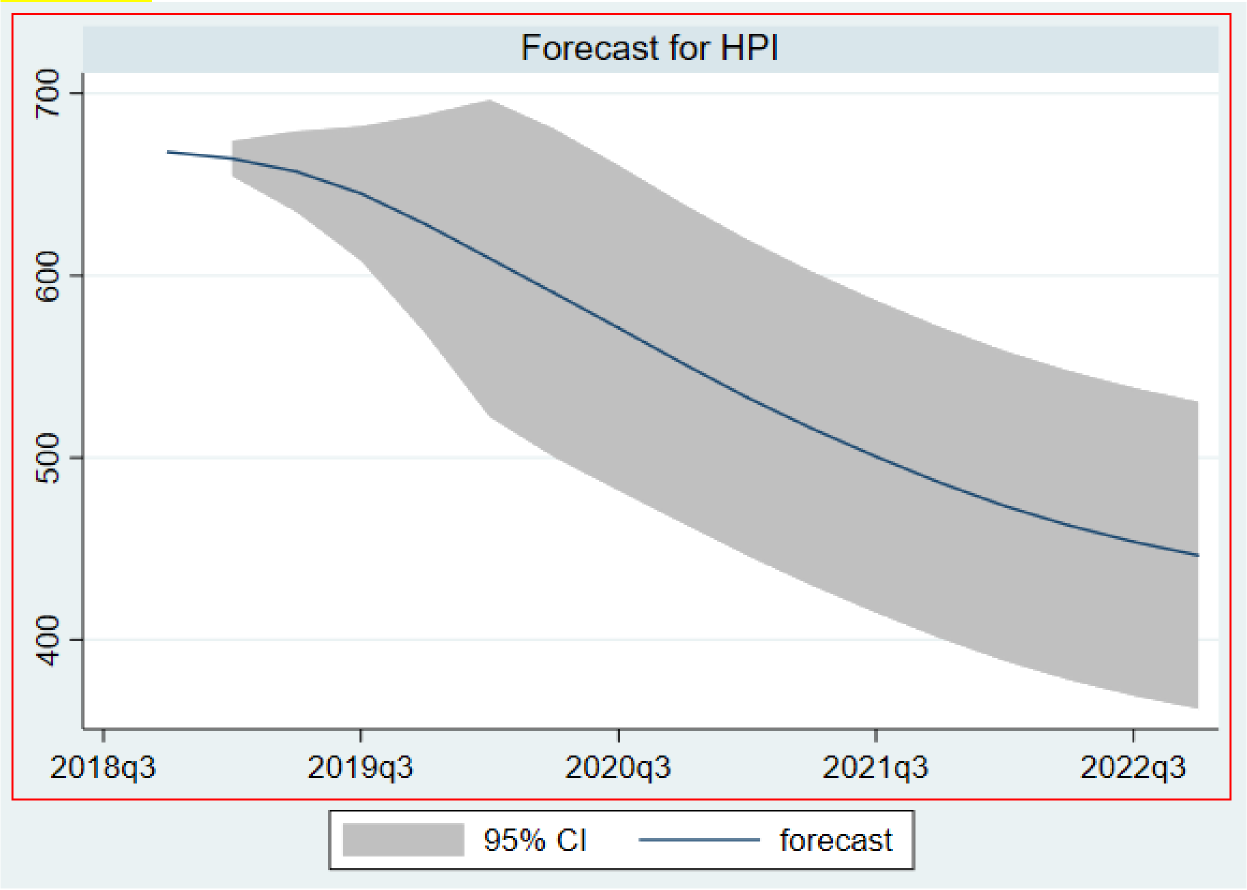
Exhibit 3.6:

Granger causality Wald tests

| Equation | Excluded | chi2 | df | Prob > chi2 |
|---|---|---|---|---|
| HPI | D2.Emp | 8.4796 | 3 | 0.037 |
| HPI | D.Inc | 1.2106 | 3 | 0.750 |
| HPI | D.T10Y2Y | 9.8189 | 3 | 0.020 |
| HPI | D.T10Y | 30.118 | 3 | 0.000 |
| HPI | D.Rent | 6.4911 | 3 | 0.090 |
| HPI | ALL | 77.612 | 15 | 0.000 |

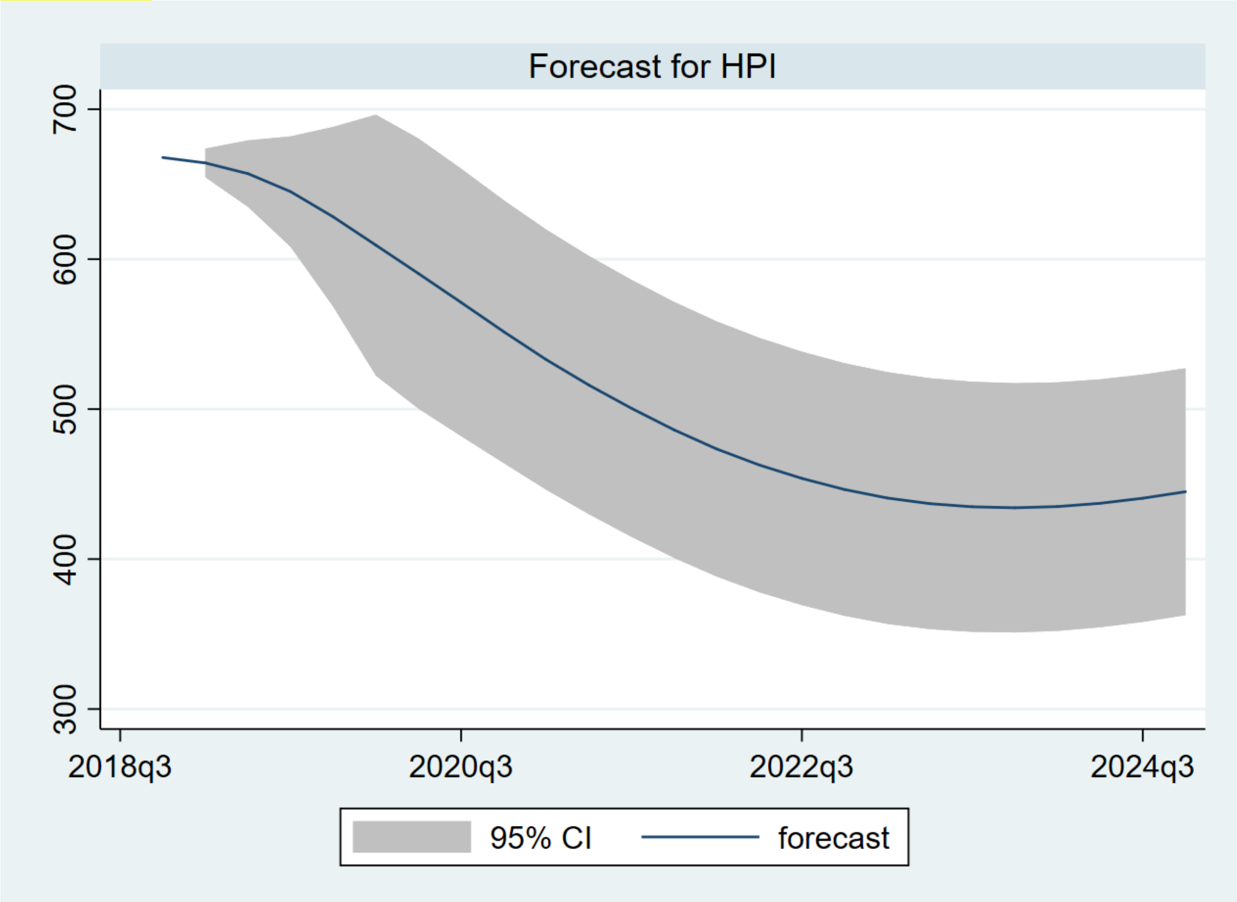
The results of all of these VAR diagnostics legitimize our model and build towards the unique predictive result of our autoregressive model. We utilize our VAR model to forecast HPI, a proxy for house prices, for the four-year period beginning in 2019:Q1. We provide our forecast with 95% confidence below:

Exhibit 3.7:




As supported by the statistical analysis outlined above, we anticipate a large decline in California home prices in the next four years. By as late as 2020:Q3, even the upper bound of our 95% confidence interval falls below the current HPI level. In the median case, we project roughly a 30 percent decline in California home prices. We forecast 6 years out in the graphic below to find that our model forecasts the bottoming out of this decline in California house prices to be around 2023:Q3:

Exhibit 3.8:


Forecast for HPI
700
600
500
400
300
2018q3
2020q3
2022q3
2024q3
95% CI
forecast

**Conclusion:**

Our three stages of analysis collectively paint a grim picture for California housing markets. Beginning with our cross-covariance analysis, we find that real estate related factors are most strongly related with home price contemporaneously, and largely fail to have statistically significant predictive power. Although the findings in our cross-covariance analysis prevent predictions of home price, we have identified that HAI is reaching all-time lows not seen since just prior to the last recession. The lack of affordable housing, as indicated by HAI, suggests that future housing demand may be unstable due to the lack of potential buyers. Similarly, our confounding economic analysis shows that current Treasury spreads are nearly identical to spreads before the 2008 meltdown. Further, our regression results in our confounding economic analysis confirm that the unemployment rate, the 10-2 Treasury spread, and XHB are all significantly related with home price one year in the future. The statistical significance of these relationships coupled with the imminent rise of unemployment rates and the recent fall of XHB allude to an impending decline in home prices. While all real estate is local, the variables described in our second analysis are not limited to California, and imply future trouble for real estate markets more broadly. Finally, the vector autoregression model enables us to forecast future price direction. Using HPI as a proxy for home values, the model parallels the first two parts of our research and predicts a substantial drop in home prices over the next four years.

**APPENDIX**

**Cross Covariance Analysis Regression Results by Region:**

**California:**

```
. regress realpriceappreciation HAIcalifornia, vce(robust)

Linear regression                               Number of obs     =        112
                                                F(1, 110)         =       3.60
                                                Prob > F          =     0.0605
                                                R-squared         =     0.0363
                                                Root MSE          =      2.928
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAIcalifornia | -5.256047 | 2.771703 | -1.90 | 0.061 | -10.74891 | .2368186 |
| _cons | 2.138009 | 1.037952 | 2.06 | 0.042 | .0810324 | 4.194986 |

```
. regress realpriceappreciation lagBPcalifornia012, vce(robust)

Linear regression                               Number of obs     =        104
                                                F(1, 102)         =       9.16
                                                Prob > F          =     0.0031
                                                R-squared         =     0.1307
                                                Root MSE          =     2.8308
```

| realpriceappreci~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPcalifornia012 | -.0002654 | .0000877 | -3.03 | 0.003 | -.0004393 | -.0000914 |
| _cons | 3.050093 | .7122889 | 4.28 | 0.000 | 1.637271 | 4.462914 |

```
. regress realpriceappreciation BPcalifornia, vce(robust)

Linear regression                               Number of obs     =        115
                                                F(1, 113)         =      31.24
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2467
                                                Root MSE          =     2.5591
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPcalifornia | .0003706 | .0000663 | 5.59 | 0.000 | .0002393 | .000502 |
| _cons | -2.998213 | .7192727 | -4.17 | 0.000 | -4.423222 | -1.573204 |

```
. regress realpriceappreciation TOMcalifornia, vce(robust)

Linear regression                               Number of obs   =       112
                                                F(1, 110)       =     93.25
                                                Prob > F        =    0.0000
                                                R-squared       =    0.3213
                                                Root MSE        =    2.4572
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TOMcalifornia | -.0996257 | .0103169 | -9.66 | 0.000 | -.1200713 | -.0791801 |
| _cons | 5.0308 | .5278127 | 9.53 | 0.000 | 3.984799 | 6.0768 |

```
. regress realpriceappreciation UIIcalifornia, vce(robust)

Linear regression                               Number of obs   =       112
                                                F(1, 110)       =     71.01
                                                Prob > F        =    0.0000
                                                R-squared       =    0.3365
                                                Root MSE        =    2.4294
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| UIIcalifornia | -.4490643 | .0532922 | -8.43 | 0.000 | -.5546768 | -.3434517 |
| _cons | 3.239877 | .389192 | 8.32 | 0.000 | 2.468589 | 4.011164 |

```
. regress realpriceappreciation tenyrtreasury, vce(robust)

Linear regression                               Number of obs   =       116
                                                F(1, 114)       =     13.28
                                                Prob > F        =    0.0004
                                                R-squared       =    0.0422
                                                Root MSE        =    2.8733
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| tenyrtreasury | -.3150183 | .086438 | -3.64 | 0.000 | -.4862514 | -.1437852 |
| _cons | 1.867085 | .5551237 | 3.36 | 0.001 | .7673895 | 2.966781 |

**Ventura:**

```
. newey realpriceappreciation HAIVent, lag(1)

Regression with Newey-West standard errors      Number of obs     =        132
maximum lag: 1                                  F(  1,       130) =       0.52
                                                Prob > F          =     0.4728
```

| realpricea~n | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAIVent | -1.174505 | 1.631197 | -0.72 | 0.473 | -4.401632 | 2.052623 |
| _cons | .4143095 | .57673 | 0.72 | 0.474 | -.7266819 | 1.555301 |

```
. regress realpriceappreciation lagBPVent036, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      17.54
                                                Prob > F          =     0.0001
                                                R-squared         =     0.1353
                                                Root MSE          =     .96358
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPVent036 | -.0005313 | .0001269 | -4.19 | 0.000 | -.0007823 | -.0002803 |
| _cons | .6926473 | .1607451 | 4.31 | 0.000 | .3746323 | 1.010662 |

```
. regress realpriceappreciation BPVent, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      14.83
                                                Prob > F          =     0.0002
                                                R-squared         =     0.0725
                                                Root MSE          =     1.0436
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPVent | .0004346 | .0001128 | 3.85 | 0.000 | .0002111 | .000658 |
| _cons | -.5271361 | .1707 | -3.09 | 0.003 | -.8651685 | -.1891037 |

```
. regress realpriceappreciation TOMVent, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      14.76
                                                Prob > F          =     0.0002
                                                R-squared         =     0.0926
                                                Root MSE          =     1.0322
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TOMVent | -.031465 | .0081904 | -3.84 | 0.000 | -.0476842 | -.0152457 |
| _cons | 1.814954 | .4783645 | 3.79 | 0.000 | .8676616 | 2.762246 |

```
. regress realpriceappreciation UIIVent, vce(robust)

Linear regression                               Number of obs     =        117
                                                F(1, 115)         =      58.12
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3394
                                                Root MSE          =     .83969
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| UIIVent | -.4461692 | .0585231 | -7.62 | 0.000 | -.5620922 | -.3302462 |
| _cons | 2.197849 | .2789629 | 7.88 | 0.000 | 1.645277 | 2.750421 |

```
. regress realpriceappreciation tenyrtreasury, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      43.24
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3266
                                                Root MSE          =     .85035
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| tenyrtreasury | -.8819993 | .1341341 | -6.58 | 0.000 | -1.147368 | -.6166311 |
| _cons | 2.321947 | .3292967 | 7.05 | 0.000 | 1.670473 | 2.973421 |

**Sacramento:**

```
. newey realpriceappreciation HAISacramento, lag(1)

Regression with Newey-West standard errors      Number of obs     =        132
maximum lag: 1                                  F(  1,        130) =       3.31
                                                Prob > F          =     0.0712
```

| realpriceap~n | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAISacramento | -2.381958 | 1.309498 | -1.82 | 0.071 | -4.972643 | .2087271 |
| _cons | 1.399263 | .7328095 | 1.91 | 0.058 | -.0505134 | 2.849038 |

```
. regress realpriceappreciation lagBPSacramento036, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =       0.13
                                                Prob > F          =     0.7187
                                                R-squared         =     0.0008
                                                Root MSE          =      1.407
```

| realpriceappreci~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPSacramento036 | -.0001648 | .0004567 | -0.36 | 0.719 | -.0010683 | .0007386 |
| _cons | .0994157 | .1680734 | 0.59 | 0.555 | -.2330974 | .4319287 |

```
. regress realpriceappreciation BPSacramento, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =       7.52
                                                Prob > F          =     0.0070
                                                R-squared         =     0.0859
                                                Root MSE          =     1.4032
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPSacramento | .0017275 | .0006298 | 2.74 | 0.007 | .0004804 | .0029746 |
| _cons | -.3516508 | .1865017 | -1.89 | 0.062 | -.720975 | .0176733 |

```
. regress realpriceappreciation TOMSacramento, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      93.36
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3374
                                                Root MSE          =     1.1946
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TOMSacramento | -.0920598 | .0095277 | -9.66 | 0.000 | -.1109272 | -.0731924 |
| _cons | 2.508636 | .2756981 | 9.10 | 0.000 | 1.962679 | 3.054593 |

```
. regress realpriceappreciation UIISacramento, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      28.76
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4233
                                                Root MSE          =     1.1144
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| UIISacramento | -.6446225 | .1202029 | -5.36 | 0.000 | -.882657 | -.406588 |
| _cons | 2.214119 | .3902119 | 5.67 | 0.000 | 1.441393 | 2.986845 |

```
. regress realpriceappreciation tenyrtreasury, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      75.77
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4344
                                                Root MSE          =     1.0586
```

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| tenyrtreasury | -1.381715 | .1587386 | -8.70 | 0.000 | -1.695761 | -1.06767 |
| _cons | 3.688247 | .4003675 | 9.21 | 0.000 | 2.896168 | 4.480326 |

**Los Angeles:**

```
. newey realpriceappreciation HAILA, lag(1)

Regression with Newey-West standard errors      Number of obs     =        132
maximum lag: 1                                  F(  1,       130) =       0.37
                                                Prob > F          =     0.5434
```

| realpricea~n | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAILA | -1.08966 | 1.788298 | -0.61 | 0.543 | -4.627593 | 2.448273 |
| _cons | .4070658 | .6396492 | 0.64 | 0.526 | -.8584036 | 1.672535 |

```
. regress realpriceappreciation lagBPLA036, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      85.61
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4845
                                                Root MSE          =     .79505
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPLA036 | -.0030639 | .0003311 | -9.25 | 0.000 | -.003719 | -.0024088 |
| _cons | .8683581 | .0980362 | 8.86 | 0.000 | .6744053 | 1.062311 |

```
. regress realpriceappreciation BPLA, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =       4.66
                                                Prob > F          =     0.0330
                                                R-squared         =     0.0443
                                                Root MSE          =       1.13
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPLA | .0019323 | .0008955 | 2.16 | 0.033 | .0001591 | .0037056 |
| _cons | -.3433194 | .17709 | -1.94 | 0.055 | -.6940059 | .007367 |

```
. regress realpriceappreciation TOMLA, vce(robust)
```

Linear regression

| | | |
|---|---|---|
| Number of obs | = | 120 |
| F(1, 118) | = | 47.06 |
| Prob > F | = | 0.0000 |
| R-squared | = | 0.2282 |
| Root MSE | = | 1.0154 |

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TOMLA | -.0502487 | .0073247 | -6.86 | 0.000 | -.0647537 | -.0357437 |
| _cons | 2.152867 | .2948874 | 7.30 | 0.000 | 1.56891 | 2.736825 |

```
. regress realpriceappreciation UIILA, vce(robust)
```

Linear regression

| | | |
|---|---|---|
| Number of obs | = | 120 |
| F(1, 118) | = | 20.54 |
| Prob > F | = | 0.0000 |
| R-squared | = | 0.4404 |
| Root MSE | = | .86467 |

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| UIILA | -.2847553 | .0628332 | -4.53 | 0.000 | -.4091822 | -.1603284 |
| _cons | 1.384249 | .2752103 | 5.03 | 0.000 | .839258 | 1.929241 |

```
. regress realpriceappreciation tenyrtreasury, vce(robust)
```

Linear regression

| | | |
|---|---|---|
| Number of obs | = | 132 |
| F(1, 130) | = | 44.84 |
| Prob > F | = | 0.0000 |
| R-squared | = | 0.3399 |
| Root MSE | = | .89972 |

| realpriceap~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| tenyrtreasury | -.9615329 | .1435969 | -6.70 | 0.000 | -1.245622 | -.6774436 |
| _cons | 2.566932 | .3540162 | 7.25 | 0.000 | 1.866553 | 3.267311 |

**San Francisco**

```
. newey realpriceappreciation HAISanFrancisco, lag(1)

Regression with Newey-West standard errors      Number of obs    =       132
maximum lag: 1                                  F(  1,       130) =      5.57
                                                Prob > F          =    0.0197
```

| realpriceappr~n | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAISanFrancisco | -5.41491 | 2.294177 | -2.36 | 0.020 | -9.953664 | -.8761552 |
| _cons | 1.244993 | .3839305 | 3.24 | 0.002 | .4854326 | 2.004554 |

```
. regress realpriceappreciation lagBPSanFrancisco036, vce(robust)

Linear regression                               Number of obs     =       132
                                                F(1, 130)         =      0.17
                                                Prob > F          =    0.6820
                                                R-squared         =    0.0010
                                                Root MSE          =    1.0114
```

| realpriceappreciat~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPSanFrancisco036 | -.0000943 | .0002296 | -0.41 | 0.682 | -.0005486 | .00036 |
| _cons | .3687264 | .1318508 | 2.80 | 0.006 | .1078753 | .6295775 |

```
. regress realpriceappreciation BPSanFrancisco, vce(robust)

Linear regression                               Number of obs     =       120
                                                F(1, 118)         =     21.68
                                                Prob > F          =    0.0000
                                                R-squared         =    0.2188
                                                Root MSE          =    .93511
```

| realpriceapp~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPSanFrancisco | .001298 | .0002787 | 4.66 | 0.000 | .000746 | .00185 |
| _cons | -.2726454 | .1587451 | -1.72 | 0.089 | -.5870039 | .0417131 |

```
. regress realpriceappreciation TOMSanFrancisco, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      76.37
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3247
                                                Root MSE          =      .8694

------------------------------------------------------------------------------
                |               Robust
realpriceappr~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
TOMSanFrancisco |  -.0489293    .0055989    -8.74   0.000    -.0600166    -.037842
          _cons |   1.939309    .1886194    10.28   0.000     1.565791    2.312827
------------------------------------------------------------------------------

. regress realpriceappreciation UIISanFrancisco, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      97.15
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4455
                                                Root MSE          =     .78783

------------------------------------------------------------------------------
                |               Robust
realpriceappr~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
UIISanFrancisco |  -.3377851    .0342709    -9.86   0.000    -.4056509   -.2699193
          _cons |   1.647534    .1246614    13.22   0.000      1.40067    1.894397
------------------------------------------------------------------------------

. regress realpriceappreciation tenyrtreasury, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      53.52
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3380
                                                Root MSE          =     .82333

------------------------------------------------------------------------------
               |               Robust
realpriceap~n  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
tenyrtreasury  |  -.8762046    .1197713    -7.32   0.000    -1.113158   -.6392514
         _cons |   2.625412    .3052644     8.60   0.000     2.021483    3.229341
------------------------------------------------------------------------------
```

**Santa Clara:**

```
. newey realpriceappreciation HAISantaClara, lag(1)

Regression with Newey-West standard errors      Number of obs     =       132
maximum lag: 1                                  F(  1,        130) =      6.42
                                                Prob > F          =    0.0125
```

| realpriceap~n | Coef. | Newey-West Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| HAISantaClara | -4.341816 | 1.713281 | -2.53 | 0.012 | -7.731338 | -.9522933 |
| _cons | 1.433735 | .4651356 | 3.08 | 0.003 | .5135202 | 2.35395 |

```
. regress realpriceappreciation lagBPSantaClara036, vce(robust)

Linear regression                               Number of obs     =       132
                                                F(1, 130)         =     10.05
                                                Prob > F          =    0.0019
                                                R-squared         =    0.1836
                                                Root MSE          =    1.0031
```

| realpriceappreci~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| lagBPSantaClara036 | -.0036154 | .0011405 | -3.17 | 0.002 | -.0058719 | -.001359 |
| _cons | .708933 | .1173716 | 6.04 | 0.000 | .4767274 | .9411386 |

```
. regress realpriceappreciation BPSantaClara, vce(robust)

Linear regression                               Number of obs     =       120
                                                F(1, 118)         =      6.26
                                                Prob > F          =    0.0137
                                                R-squared         =    0.0253
                                                Root MSE          =    1.1237
```

| realpricea~n | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| BPSantaClara | .002438 | .0009745 | 2.50 | 0.014 | .0005082 | .0043679 |
| _cons | .1325291 | .1378283 | 0.96 | 0.338 | -.1404083 | .4054666 |

```
. regress realpriceappreciation TOMSantaClara, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =     135.13
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4615
                                                Root MSE          =     .83519

------------------------------------------------------------------------------
             |               Robust
realpriceap~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
TOMSantaClara |  -.1096018   .0094283   -11.62   0.000    -.1282725   -.0909311
       _cons |   2.855403   .2109816    13.53   0.000     2.437602    3.273204
------------------------------------------------------------------------------

. regress realpriceappreciation UIISantaClara, vce(robust)

Linear regression                               Number of obs     =        120
                                                F(1, 118)         =      33.58
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4185
                                                Root MSE          =     .86789

------------------------------------------------------------------------------
             |               Robust
realpriceap~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
UIISantaClara |  -.3200901   .0552367    -5.79   0.000    -.4294738   -.2107064
       _cons |   1.372057   .1666635     8.23   0.000     1.042018    1.702097
------------------------------------------------------------------------------

. regress realpriceappreciation tenyrtreasury, vce(robust)

Linear regression                               Number of obs     =        132
                                                F(1, 130)         =      57.98
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3355
                                                Root MSE          =     .90494

------------------------------------------------------------------------------
             |               Robust
realpriceap~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
tenyrtreasury |  -.9577095   .1257742    -7.61   0.000    -1.206539   -.7088803
       _cons |   2.838393   .3235808     8.77   0.000     2.198227    3.478559
------------------------------------------------------------------------------
```

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