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Abstract

In this paper we examine the predictability power of the long term risk premium over housing prices in the U.S. for a period of 19 years (1991-2009). For reasons that are cited clearly in the text, the interest rate risk premium is preferred over the yield spread. Under a probit framework, we investigate whether the recent housing prices bust could have been predicted. We employ adaptive expectations for the formation of the agents' short-term interest rate expectations. The ability to forecast such price changes is of great importance to investors and analysts of the housing market and for the design of financial institutions' mortgage policy in a more prudential path.

JEL classification: D58; D74; E31; G21; G32; H20; R20

1. Introduction

The housing boom and bust of the recent past has put forward a vast literature for the determinants of the house prices and the ability to forecast. According to Iacoviello (2005), Iacoviello and Neri (2008) and Vargas-Silva (2008a, b), the real estate sector and more specifically housing prices constitutes a leading indicator for the economic activity in the U.S. For thit reason, many researchers investigate the effects of monetary policy on housing prices. In a factor augmented vector autoregression (FAVAR) framework, Gupta et al. (2009) indicate that housing prices in South Africa respond negatively to monetary shocks. In the same vein, J. Baffoe (1998) testing the dynamic effects of four key macroeconomic variables on the housing prices using a VAR, finds that the housing market is very sensitive to shocks in the employment growth and mortgage rate at both the national and regional levels for the U.S.

In contrast, many researchers argue that the movements of housing prices do not reflect changes in the fundamentals. More specifically, McCarthy and Peach (2002), Shiller (2005) and Gallin (2006), among many, use aggregate data on home prices, personal income, building costs, population, user costs of housing and interest rates and find that real estate prices take long swings from their fundamental values and it can take decades before they revert back to them (Mikhed et al., 2009). In a recent work, James A. Kahn (2009), argues that home price movements can be attributed to productivity movements. Changing economic fundamentals, such as, swings in labor productivity played an important role in housing prices movements. These productivity swings helped determine housing prices through their effects on income growth and long term income expectations.

Following the work of Kahn (2009), in this paper we try to forecast housing prices taking into account labor productivity changes through different long term bond risk premiums as explanatory variables. The core idea is that long term bond premiums encompass information about future economic activity and as a consequence about future short term rates. As the risk premium increases, there are expectations for a downturn of future economic activity. Expectations of future appreciations of interest rates in turn are important determinants of housing sale prices (Jack C. Harris, 1989).

The main contribution of our paper is that it tries to forecast not the level of the housing prices series in the U.S. market, but the cyclical component of such prices, or in other words their deviations from the long-run trend, using the bond risk premium in a probit framework. The results suggest that using long term bond risk premiums as a proxy for formed expectations for future economic activity, housing prices movements can be forecasted.

The rest of the paper is organized as follows, section 2 analyses the data used, section 3 refers to the methodology and to the empirical results, section 4 concludes.

2. The Data

The data used in this paper are monthly observations that range from January 1991 to December 2009 for a total of 228 observations. For the housing prices we employ the Standard and Poor's Case-Shiller Home Price Index. More specifically, we use the S&P CS-10 which is a composite index of home prices for the top ten metropolitan areas in the U.S. This index is published monthly and uses a modified version of the weighted-repeat sales methodology originated in the 1980's by Karl E. Case and Robert J. Shiller. The index is considered as the most reliable means of measuring housing price changes as it is able to adjust prices for the quality of houses sold in contrast to simple indices that use simple averages, and the index is used by government agencies as well including the Office of Federal Housing Enterprise Oversight. We render the index in real prices by taking into account the CPI. The aim of the paper is to predict the deviations of housing prices from the long run trend using the risk premium, and especially the probability that the housing prices of a particular month are going to be below their long run trend. For this reason, we first decompose the real S&P CS-10 to the long run trend and cyclical component employing the Hodrick-Prescott (1997) filter (HP). The HP filter is commonly used in the area of real business cycles to decompose a series' short-term fluctuations from the trend dynamics. It produces a smooth non-linear trend which is affected more from the long-term fluctuations rather than the short-term ones. Thus, the filter's contribution is to distinguish an observed shock into a component that causes permanent effects and a component that has transitory effects on the economy. Furthermore, we have addressed the issue described in the literature of possible bisedness of the cycle obtained by the HP filter by investigating the robustness of the results to alternative decompositions of the GDP time-series. In doing so, we first produced the cyclical component of the EU GDP using alternative specifications for the HP λ parameter (i.e. λ = 12000 and 16000). We also employed the Baxter and King (1995) filter (BK) and extract the cycle using alternatively six and twelve leads/lags. As the qualitative results of the extracted cyclical components in both the alternative λ specifications for the HP filter and the BK filter are quite similar to the ones obtained by the HP filter, for the estimation of the probit models we continue the analysis with the cycles produced by the standard HP filter with λ = 14400. Having extracted the cyclical component of the S&P CS-10 as it is depicted in Figure 1 we then construct the housing prices cycle dummy variable (HC) that takes the value of one whenever the cycle is negative implying that housing prices are below trend, and the value zero elsewhere. The explanatory variable we use to forecast the housing price cyclical component is the risk premium implied between long and short interest rates. The risk premium is estimated as:

$$premium_{L,S} = i_L - i_S^e,$$

where $premium_{L,S}$ is the risk premium and i_L and i_S^e are the long-term interest rate and the agents' expectation for the future short-term interest rates respectively. We follow Campell (2006) and Koijen et al. (2008) and assume that agents form their expectations about future short-term rates by the following naive moving average rule:

$$i_{S,t}^e = \frac{\sum_{j=1}^{m} i_{S,t-j}}{m},$$

where $i_{S,t-j}$ are a series of past short-term rates and m is the window used for the formation of the expectations. In our paper we set m = 36. The main assumption is that households do not have the required financial sophistication to solve complex investment problems. Thus, using as long-term rates the treasury's monthly constant maturity rates for one, five and ten years as reported by the Fed and for the agents' short-term rates expectations the three month, six month and one year expectations constructed as above we calculate and use eight interest rate premiums. The monthly unemployment rate is derived from the same source as well, in order to be used as a non-monetary explanatory variable in the effort to forecast housing prices. In Table 1, we present a summary of the original variables' descriptive statistics.

3. Methodology and Empirical Results

We consider one hundred and sixty alternative models of probit regressions in the effort to find the model that best fits the data and has the higher forecasting ability in terms of predicting the deviations of the S&P CS-10 cycle below trend at some point within the next h quarters:

$$prob(HC_t = 1) = \Phi[\tilde{a}_0 + \tilde{a}_1 (premium_{t-i})], \qquad i = 1,...,h. \qquad (1)$$

HC_t is the dummy variable that takes the value of one every time the cyclical component of the S&P CS-10 is negative implying below-trend housing prices, and zero elsewhere. $\Phi(.)$ denotes the standard normal cumulative distribution function, $premium_{t-i}$ represents past values of the interest rate risk premium with lags $i = 1,...,20$ and for all eight alternative premiums. Finally, $\tilde{a}_0$ and $\tilde{a}_1$ are the estimated parameters. Equation (1) is estimated for all combinations of the risk premiums and forecast windows from one to twenty quarters ahead, a total of one hundred sixty probit regressions. The results are summarized in Table 2. For all models that include the premium calculated with the five and ten year long-term rate the selected forecast window, in terms of a statistically significant $\tilde{a}_1$ at the 0.01 level and the maximum McFadden R^2, is ten months. For the premiums that are calculated with the one year interest rate as the long-term rate the selected forecast window is 3 months ahead. Having selected in Table 2 the best forecast window for all eight interest rate risk premiums and as the main purpose of this paper is the prediction of the S&P CS-10 fluctuations from the long run trend, we formally compare the above eight models in terms of their forecasting ability by calculating the root mean squared error (RMSE), mean absolute error (MAE), and the mean absolute percent error (MAPE) statistics. These statistics are calculated using the following formulas:

$$RMSE = \sqrt{\frac{1}{F}\sum_{f=1}^{F} e_{t+f}^{2}}$$

$$MAE = \frac{1}{F}\sum_{f=1}^{F} \left| e_{t+f} \right|$$

$$MAPE = \frac{1}{F}\sum_{f=1}^{F} \left| \frac{e_{t+f,t}}{y_{t+f}} \right|$$

where $e_{t+f} = y_{t+f} - y_{t+f}^{*}$, and y_{t+f} is the actual value of the series at period $t+f$, y_{t+f}^{*} is the forecast for y_{t+f} and F is the forecast window. These statistics are summarized in the last three columns of Table 2. According to all these model selection criteria the best models are models seven and eight, those that employ the risk premium derived from the one year long-term rate and the agents' expectation for the three and six months short –term rates. The McFadden R^2 is practically the same for these models and thus we use the forecasting criteria for the selection of the final model. The RMSE and the MAE select model eight, while the MAPE selects model seven. Therefore, we continue the analysis for the rest of this paper with model eight that uses the interest rate risk premium derived from the one year long rate with the agents' expectations for the six month short-term rate at a forecast window of three months ahead. The value of 0.238 for the McFadden R^2 is considered a satisfactory fit as this statistic tends to be smaller than standard R^2. Next, in an effort to examine whether a non-monetary variable from the real economy can add any informational content to the forecasts of S&P CS-10 cycle, we estimate the following probit regression:

$$prob\left(HC_t = 1\right) = \Phi[\tilde{a}_0 + \tilde{a}_1\left(premium_{t-i}\right) + \tilde{a}_u u_{t-i}] \qquad (2)$$

where u_t is the unemployment rate, and $\tilde{a}_u$, is the estimated coefficient. As we can see in Table 3, the unemployment as an explanatory variable is not statistically significant at the 0.05 level of significance for either model seven or eight. Thus, the unemployment does not add any explanatory power to the best fitted model and it will not be used as an independent variable in our forecasts. Using model eight, the best fit model as selected above, we graph in Figure 2 the forecasted probability of a below trend S&P CS-10 index along with the extracted cyclical component of the index using the HP filter. As it can be seen in Figure 2, the predictive power of the estimated model in terms of the forecasted probabilities of S&P CS-10 deviations from the trend is very high. This is especially evident in the period after 2001 when the cyclical fluctuations are substantial as compared to the ones in the pre-2001 period. Figure 3 focuses in the later period of significant price fluctuations where the importance of a correct forecast of future housing prices can be decisive. As we can see the selected model using a three-month ahead forecast window, correctly predicts the below trend S&P CS-10 index in the period May 2001 to June 2004 where the predicted probabilities are all greater than 50% ranging from 52.8% to 86.6%. For the next period where we experienced above trend prices, January 2005 to November 2007, the forecasted probability is as expected low, ranging from 6.6% to 33.5% in the last month of the upturn in the cyclical component. In January 2008 the probability of a downturn in the cyclical component of the housing prices increases to 42.9% just when we encounter the first negative value for the cyclical component. The probability, in this period of the housing market collapse, gets as high as 91.6%. It seems that the model selected can adequately predict a negative cycle of the S&P CS-10 using a three month ahead forecasting window. In Table 4, we provide the Andrews and Hosmer-Lemeshow tests of goodness of fit grouped in three quantiles of risk. According to both goodness of fit evaluation criteria, our selected model provides a very good fit and the χ^2 statistics reported at the bottom of Table 4 for the Hosmer-Lemeshow and Andrews tests are 0.070 and 0.000 respectively. The selected model, when the estimated probability lies within the third quantile, i.e. between 67.6% and 91.6%, appears to perform very well as for an actual fifty eight realizations of a below trend index, it predicts fifty nine signaling only one false alarm, a percentage of 1.69%.

4. Conclusions

In this paper we have used several probit models to examine the predictive power of the interest rate risk premium over the S&P CS-10 index. The risk premium was calculated as the difference between various long-term interest rates and the agents' expectations about future short-term rates. Our results from the best fitted model show that the interest rate risk premium of the treasury's one year constant maturity interest rate minus the three and six month rate expectations with a forecast window of three months dominate in terms of goodness of fit the risk premium of longer term interest rates. Out of the two risk premiums that best fit the data we finally select the one year interest rate minus the six month rate expectations based on the three forecasting criteria as the main purpose of this paper is the prediction of the housing prices index deviations from trend. Moreover, we have included in the estimation a model with the unemployment rate as an explanatory variable to assess whether a non-financial variable can add any power to the interest rate risk premium. The results show that the unemployment does not improve the model. Overall, the final model used for forecasting appears very efficient to forecast deviations of the S&P CS-10 index from the long run trend according to the standard formal goodness of fit tests employed. The significance of this approach is that the model does not try to forecast the time series of the index itself, but its deviations from the long-run trend. Thus, the model raises a red flag when the housing prices index is below the long-run trend even if there is a positive increase in the level of the index. The results of course generate obvious implications for investors and analysts of the housing market: they can use the information provided by the interest rate risk premium today in order to estimate the probability of obtaining a below-trend S&P CS-10 index three months ahead. Moreover, banking officials can use the information provided by the risk premium to optimize their mortgage strategic planning. A shrinking risk premium may be the signal for upcoming below-trend housing prices. Thus, the above agents that participate in the housing market can anticipate trend deviations of housing prices as a signal either for covering any exposure in this market directly or indirectly through derivatives, or for an undervalued or overvalued housing market that can be strategically exploited.

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Table 1
Descriptive Statistics

	10-Year Rate	5-Year Rate	1-Year Rate	6-Month Rate	3-Month Rate	S&P CS-20	Unemployment
Mean	5.430	4.982	4.038	3.886	3.720	0.732	5.595
Median	5.280	5.040	4.470	4.440	4.250	0.642	5.500
Maximum	8.280	7.940	7.140	6.580	6.410	1.191	9.800
Minimum	2.420	1.520	0.400	0.210	0.030	0.506	3.800
Std. Dev.	1.295	1.480	1.747	1.778	1.766	0.223	1.199
Skewness	0.189	-0.162	-0.478	-0.511	-0.519	0.759	1.047
Kurtosis	2.295	2.293	2.059	2.005	2.002	2.168	4.221
Jarque-Bera	5.996	5.672	16.852	19.089	19.424	28.076	55.111
Probability	0.050	0.059	0.000	0.000	0.000	0.000	0.000
Sum	1221.710	1120.990	908.540	874.420	837.110	164.807	1258.800
Sum Sq. Dev.	375.424	490.618	683.369	707.963	698.543	11.127	321.934
Observations	225	225	225	225	225	225	225

Table 2
Forecasting Model Selection Criteria

	Predicting Risk Premium				Forecasting Criteria		
Model	Long Term Rate	Short Term Rate	Forecast Window	McFadden R2	RMSE	MAE	MAPE
1	10-year	3-month	10-months	0.118	0.46291	0.42490	21.373
2	10-year	6-month	10-months	0.117	0.46320	0.42530	21.405
3	10-year	1-year	10-months	0.110	0.46525	0.42938	21.641
4	5-year	3-month	10-months	0.165	0.44746	0.39665	19.918
5	5-year	6-month	10-months	0.165	0.44749	0.39644	19.928
6	5-year	1-year	10-months	0.162	0.44906	0.39879	20.080
7	1-year	3-month	3-months	0.238 *	0.42056	0.35148	17.849 *
8	1-year	6-month	3-months	0.238	0.42040 *	0.35147 *	17.862

An asterisk denotes the selected model by each criterion.

Table 3
Risk Premium Models Augmented with Unemployment as an Explanatory Variable

	Predicting Risk Premium			Unemployment		
Model	Long Term Rate	Short Term Rate	Forecast Window	Coefficient	Probability	McFadden R2
7	1-year	3-month	3-months	-0.175589	0.0846	0.247255
8	1-year	6-month	3-months	-0.190494	0.0642	0.248585

An asterisk denotes the selected model by each criterion.

Table 4
Goodness-of-Fit Evaluation for Binary Specification

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.033	0.286	65	61.62	9	12.38	74	1.107
2	0.291	0.676	34	40.08	40	33.92	74	2.010
3	0.676	0.916	16	14.58	58	59.42	74	0.171
		Total	115	116.28	107	105.72	222	3.288

H-L Statistic	3.2882	Prob. Chi-Sq(1)	0.070
Andrews Statistic	23.2659	Prob. Chi-Sq(3)	0.000

Figure 1. The extracted cyclical component of the S&P CS-20

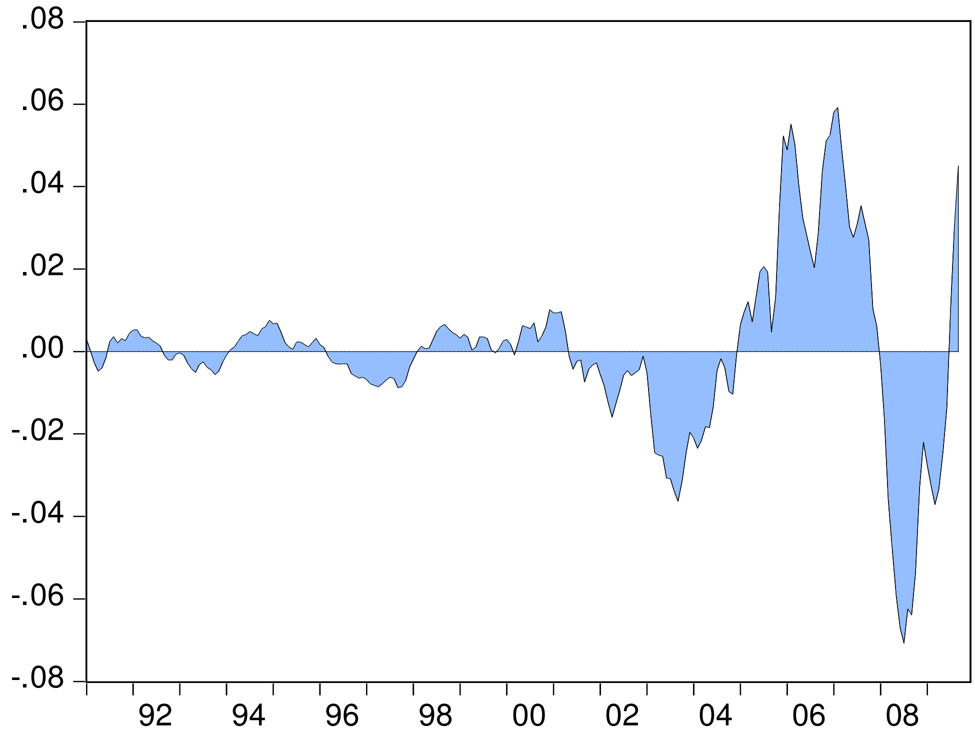

Figure 2. S&P CS-20 Cyclical Component and Forecasted Probability

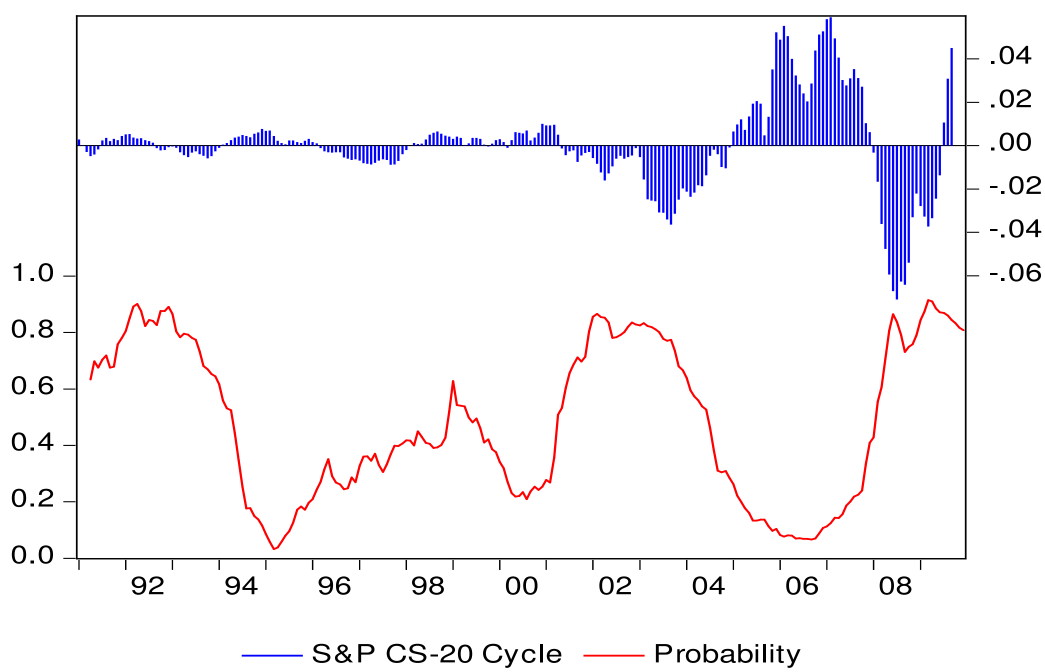

Figure 3. S&P CS-20 Cyclical Component and Forecasted Probability (2001-2009)