

2010

Forecasting the Inland Empire's Economic Recovery

Jesse C. Franklin
Claremont McKenna College

Recommended Citation

Franklin, Jesse C., "Forecasting the Inland Empire's Economic Recovery" (2010). *CMC Senior Theses*. Paper 42.
http://scholarship.claremont.edu/cmc_theses/42

This Open Access Senior Thesis is brought to you by Scholarship@Claremont. It has been accepted for inclusion in this collection by an authorized administrator. For more information, please contact scholarship@cuc.claremont.edu.

CLAREMONT MCKENNA COLLEGE
FORECASTING THE INLAND EMPIRE'S ECONOMIC RECOVERY

SUBMITTED TO

PROFESSOR MARC WEIDENMIER
AND
PROFESSOR DAVID BJERK

AND

DEAN GREGORY HESS

BY

JESSE C FRANKLIN

FOR

SENIOR THESIS

FALL/2010

NOVEMBER 29TH, 2010

Abstract

The Inland Empire -Riverside and San Bernardino Counties - was one of the hardest hit areas in all of the United States during the Great Recession. Home prices have declined over 50%, significantly more than the 25% decline in the surrounding Los Angeles County, and housing starts have declined to over 90% from 2005. The Inland Empire has one of the highest unemployment rates in the US at 14.8%. This paper attempts to forecast the recovery for the Inland Empire. Employing univariate forecasts along with VAR(12) forecasts, focusing on housing starts and unemployment rates as the underlying variables, we find that there is little hope for a recovery over the next 3 years. The model predicts unemployment to either rise even more or, at best, remain stagnant. Housing starts are predicted to remain constant over the next three years.

Table of Contents

Introduction.....1

Literature Review3

Data12

Empirical Analysis13

Discussion36

References.....38

Introduction

The Inland Empire- Riverside and San Bernardino Counties- has mostly been characterized as a region of tremendous growth and this is likely the reason why the Inland Empire was one of the hardest hit areas in all of the United States during the Great Recession. Since 1970 the Inland Empire has almost quadrupled in population, a rate nearly twice that of the rest of California and about 2.5 times that of the rest of the United States (FRED). By the year 2006, the Inland Empire housed over 4 million people. Perhaps this massive influx of people, meaning workers searching for new jobs and new houses, was the reason why this region could be considered the epicenter of the recent economic recession. According to the September 2010 labor maker numbers, the unemployment rates are 15.3% in Riverside County and 14.2% in San Bernardino County (FRED). That is a combined average of 14.8%, a rate significantly higher than the California average of 12.4% and the United States level of 9.6%. Home prices have declined from an average of nearly \$400,000 in the summer of 2006, to less than \$200,000 (RAND). This 50% decline is substantially higher than the 25% decline in the surrounding Los Angeles County. With such dramatic levels unemployment and a deteriorating housing market, we have to ask ourselves, why the Inland Empire? And even more importantly what can be done to predict and possibly prevent another similar economic catastrophe?

Most of the job loss in US recessions comes in construction and durable manufacturing. Edward Leamar (2007) has tracked fluctuations in US economy and noticed that problems the in housing industry preceded eight of the past 10 recessions. Home prices are very sticky downward, and when faced with a decline in demand, it is

the volume of sales that adjusts instead of the prices. The sluggishness of price adjustments is what makes the volume cycle so extreme, and what makes housing so influential in recessions. With the decline in sales volume comes a like decline in jobs in construction, finance and real estate brokerages. Leamer's models for identifying the year before recessions, based on the 10 components of the Index of Leading Indicators, show that housing starts offer the most accurate predictions. Leamer finds that residential investment contributes consistently and substantially to the weakness in the economy before recessions when business investment in equipment and software do not.

This paper builds on Leamer's (2007) notion that housing is the best indicator of recessions and uses housing data from the Inland Empire to forecast economic activity. Housing starts in the Inland Empire have seen a dramatic decline in the past five years falling from nearly 5,000 per month in the summer of 2005 to approximately 300 per month by the last quarter of 2009 (Keil and Weidenmier 2010). Recently, there has been a slight rebound in housing starts. July 2010 recorded housing starts above the 500 unit per month level. Employment data suggest that the rate of job losses in Inland Empire construction is finally starting to slowdown. Fortunately enough, with depreciation levels in the Inland Empire beginning to level off, there is hope for homebuilders who want to obtain credit in order to finance new housing developments.

According to Manfred Keil (2010), housing and construction is one of the most important industries in the Inland Empire. This paper will analyze data from these sectors and use autoregressive models to determine if a recovery is in sight. With housing starts on the rise and the number of foreclosures diminishing, there is still hope for a recovery in the Inland Empire.

Literature Review

The literature on residential investment and its effect on economic activity suggests that the housing market plays a direct role in predicting economic recessions. Edward Leamer (2007) goes as far as to claim that housing is the business cycle. He notes that despite accounting for only 4.2% of total long-run growth, residential investment plays an important role in predicting US recessions. Using kernel smoothing, Leamer is able to find residential investment's cumulative abnormal contribution before and after a recession. The analysis shows that residential investment subtracts from GDP growth before a recession and then starts to contribute more than normal to GDP growth in the second and third quarters of the recession. The same tests using equipment and software instead of residential investment yielded quite different results. Leamer (2007, p. 10-13) finds that residential investment contributes consistently and substantially to economic weakness before recessions while business investment and equipment and software do not. The subsequent recovery for housing takes place earlier and is completed earlier than the recovery for equipment and software. Leamer highlights the point that before the 1980 recession a decline in housing removed almost 1 percentage point from the normal GDP growth of 3% (2007, p. 13). Eight of the past 10 recorded recessions were preceded by sustained and significant problems in the residential industry.

Leamer (2007) claims that the reason why housing is so important during a recession is that homes have a volume cycle not a price cycle. He explains why home prices are considered to be very sticky downward. In other words, because we love our homes and therefore attach a lot of emotions to our homes we are very reluctant to sell

our home for anything less than we had originally paid for it. Because of this stickiness, when faced with a decrease in demand, it is the volume of sales that adjusts, not the prices. This sluggishness of price adjustments is what makes the volume cycle so extreme, and what makes housing so important in a recession. When there is a decline in sales volume there comes a corresponding increase in unemployment. This is particularly true in construction, finance and real estate brokerages.

Coulson and Kim (2000) employ a multivariate autoregressive model in order to analyze the causality and influence of non-residential investment and residential investment with respect to GDP. The VAR is made up of four equations that determine the different components of GDP: residential investment, non-residential investment, consumption and government spending, as lagged functions of each of the four components. A fifth equation was used that computes GDP as a sum of the four components. Using VAR analysis they created shocks that are associated with the four variables and used these shocks to evaluate their importance to and simulate their effects on GDP. They found that GDP's response to a shock in residential investment has several times the magnitude versus its response to a shock in non-residential investment (2000, p. 239). Coulson and Kim assume that this must be true because residential investment was found to have a significant positive effect on consumption while non-residential investment did not (2000, p. 240). Consumption plays a key role in predicting GDP as shown in a variance decomposition table. This table shows that in the first causal ordering consumption shocks accounts for 74% of the one-quarter horizon forecast variance in GDP and 64% in a year (2000, p. 245). Furthermore, the decomposition table shows that the residential shock explains much more of the variation in GDP than the

non-residential shock.

Case and Shiller (1988) present the results of a survey inspired by an article on page A1 of the June 1, 1988 *Wall Street Journal*, which described the current ‘frenzy in California’s big single family home market.’ Samples were drawn from around 2000 households, all of whom had bought a home in May 1988 from four different markets: Orange County, San Francisco, Boston, and Milwaukee. The four cities were chosen to represent hot (California), cold (Boston) and steady (Milwaukee) markets. The main question asked to homeowners was, “If you had been unable to sell your home for the price that you received what would you have done?” When a similar survey was repeated in 2003 the answers of the original 254 respondents did not materially change over the years (Case & Shiller 2003). Of the total, 37 percent said that they would have “left the price the same and waited for a buyer, knowing full well that it might take a long time.” Another 28 percent answered that they would have taken the house off the market or rented it. In addition, 30 percent answered that they would have “lowered the price step by step hoping to find a buyer.” Only 12 respondents, less than five percent, answered that they would have “lowered the price until they found a buyer.”

The results provide strong evidence that buyers are influenced by an investment motive, that they have strong expectations about future price changes in their housing markets, and that they perceive little risk. The responses to many of these questions provide further support to Leamer’s (2007) assumption that psychological factors play a significant role in house purchasing decisions.

In a more recent paper, Case and Shiller (2003) build on their previous surveys to find that home-buyers’ expectations are substantially affected by recent experience. The

researchers provide further support for the fact that buyers lower their asking prices only as a last resort. The majority of respondents claim you should 'hold up until you get what you want' and only a small minority of respondents reported that they would have "lowered the price till I found a buyer." Surveys showed that after a long boom, home-buyers typically have expectations that prices over the next 10 years will show at least double-digit annual price growth and they believe this comes with a modest level of risk. In post-boom San Francisco, 78.8% of respondents claimed they would maintain reservation prices and in Boston 93% said the same. With home owners maintaining a sticky-price attitude, the real danger in housing markets, after a fall in demand, is a sharp fall in volume. This will likely cause a lower household consumption (from a reduction in the equity withdrawal that frequently accompanies housing changes), a reduction in the consumer expenditures that are associated with housing changes, reduced fee income to financial institutions, and a reduction in the flexibility of the labour market. These types of effects could do more damage to the US economy today than a slight decline in prices.

To demonstrate the volume cycle Leamer (2002 p. 25) looks at the LA housing market. He notices a steep run-up in both prices and volumes from 1985 to 1989. After peaking in November 1988, sales volume fell by 50% in a year and a half. Despite the decline in volume, home prices continued to appreciate for nearly a year until July 1989, and then, even with the sales rates at half the previous level, prices began to level off. It was not until a year later in June 1991, when prices began their slow decline at roughly 5% annually, reaching their lowest point four and a half years later, December 1996, down a total of 27%.

Using a multivariate regression with GDP growth as the dependent variable, thus

treating all recessions as similar in temporal structure, Leamer highlights that we live in a consumer cycle not a business cycle (2007, p 23). The top four explanatory variables with significant t-statistics were residential investment, consumer services, consumer nondurables and consumer durables. Business spending on equipment and software, structures and inventory, did not significantly contribute to GDP growth in a measurable fashion. Leamer underscores the finding that the coefficient of 2 on residential investment means that any unusual residential investment contribution to GDP in one quarter predicts twice as much contribution than any other sector in the next quarter.

Looking at the graphs of the real prices of new homes sold in four different regions of the United States, Leamer concludes that it is not the housing structure that has a volatile price; it is the land (2007 p. 27-28). In regions where there is a lot of useable land the response to an increase in demand for homes is to build more, not an increase in home prices. Where there is little buildable land, a response to an increase in demand is to increase prices, just enough to discourage buyers and reequilibrate supply and demand.

Using a similar method to test market prices as pioneered by Case and Shiller (1988), where the 20 zip codes with the lowest median price are separated from the 20 zip codes with the highest median price, Leamer separates home by structure size and compares appreciation rates in the LA market (2002, p 25-26). Consistent with the findings of Case and Shiller, it turns out that smaller homes had the greatest appreciation in 2000-2006.

Comparing the correlograms of inflation against inflation in the previous month and housing starts against housing starts in the previous months, Leamer finds very different results (2007, p 39-50). Inflation is very persistent in that once inflation starts it tends to

hang around for a very long time; a correlation of .63 comparing month to month eventually declines to .2 after 4 years. For housing starts the correlation of housing starts compared to the previous month is very high at .93. It declines all the way to zero by 2 years and -.2 by 36 months. Leamer notes that this is the correlogram of a cycle. This shows that for housing it is the cycle that is persistent.

Karl Case examines a similar case using housing starts as a means to predict unemployment and national income. He explains that when existing home sales decline or housing starts drop, the economy experiences a decline in aggregate expenditure and ultimately a reduction in employment (Case 2006). A decline in residential fixed investment affects developers, builders, and the construction industry. Case notes that the multiplier for residential investment has been estimated to be 1.4. In other words, a 100 dollar drop in income from a decline in residential investment will reduce national income by about 140 dollars (2006, p.10). Case gauges this effect by comparing the performance of housing investment (Flow of Funds data) and new home construction (monthly housing starts) during its past cycles, specifically from January 1973 through October 2006. Within this 33 year period Case finds that there were four major declines, three of these declines leading to economic recessions. In all three cases, housing starts fell by about 60-65 percent, while gross residential investment fell from about 5.5 percent to about 3.5 percent of GDP.

In order to estimate the magnitude of the impacts of a decline in the housing industry on the national economy, Case, using the Fair Model (Fair 2004), simulates the effects of a substantial decline in housing investment on real GDP (2006, p. 15-16). Using housing data from October 2006, Case demonstrates how the shock will have a

great effect on the core economy. The effect of a decline in new construction of residential fixed assets produces a substantial reduction in GDP growth, significantly higher than the baseline estimate quoted in the press in December 2006. This housing decline is similar to the three described previously such that housing starts are over 2 million. The difference is that the peak of gross residential investment is at twice the height of the peaks in the last three downturns. When simulating a shock to new residential construction, consistent with the slowdown of previous post-war housing booms, the real growth rate in the US economy declines from 2.7% to about 1.0%. The same shock leads to estimated job losses of 1.4 million and to an increase in the unemployment rate of 0.8 percentage points.

Calomiris, Longhofer, and Miles employ a panel vector autoregressive model to examine how distress in the housing market interacts with macroeconomic and housing variables (2008). Using quarterly state-level data from 1981 through 2007 Calomiris et al. uses foreclosures to measure distress levels and uses housing prices, sales, housing permits, and unemployment rates to measure macroeconomic and housing market fluctuations (2008, p.10-11). He finds that foreclosure shocks (increases in the quarterly log foreclosure rate) have a significant negative effect on employment and housing prices. Additionally, he found significant effects showing that foreclosure shocks are associated with increases in sales and permits. Calomiris et al. claims that this could suggest that substantial increases in foreclosures are likely to occur late in the down stage of the housing cycle.

In order to better quantify the foreclosure-price relationship, Calomiris employs the dynamic quarterly state-level model to generate out-of-sample forecasts (8 quarters

beyond the estimation sample) of housing price changes by state and nationally (2008, p. 10-18). The researchers constructed three forecasting shock scenarios, the “zero shock scenario,” the “foreclosure shock scenario” (increasing Economy.com’s foreclosure rating by 53%), and the “extreme shock scenario” (increasing Economy.com’s foreclosure rating by 75%). On a state-by-state basis, they regressed the log level of the MBA foreclosure rate on four lags of itself and the contemporaneous value and four lags of the log level of the foreclosure start rate. Using the estimated coefficients from these regressions and Economy.com’s forecasts of the foreclosure start rate, they dynamically predicted the log level of the foreclosure rate in each state through the end of 2009. From the three scenario’s not one predicts extreme declines in housing prices. This reiterates the point made by Case and Shiller (2002) and Leamer (2007) that housing prices are very sticky. Calomiris concludes that even after taking into consideration many of the biases associated with the nonlinearities of the foreclosure-price relationship he has conservatively overestimated prices declines from 2007Q2 peak to 2009Q4 will be approximately 4.5% He makes clear that even under the extremely pessimistic scenarios for foreclosures shocks, home prices, measured by the OFHEO index, would fall only slightly or remain mostly flat in response to foreclosures.

Leamer concludes his paper by mentioning that policy targets should take into consideration housing starts (2007). He claims that the main role of the Federal Reserve is to “make us happy.” Although they do not mention residential investment in their plan to maintain this “happiness,” Leamer suggests they should. He claims that recessions are a major source of our unhappiness and attention to the housing market would make recessions less frequent and less severe.

DATA

Data for the Inland Empire's monthly unemployment rate from January 1990 to July 2010 was obtained from the St. Louis Federal Reserve of Economic Data (<http://research.stlouisfed.org/fred2/series/RIVE106URN>). The seasonally adjusted rates were computed by Professor Keil. Data for Construction Employment in the Inland empire from January, 1990 to July 2010, measured monthly in terms of 1000's of workers, was obtained from the US Bureau of Economic Analysis. Inland Empire housing starts (monthly) and housing permits (monthly) from January 1990 to July 2010 was obtained from the St. Louis Federal Reserve of Economic Data (<http://research.stlouisfed.org/fred2/series/RIVE106BP1FH>). Seasonally adjusted rates were computed by Professor Keil. The Inland Empire's levels of foreclosures, from January 2001 to June 2010, were obtained from the RAND California Business and Economic Statistics website (<http://ca.rand.org/stats/economics/foreclose.html>). Industrial, Office Space, and Retail and Shopping Vacancy rates for the Inland Empire from 2002 to 2010 (computed quarterly) were obtained from US Bureau of Economic Analysis.

Empirical Analysis

In order to develop a forecast model for housing starts in the Inland Empire I employed a univariate forecasting model. The general form of the model can be written as:

$$Y_t = \alpha + \beta Y_{t-1}$$

where Y_t is housing starts today and Y_{t-1} is the lagged level of housing starts (monthly periods). Using sample data from January 1990 to July 2010 I ran the univariate regression. Using the results from table 1, I was able to forecast housing starts for the next three years. Figure 1 displays this forecast.

Table 1 shows that regression coefficient for housing_starts_{t-1} is significant at the 1% level. This is important in developing a more accurate forecast for housing_starts. Figure 1 shows that housing starts demonstrate a historically cyclical pattern. Inland Empire housing starts were at its lowest level in February 2009 and remained relatively constant through July 2010. The forecast for the next 3 years reveals a relatively flat decrease in housing_starts. This seems accurate seeing that the forecast follows the historically cyclical pattern.

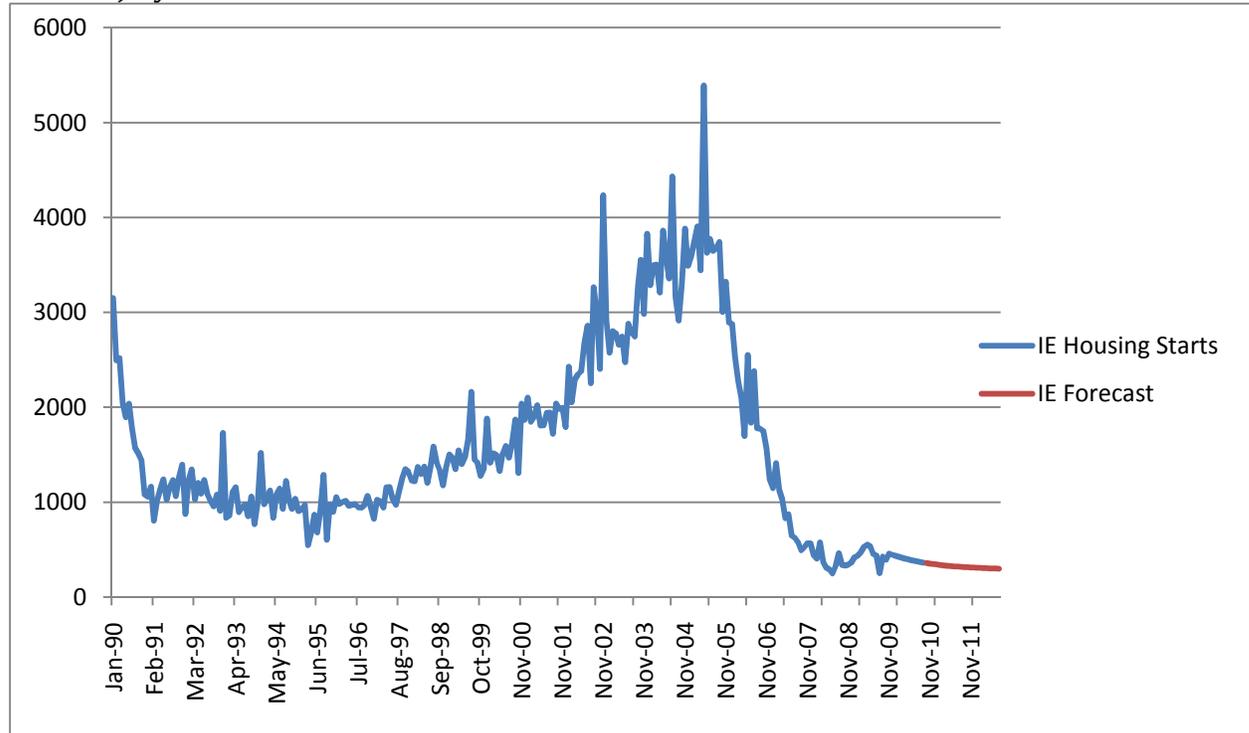
Table 1. Univariate regression results for Inland Empire's number of housing_starts (monthly) on housing_starts_{t-1}, January 1990 to June 2010.

VARIABLES	(1) housing_starts
housing_starts _{t-1}	0.927*** (0.0237)
Constant	107.4** (45.11)
Observations	246
R-squared	0.863

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 1. History and univariate forecast for Inland Empire housing_starts, January 1990 to July 2013



In order to develop a forecast model for the number of housing permits issued in the Inland Empire I employed a univariate forecasting model. The general form of the model can be written as:

$$Y_t = \alpha + \beta Y_{t-1}$$

where Y_t is housing permits issued today and Y_{t-1} is the lagged number of housing permits issued (using 1 lag and monthly periods). Using sample data from January 1990 to June 2010 I ran a univariate regression. Using the regression results from table 2, I was able to forecast the number of housing permits issued for the next three years. Figure 2 displays this forecast.

Table 2 shows that regression coefficient for $\text{housing_permits}_{t-1}$ is significant at the 1% level. This is important in developing a more accurate forecast for housing_permits because the past data significantly affects the current data. Figure 2 shows that the number housing permits issued demonstrate a similar historically cyclical pattern as housing_starts. Housing starts appear to lag behind housing permits. This is logical seeing that one must obtain a housing permit before commencing the building of a house. The Inland Empire issued its lowest number of housing permits in September 2008 and remained relatively constant through July 2010. The forecast for the next 3 years reveals a slight recovery in the number of housing permits issued. The forecast shows the number of housing permits being

issued increasing at a decreasing rate. This seems accurate seeing that the forecast follows the historically cyclical pattern for housing permits.

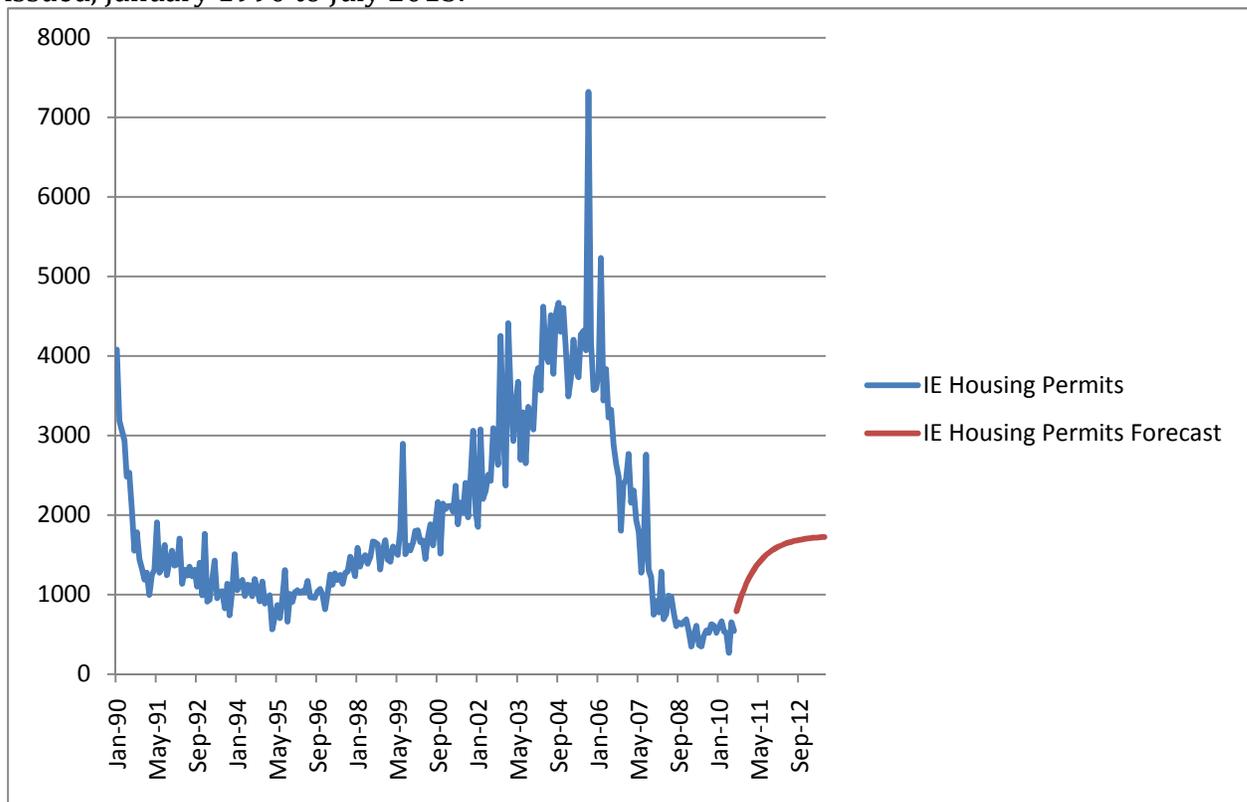
Table 2. Univariate regression results for Inland Empire's number of housing_permits issued (monthly) on number of housing_permits_{t-1} issued, January 1990 to July 2010.

VARIABLES	(1) housing_permits
housing_permits _{t-1}	0.891*** (0.0284)
Constant	189.5*** (62.56)
Observations	246
R-squared	0.802

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 2. History and univariate forecast for Inland Empire's housing_permits issued, January 1990 to July 2013.



In order to develop a forecast model for the number of foreclosures in the Inland Empire I employed a univariate forecasting model. The general form of the model can be written as:

$$Y_t = \alpha + \beta Y_{t-1}$$

where Y_t is foreclosures today and Y_{t-1} is the lag of foreclosures (using monthly periods). Using sample data from January 2002 to June 2010 I ran a univariate regression. Using the regression results from table 3, I was able to forecast the number of foreclosures for the next three years. Figure 3 displays the forecast.

Table 3 shows that the regression coefficient for foreclosures_{t-1} is significant at the 1% level. This is important in creating a more accurate forecast for foreclosures seeing that past foreclosure data significantly affects current data. Figure 3 displays the Inland Empire's volatile foreclosure history over the past 8 years, starting in January 2002. The Inland Empire foreclosure level reached its peak of 6,574 in August 2008. After the peak in August 2008, until June 2010, the foreclosure level had decreased and has been fluctuating above and below 3500. The forecast for the following three years implies a relatively flat decrease in the foreclosure level. From June 2010 until June 2013 the foreclosure level, as predicted by the univariate regression, will decrease at an increasing rate.

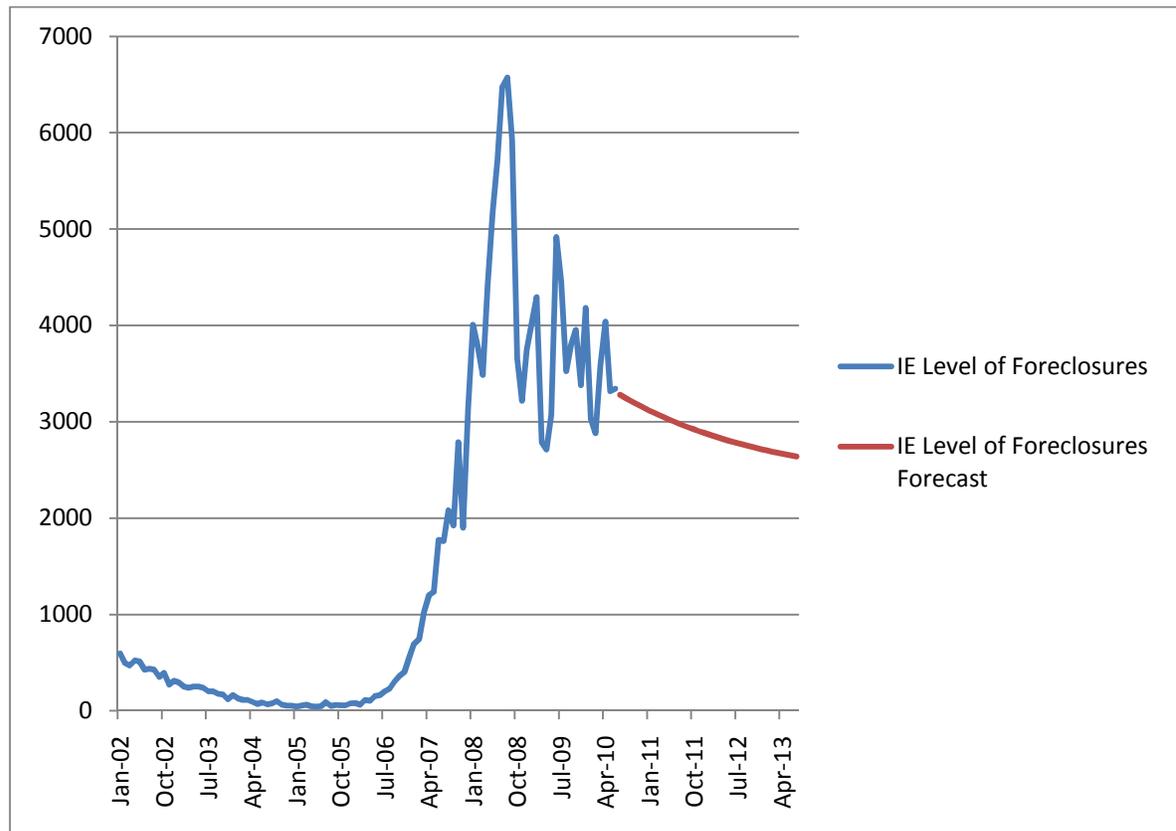
Table 3. Univariate regression results for Inland Empire's number of foreclosures (monthly) on number of foreclosures_{t-1}, January 1990 to June 2010

VARIABLES	(1) foreclosures
foreclosures _{t-1}	0.968*** (0.0266)
Constant	74.54 (62.48)
Observations	101
R-squared	0.930

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 3. History and univariate forecast for Inland Empire’s number of foreclosures, January 1990 to June 2013



Similar forecasting methods were employed for the Inland Empire’s commercial real estate vacancy rates. I regressed the level of industrial_space_vacancy on the level of industrial_space_vacancy_{t-1} (Table 4), the level of office_space_vacancy on the level of office_space_vacancy_{t-1} (Table 5), and finally the level of retail_shopping_space_vacancy on the level of retail_shopping_space_vacancy_{t-1} (Table 6). The sample periods were gathered quarterly from 2000Q2 to 2009Q4. The forecasts for industrial_space_vacancy, office_space_vacancy, and retail_shopping_space_vacancy are displayed in Figure 4.

The regression results for all three vacancy rates (industrial space, office space, and retail and shopping space) show a regression coefficient that is significant at the 1% level. Figure 4 shows that the vacancy rates for the three categories of commercial real-estate have been increasing continuously from the first quarter of the 2000 fiscal year. There is a sharp increase in vacancy rate slopes starting in first quarter of 2007. All three vacancy rates peak in the first two quarters of 2009. Industrial space vacancy rates reach their peak at 11.5%, office space vacancy reach their peak at 16.8%, and retail and shopping vacancy rates reach their peak at 8.7%. The forecasts in figure 4 reveal a steady increase in vacancy rates for the next 12

quarters. Office space vacancy rates appear to have the steepest increase. Industrial and shopping and retail space vacancy rates have relatively parallel forecasts.

Table 4. Univariate regression results for Inland Empire's level of industrial_space_vacancy on level of industrial_space_vacancy_{t-1}, 2000Q1-2013Q4 (Quarterly)

VARIABLES	(1) industrial_space_vacancy
industrial_space_vacancy _{t-1}	1.005***
	(0.0515)
Constant	0.00134
	(0.00364)
Observations	39
R-squared	0.911

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Univariate regression results for Inland Empire's level of office_space_vacancy on level of office_space_vacancy_{t-1}, 2000Q1-2013Q4 (Quarterly)

VARIABLES	office_space_vacancy
office_space_vacancy _{t-1}	1.022***
	(0.0337)
Constant	0.000177
	(0.00336)
Observations	39
R-squared	0.961

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

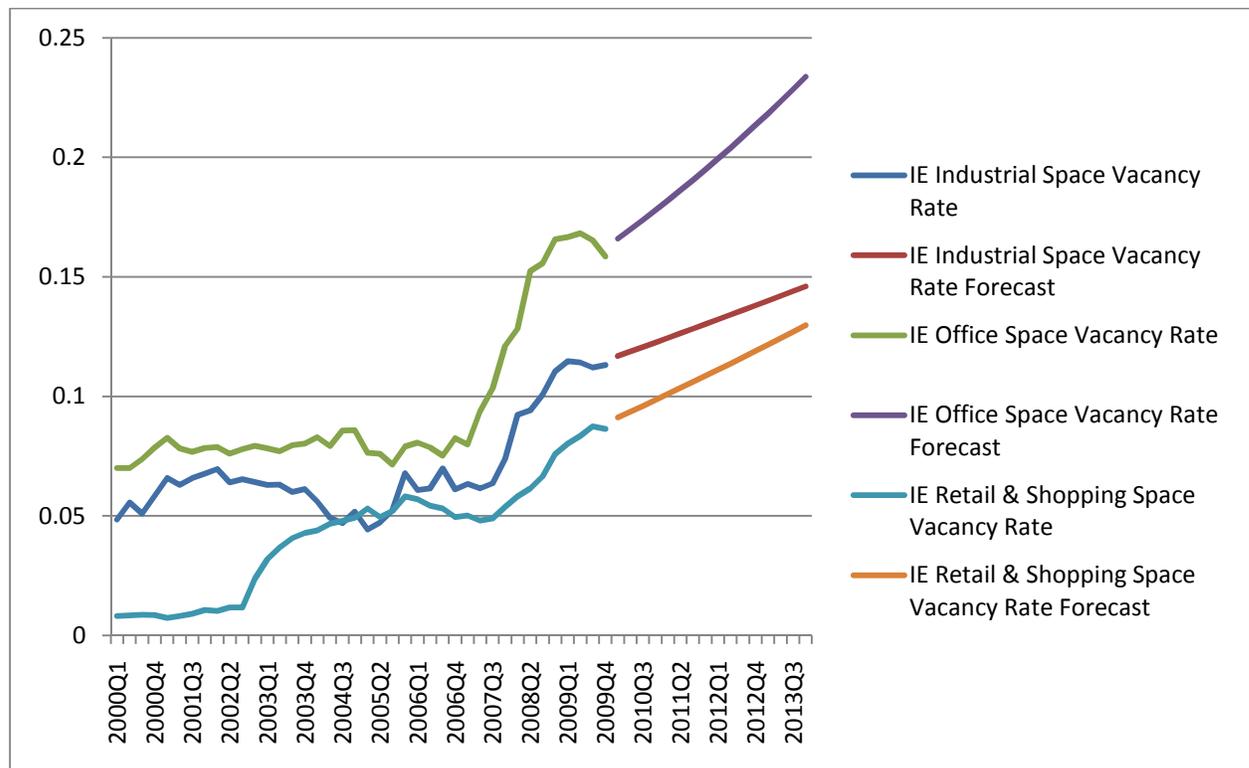
Table 6. Univariate regression results for Inland Empire's level of retail_shopping_space_vacancy on level of retail_shopping_space_vacancy_{t-1} , 2000Q1-2013Q4 (Quarterly)

VARIABLES	(1) retail_shopping_space_vacancy
retail_shopping_space_vacancy _{t-1}	1.008*** (0.0232)
Constant	0.00166 (0.00110)
Observations	39
R-squared	0.981

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 4. Vacancy rate histories and univariate forecasts for Inland Empire's industrial space, office space, and retail and shopping space vacancies, 2000Q1-2013Q4



A univariate regression and forecast model was employed in order to forecast unemployment rates and the level of construction workforce for the Inland Empire. The sample data was obtained monthly from January 1990 to July 2010. I regressed the level of unemployment on the level of unemployment_{t-1} and then, using the regression coefficients, I forecasted unemployment rates for the next three years. The regression results can be found in table 6 and the forecast for unemployment is displayed in figure 5. I also regressed the level of construction workers on the level of construction_workers_{t-1} and then forecasted the level of construction workers for the next three years using the regression coefficients. The regression results can be found in table 7 and the forecast for the number of new construction workers is displayed in figure 6.

The regression results in table 6 show that the regression coefficient on Unemployment_{t-1} is significant at the 1% level. The corresponding 3 year forecast suggests that the Inland Empire's unemployment level will continue to increase as it has for the past 4 years. According the forecast, the unemployment rate is predicted to reach its highest level in the past 20 years at nearly 18% by July 2013. The regression results in table 7 show that the regression coefficient on construction_workers_{t-1} is significant at the 1% level. After steadily declining since its peak in June 2006, the corresponding 3 year forecast suggests that the Inland Empire's construction work force level will began to flatten out. This is logical seeing that this forecast is analogous to the housing starts forecast. Construction workers are required to build houses and thus it is logical that the forecast for the number of housing starts and the number of construction workers will follow a similar trend.

Table 6. Univariate regression results for Inland Empire's lagged level of unemployment rates on current unemployment rates, January 1990 to July 2010

VARIABLES	(1) Unemployment rate
Unemployment _{t-1}	1.006*** (0.00598)
Constant	-6.80e-05 (0.000479)
Observations	246
R-squared	0.991

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 5. Univariate history and forecast of Inland Empire's unemployment rates, January 1990 to July 2013

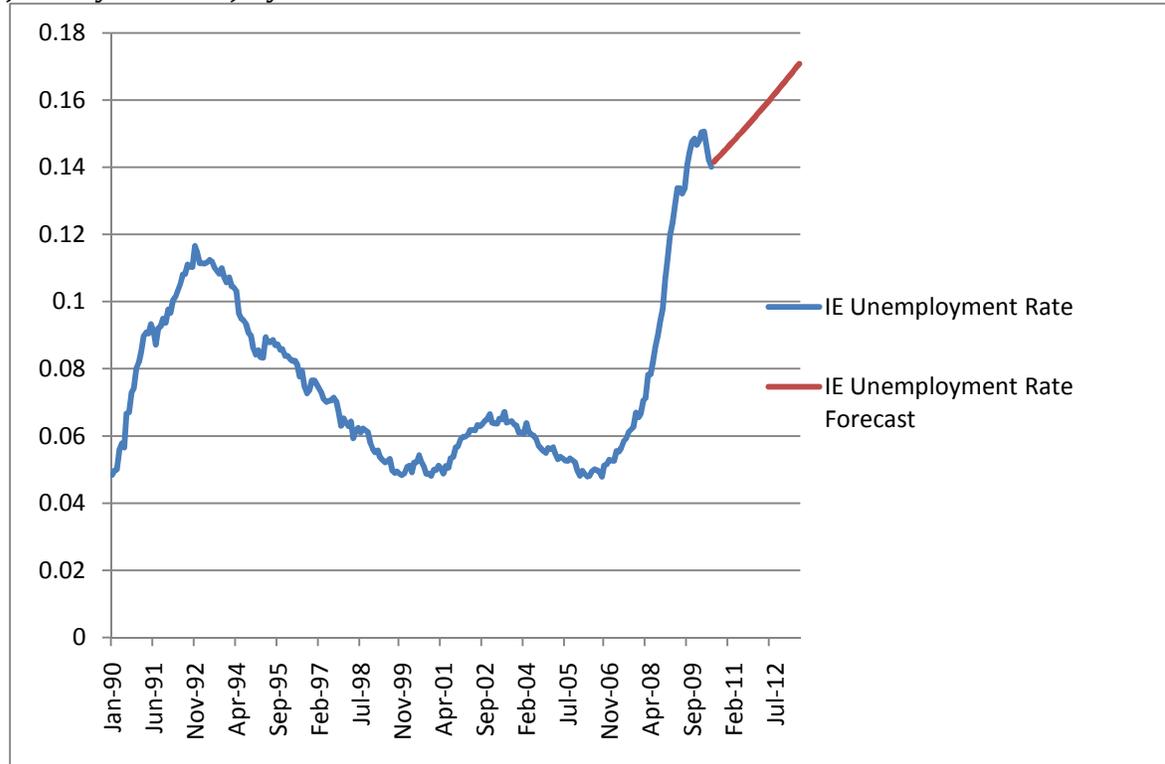


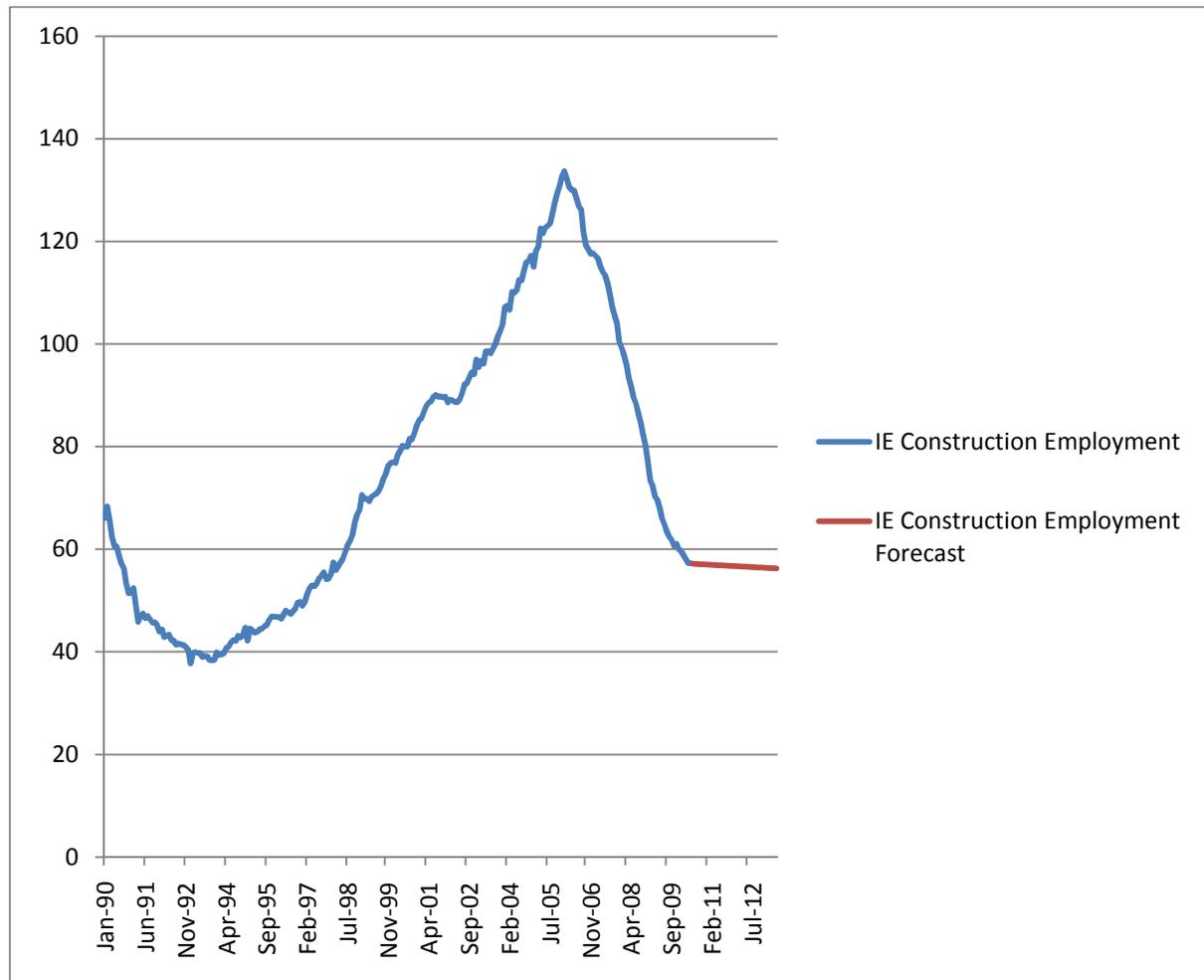
Table 7. Univariate regression results for Inland Empire's number of construction_workers on number of construction_workers_{t-1}, January 1990 to July 2010

VARIABLES	(1) construction_workers
construction_workers _{t-1}	0.999*** (0.00308)
Constant	0.00712 (0.246)
Observations	246
R-squared	0.998

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 6. History and forecast for Inland Empire's number of construction_workers, January 1990 to July 2013.



In order to fully capture the relationship between housing starts and unemployment I employed a multivariate regression using a VAR model. The two variable VAR(12) requires two equations, one for each variable. In each equation I regressed the relevant left-hand-side variable on 12 lags of itself and 12 lags of the other variable. The equations can be written as follows:

$$y_{1,t} = \varphi_{11}y_{1,t-1} + \varphi_{12}y_{1,t-2} + \dots + \varphi_{112}y_{1,t-12} + \varphi_{113}y_{2,t-1} + \varphi_{114}y_{2,t-2} + \dots + \varphi_{124}y_{2,t-12} + \varepsilon_{1,t}$$

$$y_{2,t} = \varphi_{21}y_{1,t-1} + \varphi_{22}y_{1,t-2} + \dots + \varphi_{212}y_{1,t-12} + \varphi_{213}y_{2,t-1} + \varphi_{214}y_{2,t-2} + \dots + \varphi_{224}y_{2,t-12} + \varepsilon_{2,t}$$

$y_{1,t}$ represents housing starts and $y_{2,t}$ represents the unemployment rate. In contrast to the univariate case, the VAR model allows for cross-variable dynamics. Each variable is related not only to its own past but also to the past of the other variable. In our case, the number housing starts is being related to the past of housing starts and the past of unemployment rates. The same is true for unemployment rates. The VAR forecast is constructed in a way that precisely

parallels the univariate forecast. The 12-step-ahead forecast can be generated immediately because all the variables on the right hand side have already been lagged by 12 periods. Using the 12-step-ahead forecast I constructed the corresponding 36 month, out-of-sample forecast for housing starts. This forecast is displayed in figure 7. The forecast for unemployment is displayed in figure 8.

Similar to the univariate forecast for housing starts, the VAR forecast (Figure 7) suggests that housing starts will remain constant over the next 3 years. Contrary to the univariate forecast for unemployment (figure 5), suggesting that the unemployment level will increase steadily during the next 3 years, the VAR forecast (figure 8) predicts an optimistic, steady decline in the unemployment level over the next 3 years. The VAR forecast in figure 8 has the opposite prediction for level of unemployment compared to the univariate forecast for unemployment rates in figure 5. The VAR forecasts predicts a recovery in the unemployment rate over the next 36 months, declining to almost 7%, whereas the univariate forecast for unemployment rates predicts a sharp increase in the unemployment rate to nearly 18%. When developing the best possible forecast we must consider the possibility that the unemployment rate may not only be related to its own past but also to the pasts of other variables; in this case the unemployment rate is related to housing starts.

Figure 7. VAR forecast for housing starts using housing starts and unemployment as the underlying variables, July 2010-July 2013

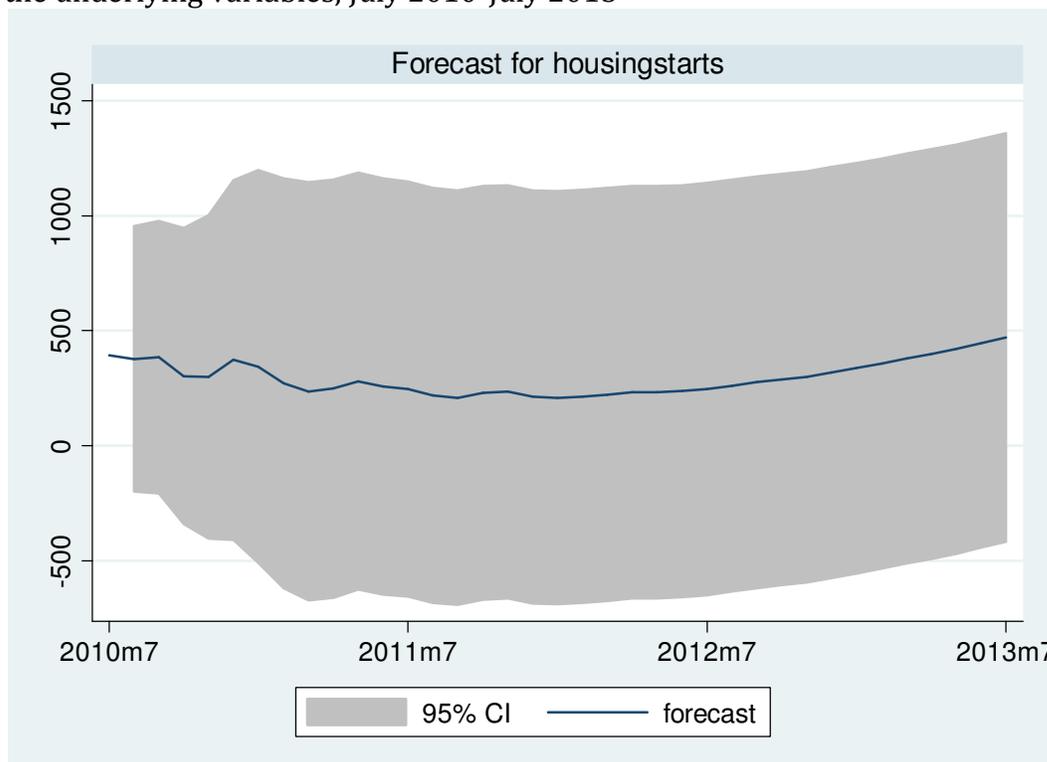
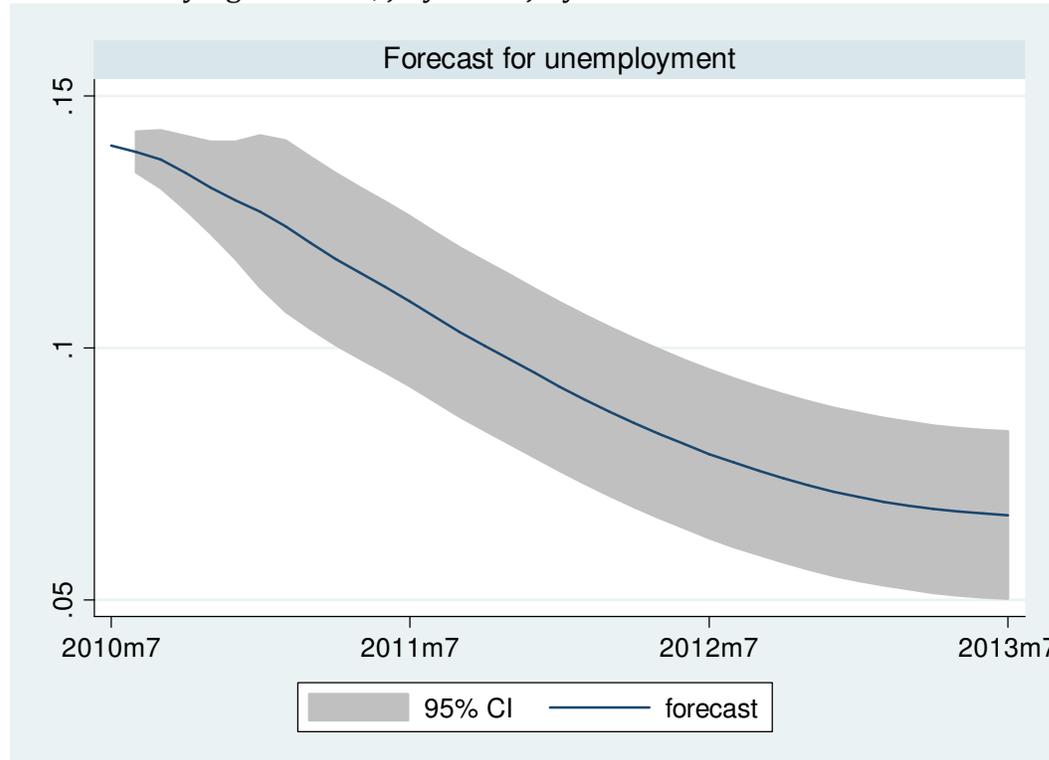


Figure 8. VAR forecast for unemployment using housing starts and unemployment as the underlying variables, July 2010-July 2013



In order to analyze the relationship between unemployment and the number of construction workers I repeated the two variable VAR(12) forecast using the Inland Empire's unemployment rate and the Inland Empire's number of construction workers as the underlying variables.

Figure 9 displays the 36 month forecast for unemployment using unemployment and the number of construction workers as the underlying variables. The forecast appears very similar to the VAR forecast for unemployment in figure 8. This is logical seeing that the actual trend in the number of construction workers is highly relative to actual trend of housing starts. Figure 8 shows a slightly steeper negative slope than figure 9. Again we see that the VAR forecast in figure 9 has the opposite prediction for the level of unemployment compared to the univariate forecast for the unemployment rate in figure 5.

Figure 10 displays the 36 month VAR forecast for the number of construction workers in the Inland Empire. Similar to the univariate forecast in figure 6, the number of construction workers appears to stay relatively constant over the next 36 months.

Figure 9. VAR forecast for unemployment using unemployment and number of construction workers as the underlying variables, July 2010-July 2013

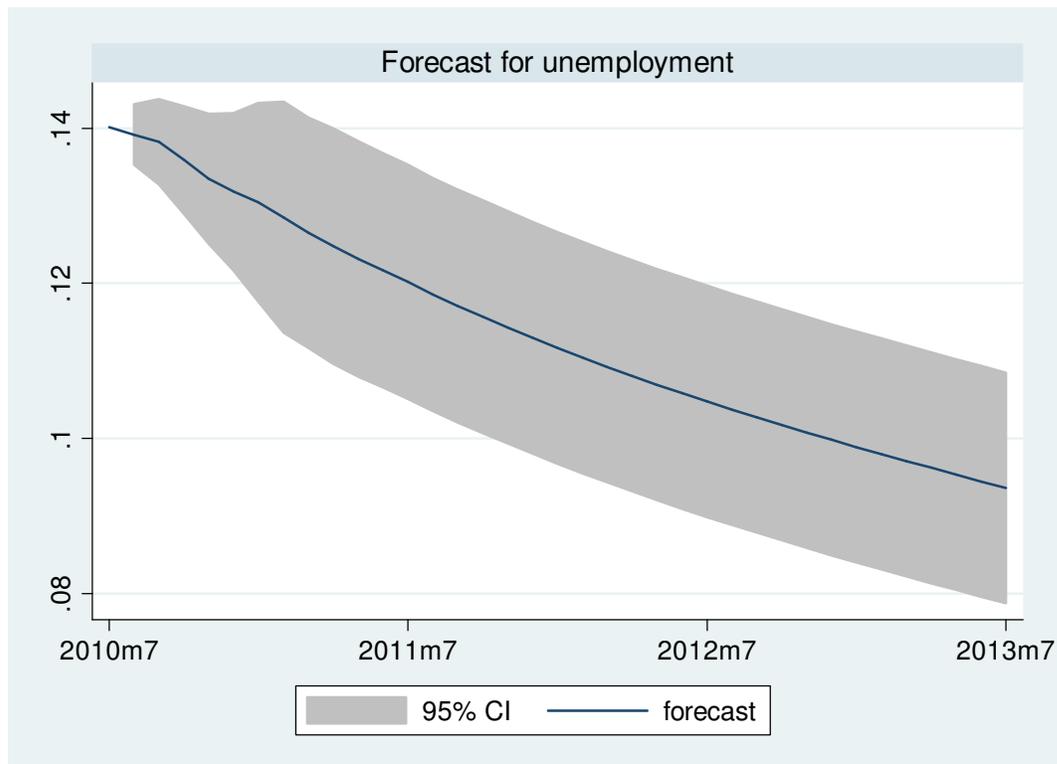
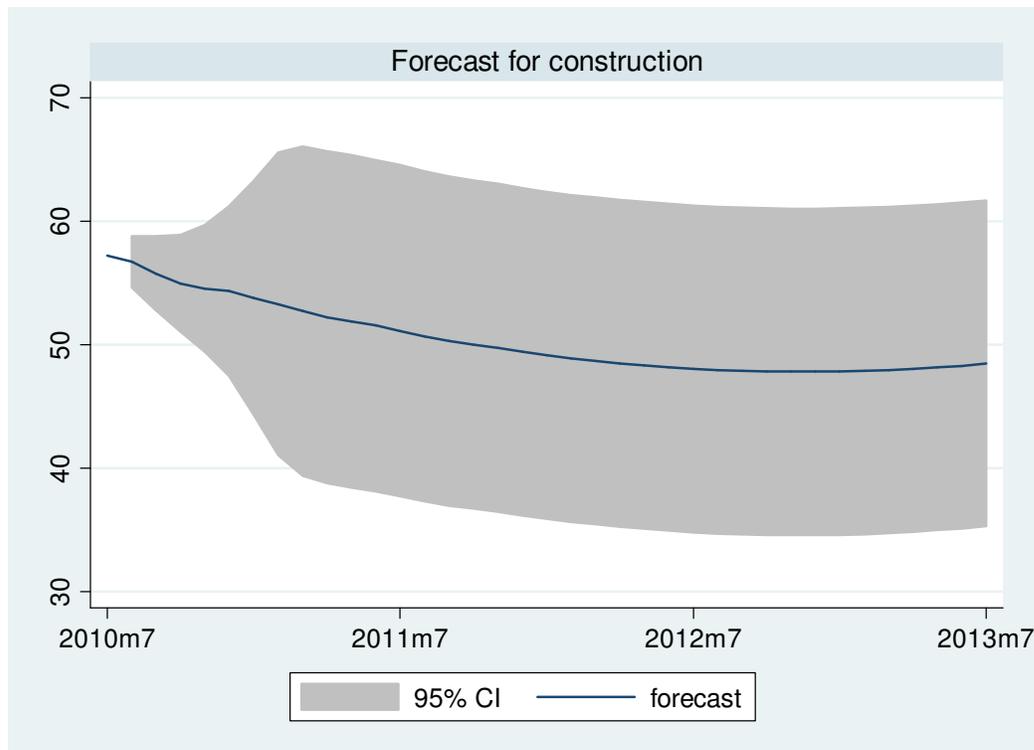


Figure 10. VAR forecast for the number of construction workers using unemployment and number of construction workers as the underlying variables, July 2010-July 2013



In order to analyze the relationship between unemployment and the number of housing permits issued I repeated the two variable VAR(12) forecast using the Inland Empire's unemployment rate and the Inland Empire's number of housing permits issued as the underlying variables.

Figure 11 displays the 36 month forecast for unemployment using unemployment and the number of housing permits as the underlying variables. The forecast appears very similar to the VAR forecast for unemployment in figure 8. Seeing that the trend in the number of housing permits issued is highly relative to trend of housing starts (a permit is required to build a house) it is logical that both figure 11 and figure 8 appear similar. Again we see that the VAR forecast in figure 11 has the opposite prediction for the level of unemployment compared to the univariate forecast for the unemployment rate in figure 5.

Figure 11. VAR forecast for unemployment using unemployment and number of housing permits issued as the underlying variables, July 2010-July 2013

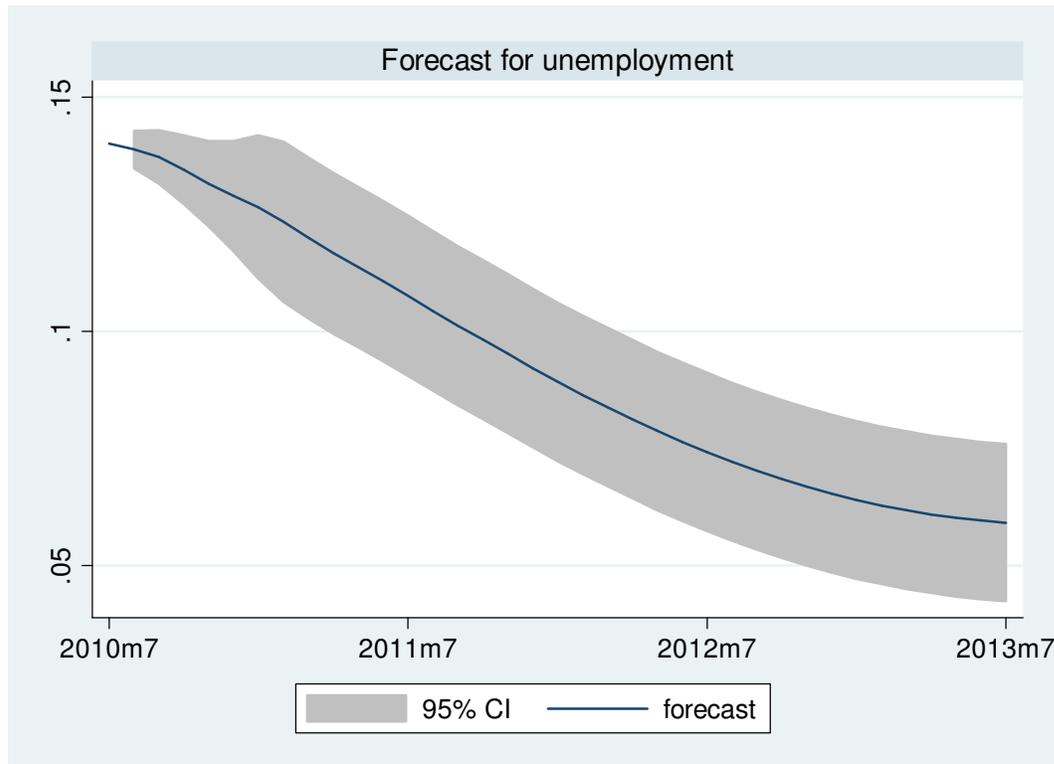
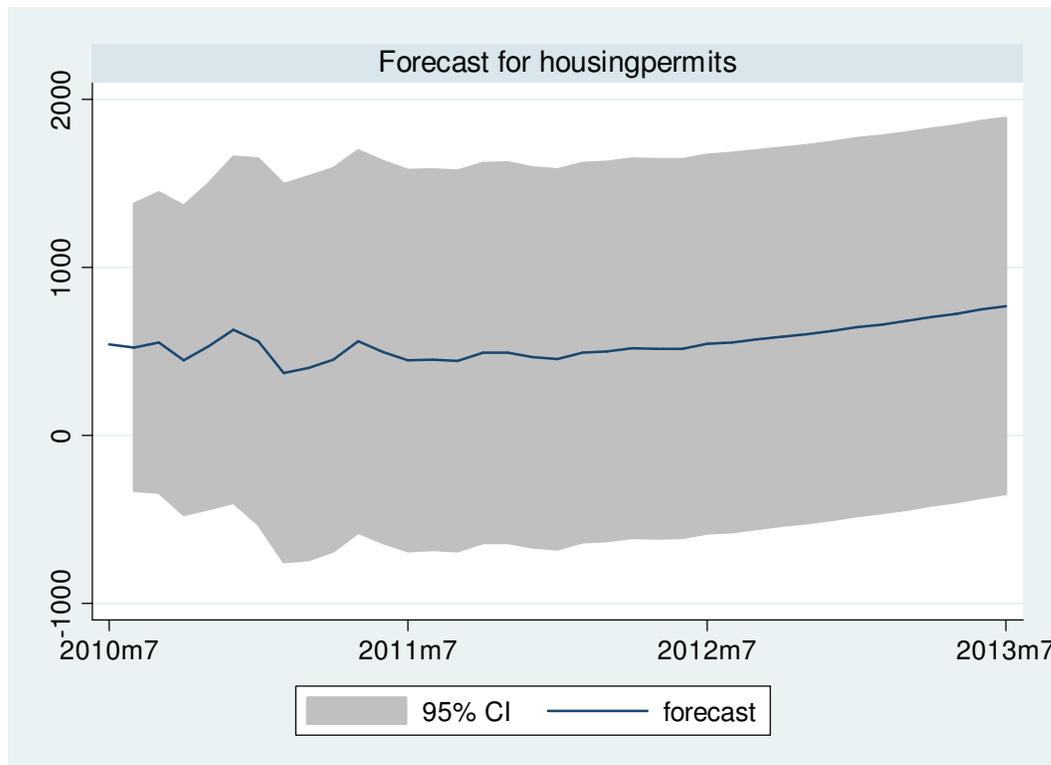


Figure 12. VAR forecast for the number of housing permits issued using unemployment and number of housing permits issued as the underlying variables, July 2010-July 2013



In order to test the reliability of the two variable VAR forecasts I compared the actual trend in the last 36 of months of data to the in-sample forecasted trend. If the in-sample forecasts are comparable to the actual trend then we can assume that the out-of-sample forecasts have a higher prediction power. In order to develop an in-sample forecast from July 2007 to July 2010 I used sample data from January 1990 to June 2007, employed multivariate VAR(12) models, similar to the models used to develop out-of-sample forecasts, and then forecasted based on the model's results.

Figure 12 displays the actual trend of the Inland Empire's unemployment rate data from July 2007 to July 2010. Figure 13 displays the actual trend of the Inland Empire's housing start data from July 2007 to July 2010. Figure 14 displays the actual trend of the Inland Empire's construction worker data from July 2007 to July 2010. Figure 15 displays the actual trend of the Inland Empire's housing permits data from July 2007 to July 2010.

Figure 12. Actual trend of the Inland Empire’s unemployment rate data, July 2007-July 2010.

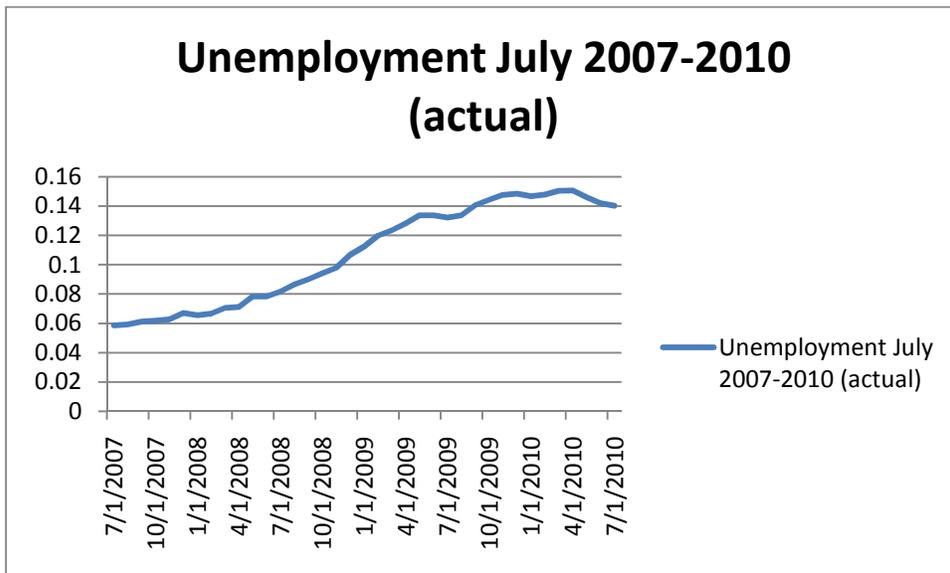


Figure 13. Actual trend of Inland Empire’s housing start data, July 2007-July 2010.

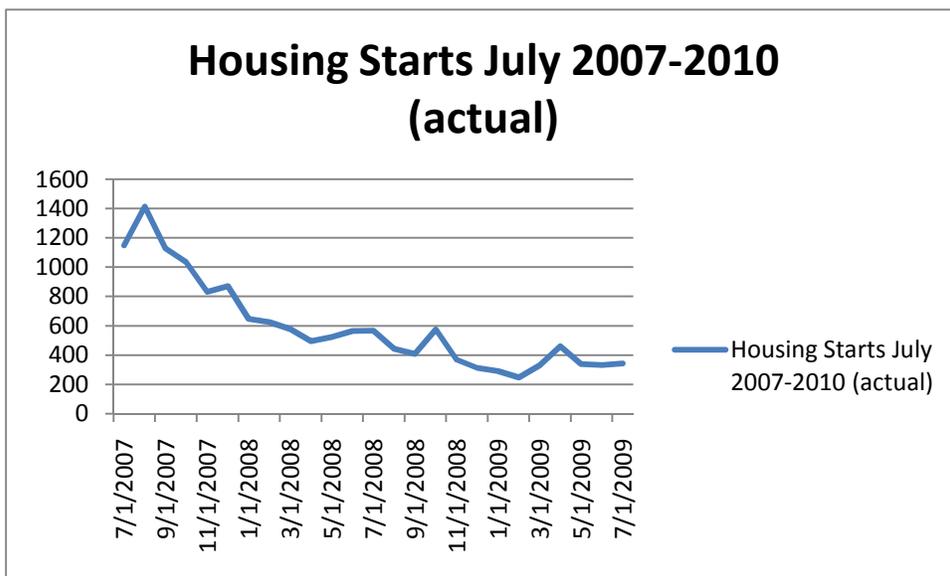


Figure 14. Actual trend of Inland Empire's construction employment data (thousands), July 2007-July 2010.

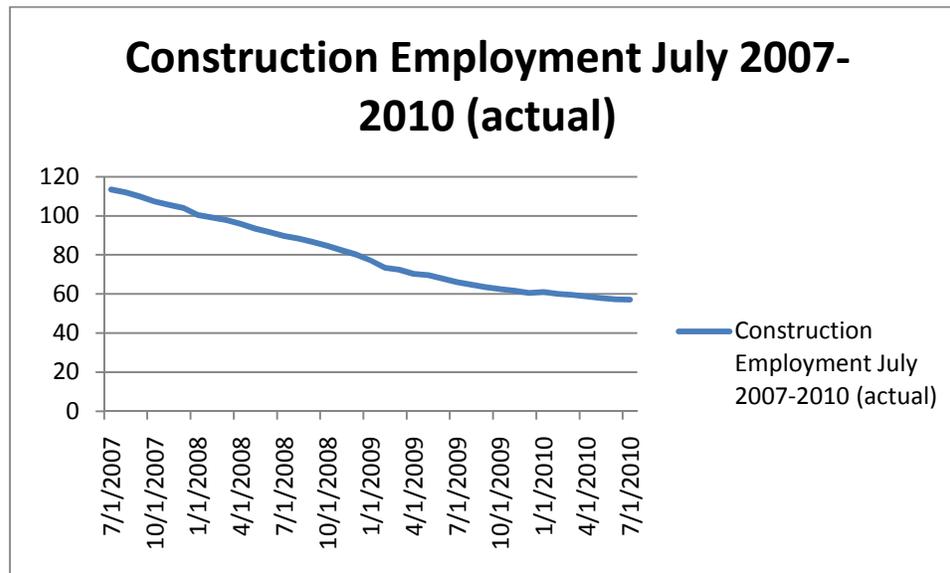
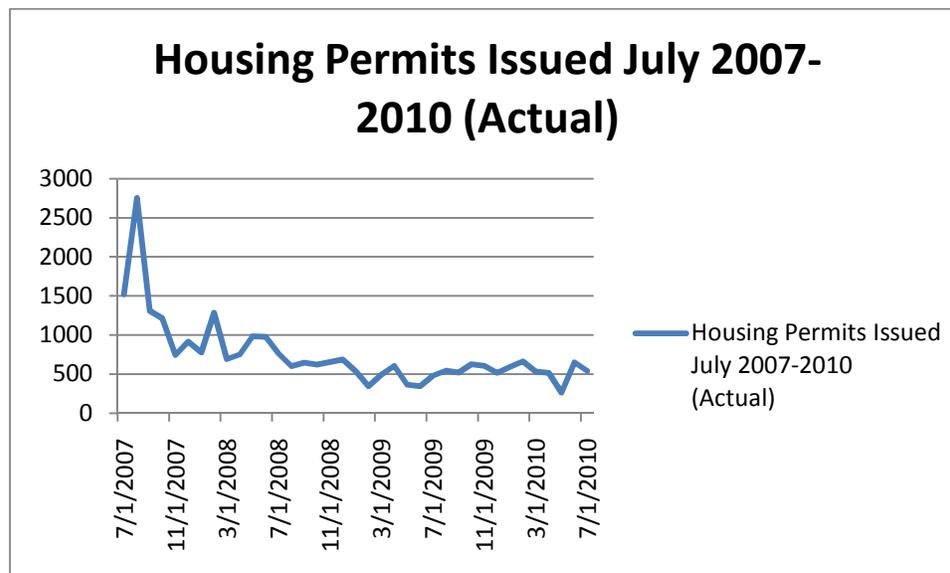


Figure 15. Actual trend of the Inland Empire's housing permit data, July 2007-July 2010.



I repeated the multivariate regression and VAR forecast from figures 7 and 8 (unemployment and housing starts) excluding the sample data from July 2007 through July 2010. The in-sample forecast for the unemployment rate is displayed in figure 16. Comparing the actual trend in figure 12 with the forecasted trend in figure 16 we find that the two graphs are very similar. Although the actual trend shows

that unemployment reaches above 14% by July 2010 while the forecast predicts unemployment rates reaches only 7%, both the forecasted and actual trends have similar patterns. This seemingly large difference in magnitude is reflected in the unexpected volatility of original data. It is not until the last 3 years, 2007 to 2010, when unemployment rates more than double, rising from 6% to 14%. The in-sample VAR forecast excludes the last three years of data in the regression and therefore is unable to capture this extreme increase in the unemployment rate. Despite magnitude differences of the graphs, the in-sample forecast and actual trend display very similar patterns. This suggests that the VAR model, using unemployment and housing starts as the underlying variables, is an acceptable model for forecasting unemployment. The in-sample forecast for housing starts is displayed in figure 17. Comparing the actual trend in figure 13 with the forecasted trend in figure 17 we find that the two graphs appear unrelated. Perhaps regressing the past unemployment rates in combination with the past housing starts is not the best model for predicting housing starts. The two in-sample forecasts suggest that the past housing starts may have an important affect in predicting the unemployment rate whereas the past unemployment rates may not be as important in predicting housing starts.

Figure 16. In-sample VAR forecast for unemployment using housing starts and unemployment as the underlying variables, July 2007-July 2010

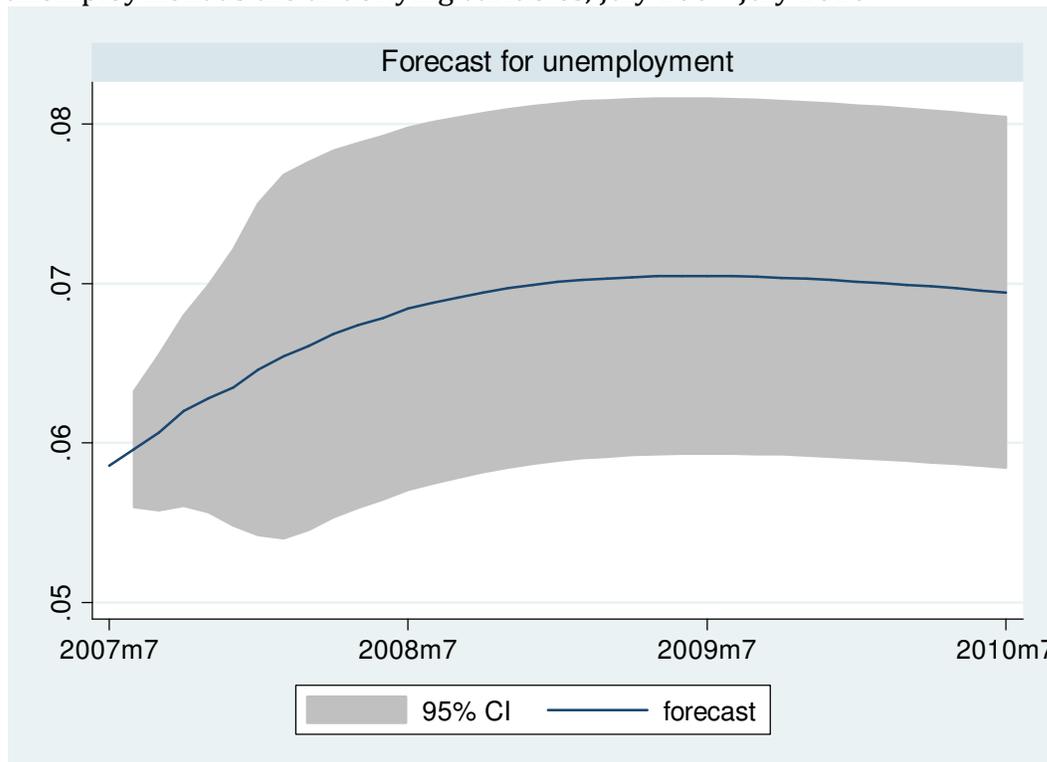
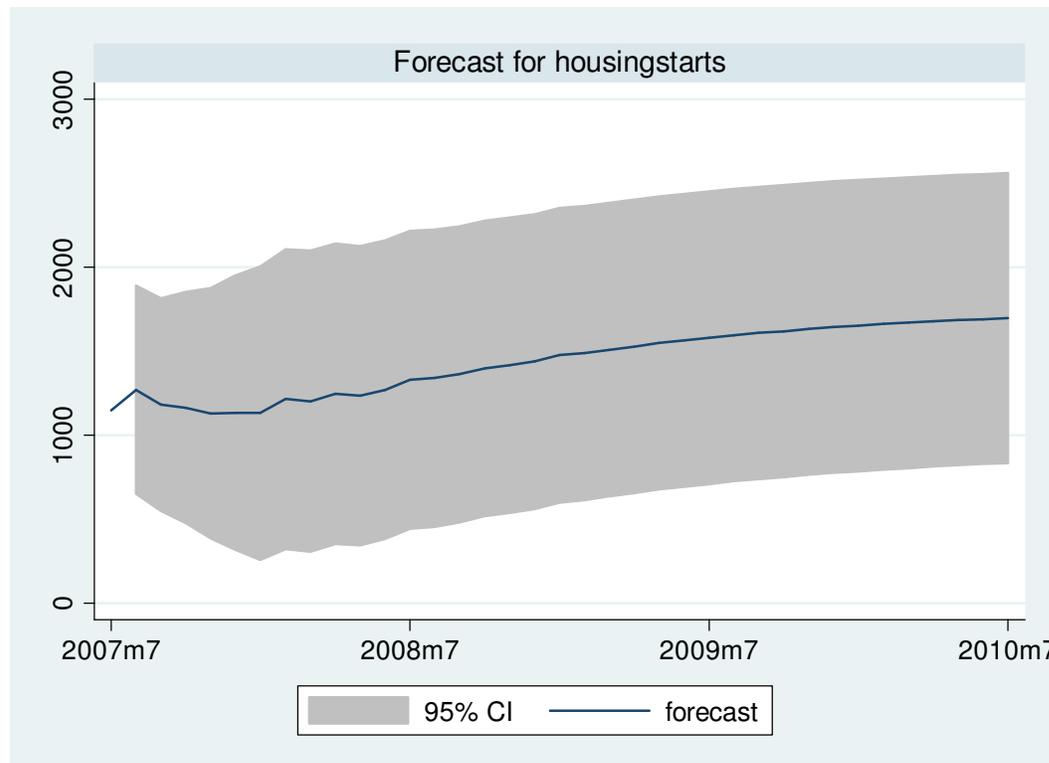


Figure 17. In-sample VAR forecast for housing starts using housing starts and unemployment as the underlying variables, July 2007-July 2010



I repeated the multivariate regression and VAR forecast displayed in figures 9 and 10 (unemployment and construction workers) excluding the sample data from July 2007 through July 2010. The in-sample forecast for the Inland Empire's unemployment rate is displayed in figure 18. Comparing the actual trend in figure 12 with the forecasted trend in figure 18 we find that the two graphs are very similar. Although the actual trend shows that unemployment reaches above 14% by July 2010 while the forecast predicts unemployment rates reaches only 8%, both the forecasted and actual trends have similar patterns. This seemingly large difference in magnitude is reflected in the unexpected volatility of original data. It is not until the last 3 years, 2007 to 2010, when unemployment rates more than double, rising from 6% to 14%. The in-sample VAR forecast excludes the last three years of data in the regression and therefore is unable to capture this extreme increase in the unemployment rate. Despite the magnitude differences of the graphs, the in-sample forecast and actual trend display very similar patterns. This suggests that the VAR model, using the unemployment rate and the number of construction workers as the

underlying variables, is an acceptable model for forecasting unemployment. The in-sample forecast for the number of construction workers is displayed in figure 19. Comparing the actual trend in figure 14 with the forecasted trend in figure 19 we find that the two graphs are highly relative. The two in-sample forecasts suggest that the past numbers of construction workers may play an important role in predicting unemployment rates and the past unemployment rates may play an important role in predicting housing starts.

Figure 18. In-sample VAR forecast for unemployment using unemployment and the number of construction workers as the underlying variables, July 2007-July 2010

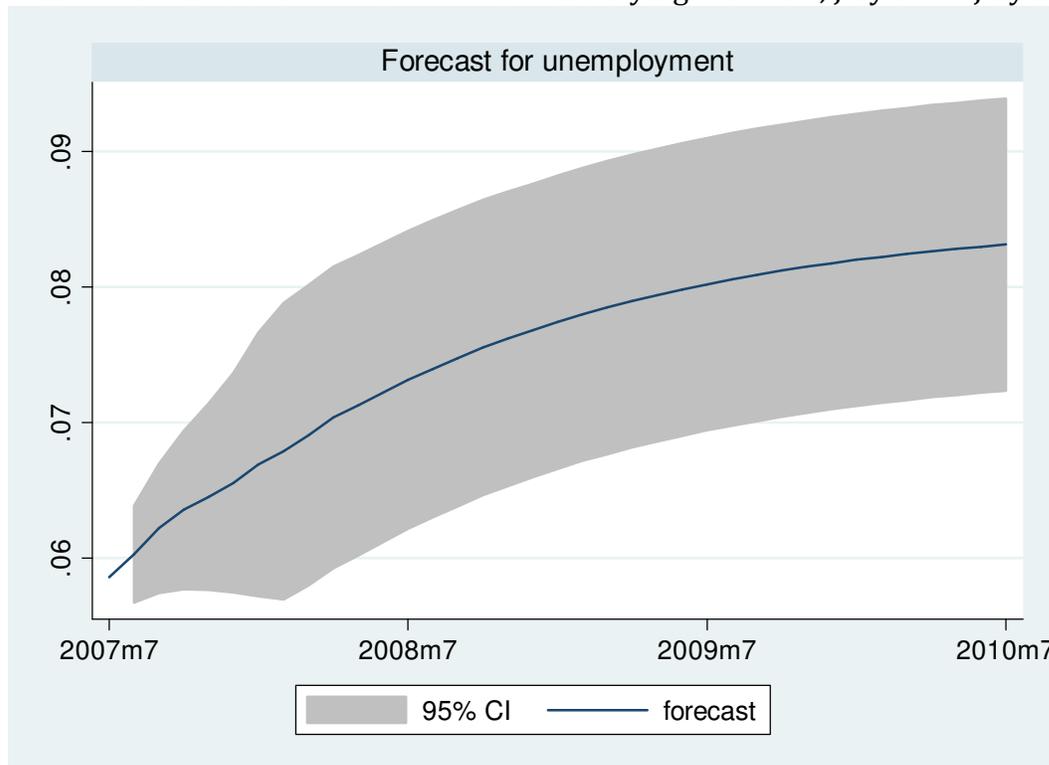
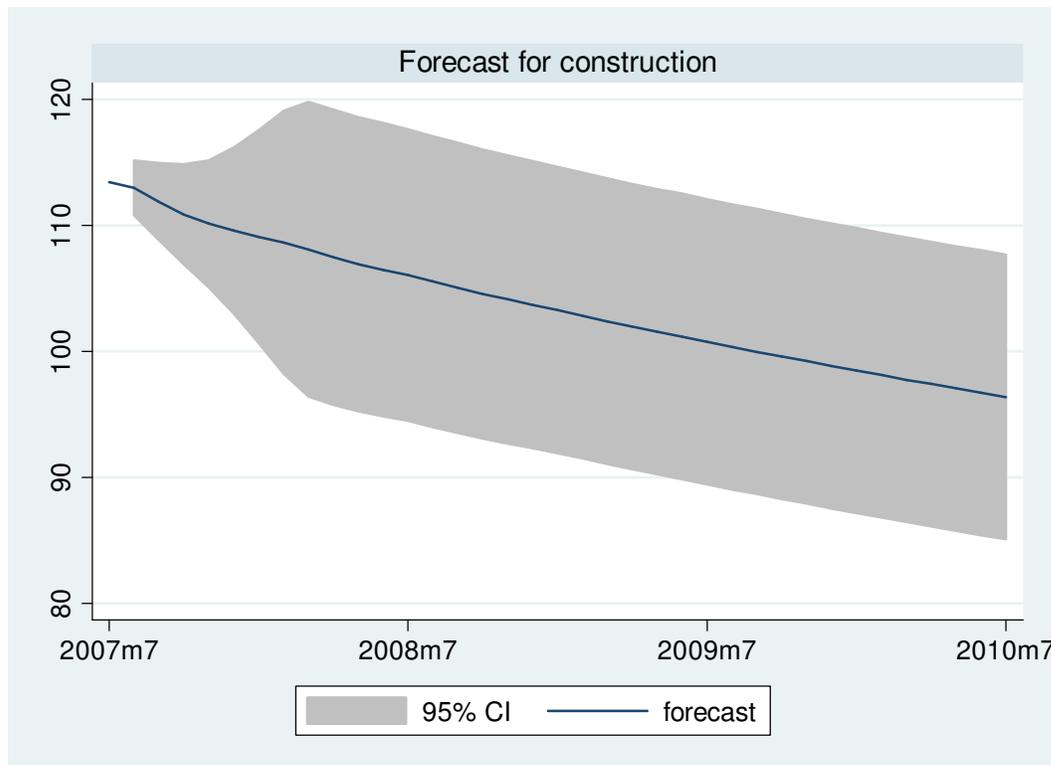


Figure 19. In-sample VAR forecast for the number of construction workers using unemployment and the number of construction workers as the underlying variables, July 2007-July 2010



I repeated the multivariate regression and VAR forecast displayed in figures 11 and 12 (unemployment and construction workers) excluding the sample data from July 2007 through July 2010. The in-sample forecast for the Inland Empire's unemployment rate is displayed in figure 20. Comparing the actual trend in figure 12 with the forecasted trend in figure 20 we find that the two graphs are relative. Although the actual trend shows that unemployment reaches above 14% by July 2010 while the forecast predicts unemployment rates reaches only 7%, both the forecasted and actual trends have similar patterns (see page 31 for in depth explanation for magnitude difference). This suggests that the VAR model, using the unemployment rate and the number of housing permits issued as the underlying variables, is an acceptable model for forecasting unemployment. The in-sample forecast for the number of housing permits issued is displayed in figure 21. Comparing the actual trend in figure 15 with the forecasted trend in figure 21 we find that the two graphs are mostly unrelated despite both showing constant rates of change from July 2009 to July 2010. The two in-sample forecasts suggest that the past numbers of housing permits issued may play an important role in predicting unemployment rates while the past unemployment rates may not play an important role in predicting the number of housing permits issued. Because housing permits are required to start the building of a house it is logical that both, the past housing starts and the past number of housing permits issued, are not key players in

predicting unemployment. Furthermore, it is logical that the past of unemployment plays a key role in predicting both housing starts and the number of housing permits issued.

Figure 20. In-sample VAR forecast for unemployment using unemployment and the number of housing permits issued as the underlying variables, July 2007-July 2010

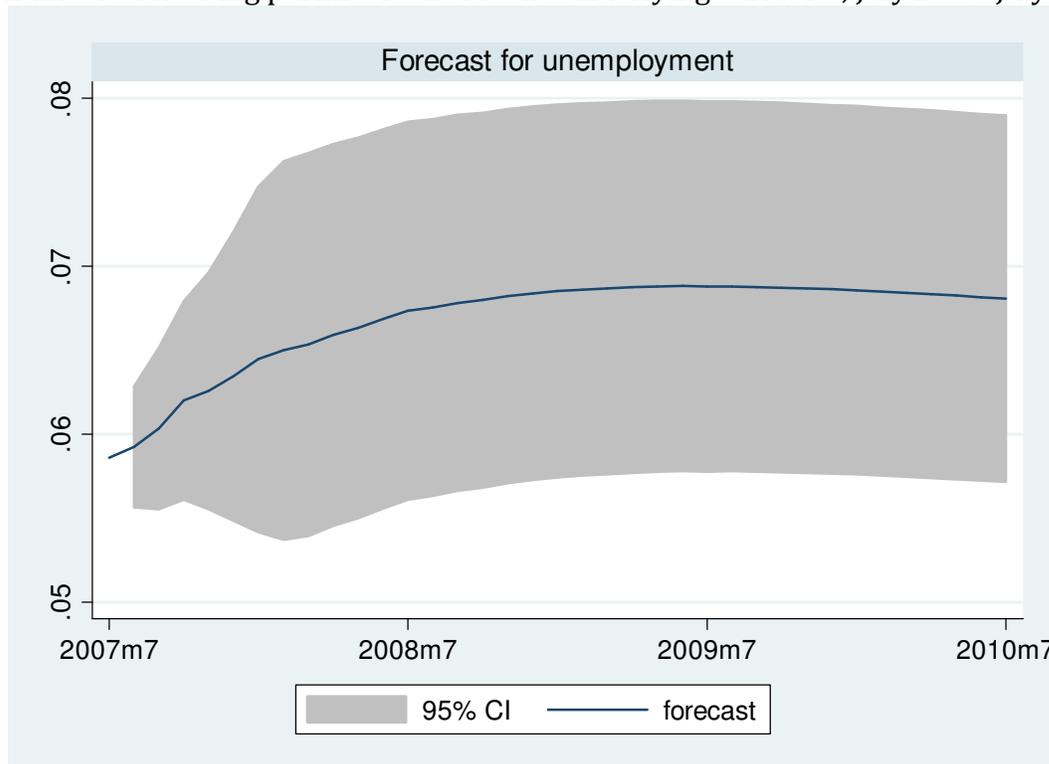
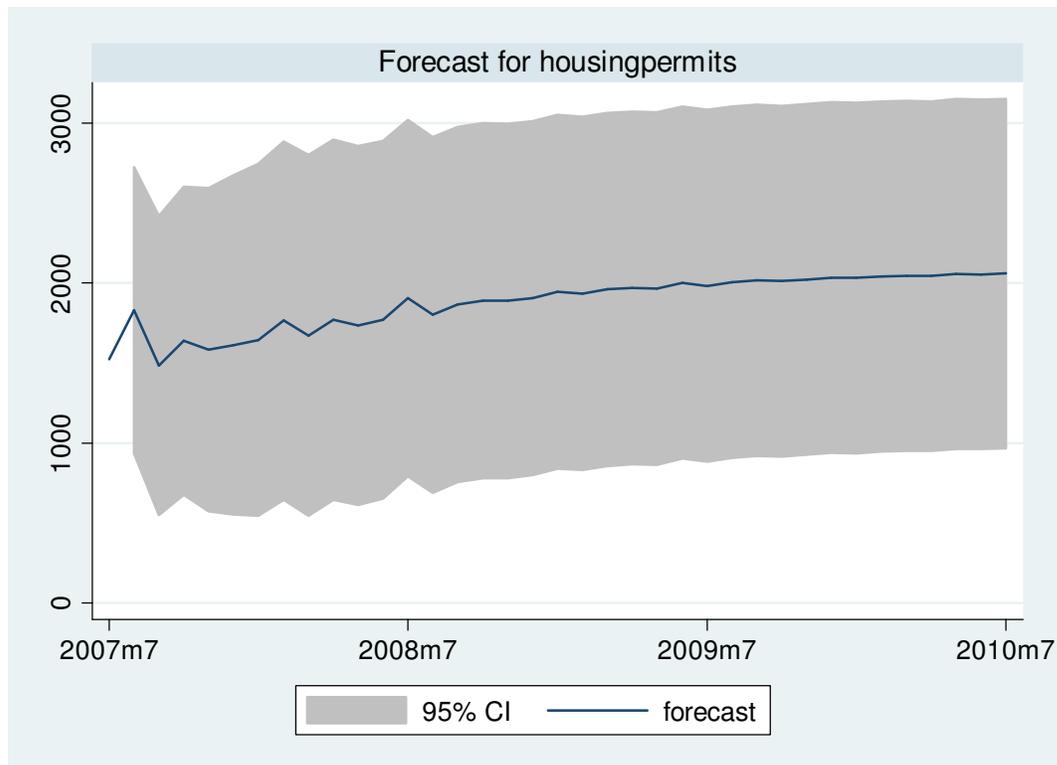


Figure 21. In-sample VAR forecast for the number of housing permits issued using unemployment and the number of construction workers as the underlying variables, July 2007-July 2010



Discussion

The models above provide compelling evidence that the Inland Empire's housing market, as measured by housing starts, the number of construction workers, and the number of housing permits issued, has hit rock bottom and is likely to remain stagnant for the next three years. The univariate forecasts suggest that unemployment will rise substantially over the next 3 years, reaching nearly 18%. However, the multivariate regressions and corresponding VAR forecasts suggest just the opposite. By employing a two-variable VAR(12) model, using the Inland Empire's housing starts and the Inland Empire's unemployment rates as the underlying variables, a corresponding forecast was constructed that suggested a slight recovery in the unemployment rate and a leveling off of housing starts. This is consistent with Case's (2002) finding that when housing starts remain stable there is an increase in national expenditure and ultimately a growth in employment.

When substituting housing permits for housing starts, the VAR model suggested similar results; unemployment makes a recovery (from 14% down to 8%) and housing permits level off and remain constant over the next three years. And, when substituting the number of construction workers for housing starts, the model again showed similar results; unemployment makes a recovery (from 14% down to 8%) and the number of construction workers levels off and remains constant over the next three years. The univariate forecasts produced similar forecasts for housing starts, housing permits and the number of construction workers, suggesting all three will remain relatively stagnant over the next three years.

A comparison of the graphs of the in-sample VAR forecast to the actual trend from July 2007 to July 2010 suggests that the out-of-sample VAR forecast was an adequate predictor of the unemployment rate and the number of construction workers. Despite the large differences in magnitude, the actual trend rises to 14% whereas the forecasted models only raise to 7-8%, both graphs display very similar shapes. This seemingly large difference in magnitude is reflected in the unexpected volatility of original data. It is not until the last 3 years, July 2007 to July 2010, when unemployment rates more than double, rising from 6% to 14%. The in-sample VAR(12) forecast excludes the last three years of data (July 2007-July 2010) in the regression and therefore is unable to capture this extreme increase in the unemployment rate in the corresponding forecast. Despite magnitude differences apparent in the graphs, the in-sample forecast and actual trend display very similar patterns. This suggests that the VAR model, using unemployment and housing starts as the underlying variables, is an acceptable model for forecasting unemployment.

Although the actual trend and in-sample VAR forecast for housing starts were not consistent, the model suggests that housing starts predict future unemployment. This is consistent with the theoretical model because unemployment is lagged relative to housing starts. This is an important finding and provides scope for future research. A new question arising from this paper asks, if we can affect the level of housing starts today, then is it possible to affect the unemployment rate in the future? If we can anticipate a downturn in housing starts we might be able to adjust interest rates in order to stimulate the economy.

According the Coulson and Kim's (2000) study of residential investment, residential

investment evidently Granger-causes consumption expenditure, the largest component of GDP in the model. Therefore, if we can anticipate a downturn in residential investment then we should be able to lessen the blow on the economy by decreasing interest rates and thereby increasing consumption. This might help to prevent unemployment rates from getting out of control in the future.

References

Calomiris, Charles W., S.D Longhofer, and W. Miles (2008). "The Foreclosure-House Price Nexus:Lessons From The 2007-2008 Housing Turmoil," *NBER Working paper 14294*.

Case, Karl E.and John M. Quigley (2006). "How Housing Booms Unwind:Income Effects, Wealth Effects, and Sticky Prices"

Case, Karl E. and Robert J. Shiller, "Is There a Bubble in the Housing Market?" *Brookings Papers on Economic Activity*, 2, 2003: 299-362.

Case, Karl E. and Robert J. Shiller, "The Behavior of Home Buyers in Boom and Post Boom Markets, *New England Economic Review*, November/December 1988: 29-46.

Coulson, N. E. and M. Kim (2000). "Residential Investment, Non-Residential Investment and GDP." *Real Estate Economics*, 28, 233-247.

Keil, Manfred and M. Weidenmier (2010). *The Inland Empire Report: The Great Recession in the Inland Empire*.

Leamer, E. (2007). "Housing IS the Business Cycle," *NBER Working paper 13428*.

"Privately Owned Housing Starts: 1-Unit Structures for Riverside-San Bernardino-Ontario, CA (MSA) (RIVE106BP1FH) - FRED - St. Louis Fed." *St. Louis Fed: Economic Research*. Web. 21 Nov. 2010.
<<http://research.stlouisfed.org/fred2/series/RIVE106BP1FH>>.

"RAND California Housing Foreclosure Statistics." *RAND California: Comprehensive California and U.S. Statistics Oneconomics, Demographics, Education, Health, Environment, Community and Government Finance*. Web. 21 Nov. 2010.
<<http://ca.rand.org/stats/economics/foreclose.html>>.

"Unemployment Rate in Riverside-San Bernardino-Ontario, CA (MSA) (RIVE106URN) - FRED - St. Louis Fed." *St. Louis Fed: Economic Research*. Web. 21 Nov. 2010.
<<http://research.stlouisfed.org/fred2/series/RIVE106URN>>.

U.S. Bureau of Economic Analysis (BEA) - Bea.gov Home Page. Web. 21 Nov. 2010.
<<http://www.bea.gov/>>.