FORECASTING THE REAL ESTATE MARKET: A COINTEGRATED APPROACH

A Thesis

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Master of Arts

By

Jaweria Seth

August, 2011

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ABSTRACT

Research has shown that a decline in residential investments signals an impending decline in economic activity. Sources of demand for both residential and commercial real estate sectors are similar and this should move the markets in the same direction over the long-run. Since the residential market has already collapsed, the study of real estate investments is important. This paper utilizes real estate and macroeconomic data to forecast investment loans. Cointegration methods are used for the forecast because the data displays a tendency to move together. The results show that the forecast is inconsistent with the positive relationship between both real estate markets; the residential market will continue to decline, whereas the commercial market with see a positive growth from 2011-2012.

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1. INTRODUCTION

Research has shown that a decline in residential investments signals an impending decline in economic activity (Leamer, 2007). This is confirmed by the burst of the most recent housing bubble in 2007. The financial crisis that followed forced large institutions to fail which caused a major recession. Specifically, Leamer (2007) shows that in the year proceeding recessions, problems in the residential investment market contributed to 26% of the decline in the economy. Many previous studies have focused on the housing market since it affects people on a personal level; however, the study of the commercial market is also important because this sector is large with a high financial leverage. Additionally, problems in housing market lead to problems in the commercial market. This is cause for great concern given the current state of the economy. Companies that are associated with the residential market, such as construction and retail industries, grew quickly as well and expanded the demand for commercial real estate. As a result of the housing bubble burst, a decline in residential investment caused greater declines in consumer spending, decreasing the demand for commercial real estate (Feldstein, 2007). Since the fundamental sources of demand for both real estate sectors are similar, the markets should move in the same direction over the long-run (Gyourko, 2009).

In order to study how real estate investments will perform, this paper focuses on forecasting commercial and residential real estate loans. Previous research has focused on using investment returns to determine the state of the real estate market; however loans are used since they are a more direct measure of the investment. Since the loans series and other variables of interest display a tendency to move together in the long run, the Johansen test for cointegration is first used to analyse whether real estate loans and other real estate variables and macroeconomic variables endogenously related to loans are cointegrated. Several model specifications are used, including variables that seem to move together in the long run, to determine which combination of variables best models the real estate loan market. Using information criteria, the cointegrated VAR models are assessed to choose the optimal model, which best represents each real estate sector. Models are assessed both with the inclusion and the exclusion of structural breaks because different models vary in regards to their sensitivity to breaks (Timmermann, 2006). This suggests that the model, and specifically the forecast, accuracy does not depend on the whether breaks are included in the model.

After choosing the optimal model specification, with and without breaks, for the commercial and residential real estate sectors, a forecasting exercise for all models is done. Rolling and recursive forecasting methods are used on the 2 best model specifications in each sector to determine which one is more accurate in forecast ability on average throughout the full sample. Forecast accuracy is based on minimizing the root mean square error (RMSE). The optimal specification is then used to model both commercial and residential real estate sectors, and to forecast the 2011-2013 period.

Though there have been several studies employing cointegration techniques to the real estate market, much of that research has focused on finding long-run relationships between real estate variables and financial assets[1]. Additionally, the real estate studies were more concentrated on the residential market, with the exception of Chaudhry, Myer,

[1] These studies find long-run cointegrating relationships between real estate variables and financial asset variables using the Johansen method. Ullah & Zhou (2003) studied the relationship between housing sales, housing prices, the 30-year mortgage rate and the NYSE stock index returns. Tuluca, Seiler, Myer, & Webb (1998) studied the relationship between the financial assets (t-bill, bonds, and stocks) and securitized/un-securitized real estate loans. Chaudhry, Myer, & Webb (1999) studied the relationship between financial assets and commercial real estate.

& Webb (1999), who studied the commercial real estate market. This is also the case with studies that looked at the connection between real estate variables and macroeconomic variables[2].

Furthermore, there have not been many studies undertaken that forecast real estate variables using the cointegrated VAR model. Zhou (1997) forecasted residential sales and prices using the recursive technique. However, the author used the Engle and Granger method of cointegration. On the other hand, Tuluca, Seiler, Myer, & Webb (1998) employed the Johansen method and performed a straightforward forecast with a holdout period of 8 observations to forecast the returns on securitized and un-securitized real estate as well as returns on other financial assets (including t-bill, stocks, and bonds). However, they were interested in the relationships between different financial assets for portfolio investment decisions, rather than the real estate assets' relationship to the macroeconomy.

The lack of research on multivariate cointegrating relationships between real estate variables (including loans) and macroeconomic variables (including interest rates, GDP, and employment) and is due to the non-stationarity of the real estate variables. Conventional time series analysis, such as ARMA and VARs, requires stationary variables. The use of non-stationary variables in these procedures would be incorrect because the standard assumptions for asymptotic analysis will not be valid (Brooks & Tsolacos, 2010). Also, the studies that applied cointegration techniques to the real estate sector were more interested in modeling and explaining the long-run relationships

[2] Kim, Goodman, & Kozar (2006) studied the relationship between home sales/construction market and interest rate changes. Fei, Yun, and Cheng (2010) studied the relationship between housing prices in different cities. Zhou (1997) found a cointegrating relationship between home sales and home sale prices.

between the variables rather than forecasting certain variables.

This paper contributes to the existing literature in two ways: First, it applies a cointegrated VAR model to model real estate loans in both the commercial and residential sectors. Second, this paper assesses forecast accuracy using both rolling and recursive forecasting methods under a cointegrated VAR model. The results of this exercise is then used to forecast commercial and residential real estate loans to predict the evolution of the real estate market from 2011-2013.

The rest of the paper is as follows: Section 2 describes the data and methodology used to forecast a cointegrated VAR model. Section 3 presents the results from the cointegration analysis and the forecasts. Section 5 concludes this study.

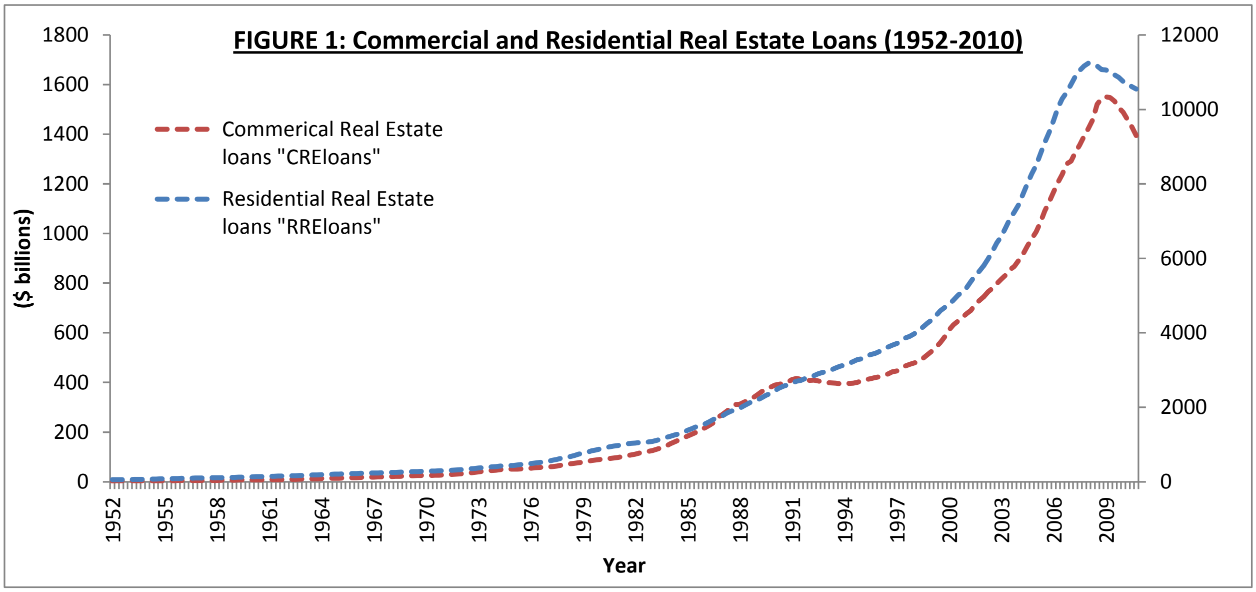
2. METHODOLOGY

2.1 Data

The commercial and residential real estate data used in this study was acquired from BBVA Research. National data was obtained from 1950 to 2010 in quarterly measures. Apart from the variables that were already in percentages, variables were transformed into their logarithmic forms to rescale the data (Brooks & Tsolacos, 2010).

Commercial real estate variables comprise of total loans in dollars ("creloans"), investment returns ("creret"), vacancy ("crevac") and delinquency ("credel") rates, consumer price index ("cpi"), gross domestic product ("gdp"), service employment ("service"), and interest rate variables including the federal funds rate ("fed") and the ten year treasury bill rate ("tenyr"). Residential real estate variables comprise of total loans in dollars ("rreloans"), total number of existing home sales ("exist"), delinquency rates ("rredel"), house price index ("hp"), gross domestic product ("gdp"), unemployment rate (“ur”), and interest rate variables including the federal funds rate (“fed”) and the 30-year mortgage rate (“mort30y”).

These variables are tested for unit root as a preliminary step to the cointegration method. The specific variables of interest are commercial and residential real estate loans. This data shows an increase in both sectors’ loans since 1950 with a decline in late 2000’s. Figure 1 shows that possible structural breaks may occur in the data due to the slope change in the trend function. The following section provides the method and results of unit root testing and obtaining break points in the data.



2.1.1 DF-GLS Test for Unit Root:

The Dickey-Fuller General Least Squares (DF-GLS) test (1996) is used in this study to determine the existence of unit root in the variables in level form. Commonly used tests consist of the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests. However, this study employs the DF-GLS test since it has been shown that the DF-GLS test has substantially improved power when an unknown mean or trend is present when compared to previous forms of the ADF test (Elliott, Rothenberg, & Stock, 1996). Also, since Elliot, Rothenberg, and Stock have determined that the DF-GLS test works well in small samples, this serves as an additional advantage given the dataset used in this study.

The DF-GLS test is a modified version of the Dickey-Fuller (DF) test where the series is detrended via a GLS regression prior to performing the DF test for unit root. First, a GLS regression is used to estimate the intercept and trend. The regression is then detrended using OLS regression estimators. Second, the ADF test is used on the detrended variable by fitting the OLS regression:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta_t + \lambda_0 \Delta y_{t-1} + \lambda_2 \Delta y_{t-2} + \ldots + \lambda_k \Delta y_{t-k} + \varepsilon t, \tag{1}$$

and testing the null hypothesis of unit root, H_0: $\beta = 0$, against an alternative that y_t is stationary (Moody, 2009). In the above regression, k is the lag order chosen by minimizing the modified Akaike Information Criteria (MAIC).

Ng and Perron (2001) have found that using the MAIC to determine lag length in a DF-GLS context produces significant size and power improvements over the standard Akaike and Schwartz-Bayesian Information Criterion (AIC and SBC). This is because the MAIC considers the bias in the estimate of the sum of the autoregressive coefficients when choosing the lag order (Ng & Perron, 2001). This study relies on the lag order chosen from minimizing the MAIC when determining if variables are unit root processes.

If the DF-GLS test statistic is lower than the critical value, the null hypothesis of unit root is rejected. According to Table 1, all of the variables are non-stationary; the null hypothesis cannot be rejected at the 5% significance level. Therefore, it can be concluded that all of the variables follow unit root processes.

TABLE 1: DF-GLS Test for Unit Root						
Variables	Min MAIC	P[1]	RMSE[2]	DF-GLS test statistic	5% Critical Value	Null Hypothesis (H_0=unit root)
Commercial Real Estate (CRE)						
logCREloans	-9.078	5	0.010	-0.936	-2.894	Fail to Reject
logservice	-12.072	11	0.002	-0.145	-2.841	Fail to Reject
logcreret	-8.793	7	0.011	-1.027	-2.895	Fail to Reject
logcpi	-10.716	4	0.005	-1.289	-2.901	Fail to Reject
loggdp	-9.391	2	0.009	-0.228	-2.915	Fail to Reject
crevac	-1.750	2	0.389	-1.898	-3.027	Fail to Reject
fed	0.773	9	1.316	-2.040	-2.858	Fail to Reject
tenyr	-1.072	7	0.550	-1.183	-2.890	Fail to Reject
credel	-3.805	2	0.144	-0.346	-3.089	Fail to Reject
Residential Real Estate (RRE)						
logRREloans	-10.368	12	0.005	-1.806	-2.832	Fail to Reject
loggdp	-9.391	2	0.009	-0.228	-2.915	Fail to Reject
loghp	-10.228	8	0.006	-0.984	-2.875	Fail to Reject
logexist	-5.705	1	0.056	-1.776	-2.959	Fail to Reject
mort30y	-1.300	1	0.511	-1.309	-2.973	Fail to Reject
fed	0.773	9	1.316	-2.040	-2.858	Fail to Reject
ur	-2.565	12	0.252	-2.499	-2.832	Fail to Reject
rredel	-4.024	3	0.124	-1.144	-3.056	Fail to Reject

Notes: 1. P is the chosen lag length determined by minimizing the MIAC (Modified Akaike Information Criteria).
2. The RMSE corresponds to the lag length chosen by the MAIC.

2.1.2 Structural Breaks:

Testing for structural changes is an important aspect of forecasting because the presence of breaks in the data may cause inaccurate forecasts. However, Timmermann (2006) implies that the forecast, accuracy may not depend on the whether breaks are included in the model since different models vary in regards to their sensitivity to breaks. Figure 1 indicates possible slope breaks in both commercial and residential real estate loans. The Bai (1999) likelihood ratio test is used to confirm multiple structural changes and the location of the breaks in the data.

The Bai (1999) test is used because the model allows for lagged dependent variables and trends in the regressors; both series that are tested for multiple breaks seem to be trending. The testing procedure is as follows: The model is estimated under the null hypothesis of no breaks against a single break. If the null hypothesis is rejected, the model is estimated under the null of single break versus two breaks, and so on. This procedure is repeated until the test failed to reject the null of no additional breaks (Prodan, 2008).

Results show evidence of 3 significant breaks in both variables being tested; commercial and residential real estate loans. The locations of the breaks are consistent with historical events. For commercial real estate loans, the breaks occurred in 1989 Q2, 1992 Q4, and 2008 Q2. The first and second breaks correspond to the collapse and subsequent recovery of the commercial real estate market. The third break corresponds to the most recent financial crises, in which the real estate bubble burst after property values peaked in 2007 (Gyourko, 2009). In regards to residential real estate loans, the breaks occurred in 1990 Q1, 1999 Q1, and 2006 Q2. The first break occurred after the 1980's housing bubble burst (Glaeser, Gyourko, & Saiz, 2008). The second and third breaks correspond to the most recent housing bubble of 2000-2006, during which housing prices increased sharply prior to the financial crisis (Feldstein, 2007).

2.2 Modeling

Classical regression model assumptions require that all series be stationary with zero mean and finite variance. Since the series in this study are non-stationary, a simple VAR model would not be valid. If non-stationary variables are present, the model may result in a spurious regression[3] (Enders, 1995). An exception to this is a model that removes the stochastic trends and produces stationary linear relationships between variables. Cointegration implies that certain linear combinations of the variables of the

[3] Enders (1995): A spurious regression is a relationship between variables that give a high r2, and t-statistics that seem to be significant, but in fact there does not appear to be a direct causal connection. The results have no economic meaning.

vector process are integrated of lower order than the process itself (Juselius, 2003). Typically, cointegration is a linear stationary relationship between non-stationary variables integrated to the order of 1. Variables that are cointegrated tend to move together in the long-run. In order to test for cointegration between variables, the variables must first be tested to determine if they are non-stationary (also known as unit root processes).

Since the results of the DF-GLS test indicate that the variables are non-stationary, the next step is testing for cointegration between the variables. The Johansen test is used model the commercial and residential real estate markets since this method has the option of choosing multiple cointegrating relationships; the number of stationary long-run relationships between variables. Typically, as the number of variables in a model increases, so does the number of cointegrating relationships. This test employs the use of likelihood ratio tests to determine the number of cointegrating relationships. The number of cointegrating relationships, the rank, is then used to estimate the cointegrated VAR model (Juselius, 2003). In this study, the Johansen test is broken down into four steps: (1) lag length determination and residual analysis, (2) rank test, (3) variable exclusion test, and (4) estimating the cointegrated VAR model. The results are obtained using CATS in RATS, version 2.

It is important to identify the optimal lag length when estimating VAR models since results of the test can be sensitive to the number of lags (Enders, 1995). A mis-specified model can result in a different number of cointegrating relationships. Different information criterion, such as the AIC, SBC, and H-Q, are based on the maximum likelihood test including a penalizing factor for the addition of extra lags (Juselius, 2003).

This test calculates the AIC and SBC for different values of k lags, and displays the values that correspond to each lag. The lag lengths were chosen accordingly in each model depending on the results of both AIC and SBC tests. If both tests give identical results, in regards to the lag order *k* that minimized AIC and SBC values, lag *k* is chosen to estimate the model. After the correct lag order is chosen, the VAR is modeled. All specifications of the model are analyzed in regards to their residual autocorrelation by evaluating the Lagrange multiplier (LM) test statistics[4]. When both information criteria indicate the same lag order *k*, the residuals do not show significant autocorrelation. However, when both tests give different results, the two VAR models are compared to determine which models are white noise processes, in which the residuals cause less autocorrelation. Typically, the smaller lag order shows significant autocorrelation in the residuals; therefore, the higher lag order is used to estimate the model.

The most important step is determining the cointegrating rank. The rank separates out *r* equilibrium errors in which the system is adjusting back towards long-run steady state. The number of unit roots, which are the driving trends in the system, is given by *p-r* where p is the number of variables in the system. The rank is chosen by using the likelihood ratio trace test at the 5% significance level. The null hypothesis is rank=r, with p-r unit roots in the system (Dennis, Hansen, Johansen, & Juselius, 2005). If r=0, there are no cointegrating relationships between the variables implying that the variables do not have any common stochastic trends and do not move together in long-run. If p>r>0, then there is/are r relation(s) that push the system towards stationary, and if p=r, then the system is already at its long-run steady-state (Juselius, 2003).

[4] Smith (2008) found that the Lagrange multiplier (LM) test for autocorrelation performs better than the Ljung-Box test since it has better size and power properties.

For small sample size models, the standard rank test's asymptotic distribution does not give a good approximation to the finite sample distribution. In this case, the Bartlett correction is relied on when determining rank. The correction takes into account the number of parameters, lag length, rank, number of restricted deterministic terms, and the number of unrestricted terms (Johansen, 2000). The Bartlett correction is relevant in this study since the sample size ranges from 74 to 140 observations in quarterly measures[5]. Also, it has been shown that when known structural breaks are included in a multivariate model, new asymptotic tables are required (Johansen, Mosconi, & Nielson, 2000). In this case, the cointegration analysis involves an additional step: simulating asymptotic trace test distributions for models that include breaks.

The rank determines the number of error correction parameters in the model, but cannot be given economic interpretation until restrictions are placed on the cointegrating vectors. When the number of variables in the model is large, so is the number of cointegrating vectors. When there are multiple cointegrating vectors, it may not be possible to identify the relationships since the number of combinations between the variables is large (Juselius, 2003). In general, the rank describes the number of cointegrating vectors that pull forces toward long-run steady state equilibrium; the higher the rank, the more stable the system.

The variable exclusion test indicates which variables should be omitted in the long-run. In certain cases, the cointegrated VAR model does not require all variables to be present in the cointegrating relationship (Dennis et al., 2005). Models in which

[5] According to Juselius (2003), a small sample size is typically 50-100 observations in quarterly measures.

variables that can be significantly excluded at the 5% are discarded. After the correct model specification and rank is chosen, the cointegrated VAR model is estimated.

For a n-variable model, the (n x 1) vector xt = (x_{1t}, x_{2t}, …, x_{nt})' has an error-correction representation if it can be expressed in the form:

$$\Delta x_t = \pi_0 + \pi x_{t-1} + \pi_1 \Delta x_{t-1} + \pi_2 \Delta x_{t-2} + \ldots + \pi_p \Delta x_{t-p} + \varepsilon_t , \quad (2)$$

where π_0 = an (n x 1) vector of intercept terms with elements π_{i0}

π_i = (n x n) coefficient matrices with elements $\pi_{jk}(i)$

π = is a matrix with elements π_{jk} such that one or more of the $\pi_{jk} \neq 0$

ε_i = an (n x 1) vector with elements ε_{it}

(*Enders, 1995*)

Using the full sample, the VAR Error-Correction Model (VECM) is estimated. The estimates of a VECM model can be interpreted as both short-run and long-run effects. The long-run relationship measures the relations between the levels of the variables, while the short-run dynamics measures the adjustment between the first differences of the variables. However, the model cannot be interpreted when two or more cointegrating vectors are present since it requires restrictions on the rank. With two or more cointegrating vectors, there is an identification problem (Juselius, 2003).

Restrictions on the cointegrating vectors are not tested since the focus of this paper is forecasting real estate loans, not interpreting the relationships between the variables in the model. For each model specification, the AIC and SBC is calculated to determine which model specification best fits the data. The optimal model is one which minimizes both information criterions in each real estate sector, with and without their respective structural breaks included.

2.3 Forecasting

Since the variables are proven to be cointegrated, forecasting is done using VAR models with error correction terms since this method would be superior, especially in multi-step horizons, to VAR in differences and in levels (Engle & Yoo, 1987). Clements and Hendry (1995) showed that, in a cointegrating model, the VAR in differences forecasted worse than the unrestricted VAR and the VAR with error corrections terms. With small samples, the differences between an unrestricted VAR and a VAR with error correction terms become more apparent, favouring the VAR with error correction terms. The results also supported earlier work that as the forecast horizon increases, the cointegrated VAR model (VECM) becomes the better choice for forecasting a cointegrated series. Tuluca, Seiler, Myer, & Webb (1998) found that the cointegrated VAR model forecasts are better, if not the same, compared to the VAR model forecasts[6].

The full sample estimation provides four models to be used to perform the out-of-sample forecast exercise. This forecasting exercise is done to determine which model forecasts with the lowest root mean square forecast error (RMSE) on average in each sector; the model that includes the breaks or the model that does not. Forecast evaluations are carried out using two methods: rolling and recursive forecasting.

Forecasting is made difficult after a break has occurred because the new data generating process is unknown. In this study, forecasting accuracy is compared between the best model excluding breaks and the best model including breaks. This is done to assess whether including structural breaks in the models will reduce forecasting errors.

[6] The authors found that un-securitized real estate returns' cointegrated VAR model forecast was superior to the VAR model forecast. For the t-bill series, the choice between the different VAR model techniques did not make a difference in the forecasts.

For all models, forecasting methods that are robust to breaks are used, such as rolling and recursive forecasting (Eklund, Kapetanios, & Price, 2009). These methods allow for time variation and are useful in assessing a model's stability over time.

In a rolling window forecast, a window of size *n* less than the entire sample, is modeled and forecasted. The window is then moved 4 quarters into the future and the process is repeated. In a recursive window forecast, the window is expanded 4 quarters into the futures at each step. Both methods are used because there exists a bias-variance tradeoff between the two that is taken into account when deciding on which model forecasts better on average. If there happens to be a different data generating process throughout the series, then using the earlier data may lead to bias in the parameter estimates and forecasts. In a recursive window scheme, the earlier data is used in all windows and this bias can accumulate to cause higher RMSE's in the forecasts than compared to models that use a smaller sample that only covers the present data generating process. However, decreasing the sample size increases the variance of the parameter estimates, also leading to higher RMSEs in the forecasts. This occurs in a rolling window scheme, where the number of observations is reduced in all windows (Clark & McCracken, 2004).

The data used in this study consists of both macroeconomic and financial series, including GDP and investment returns, which are known to include structural breaks. Both rolling and recursive forecasts are used because the sample size is small, so relying only on the rolling scheme would cause an increase in parameter variance. Additionally, since there are known structural changes in the series, relying only on the recursive scheme will definitely cause an increase in parameter estimate bias.

The forecast exercise provides the optimal model for both commercial and residential real estate sectors. The forecast for these models has the lowest RMSE on average throughout the sample. This indicates that the model's forecast ability is superior compared to others in its sector. Using the models' full sample estimation, the VECM is forecasted 3-years out to predict how the economy will progress in terms of investments in real estate.The forecast error variance decomposition analysis is performed in order to understand short-run behavior in individual variables in response to shocks. The analysis determines what proportion of the h-step-ahead error variance for a variable i is explained by shocks to variable j. A shock to the i-th variable will evidently directly affect that variable, but it will also affect all the other variables in the VAR system (Brooks & Tsolacos, 2010).

3. RESULTS

3.1 Modeling

3.1.1 Residential Real Estate (RRE):

The restricted specification for residential real estate (RRE) loans model is comprised of the following variables: GDP, house price index, number of existing home sales, and the 30-year mortgage rate. These variables directly influence the demand for RRE investment. RRE loans were modeled given different combinations of interest rate, unemployment rate, and delinquency rate variables. Table 3.1 shows models whose residuals are white noise processes, all parameters included are significant, and long-run relationships are present among the variables. As shown, Model A minimizes both information criteria from the specifications that exclude the structural breaks.

Alternatively, Model E minimizes both information criteria from the models that include the breaks. The breaks are included in the model as dummy variables, such that: sb901 = t*(T>=1990:1); sb991 = t*(T>=1999:1); and sb062 = t*(T>=2006:2).

3.1.2 Commercial Real Estate (CRE):

The restricted specification for commercial real estate (CRE) loans model is comprised of the following variables: service employment, CRE returns, CPI, GDP, and CRE vacancy rates. These variables directly influence the demand for CRE investment. Using the full sample, CRE loans are modeled with different combinations of interest rate and delinquency rate variables. Table 2.1 shows models whose residuals are white noise processes, all parameters included are significant, and long-run relationships are present among the variables. As shown, Model B minimizes both information criteria from the models that exclude the breaks. Alternatively, Model F minimizes both information criteria from the models that include the breaks. The breaks are included in the models as dummy variables, such that:

sb892 = t*(T>=1989:2); sb924 = t*(T>=1992:4); and sb082 = t*(T>=2008:2).

Short-run parameters only give a rough indication of possible short-run dynamics. For both real estate sectors, the coefficients for the differenced lagged variables are nonzero, implying that both stationary real estate loan variables, ΔlogCREloans and ΔlogRREloans, respond to previous period's deviation from long-run steady-state. The lagged levels of the variables represent the long-run cointegrating relationships, and their interpretation depends on the restrictions to the ranks. Since restrictions on the cointegrating vectors are not tested, the parameters of the model specifications cannot be given economic interpretation (Dennis et al., 2005).

TABLE 2.1: RRE Models- Full Sample Estimation

Dependent Variable: D_logRREloans

	Models[1]							
	[A]*	[B]	[C]	[D]	[E]*	[F]	[G]	[H]
Variables								
Constant	0.0200	0.0027	1.6645	-0.0808	-0.3180	0.0697	1.1974	0.1045
R_Trend[2]			0.0045	0.0009			0.0039	0.0015
logRREloans{1}	-0.0787	-0.0921	-0.2305	-0.1477	-0.1661	-0.0898	-0.1421	-0.1654
loggdp{1}	0.0371	0.0463	-0.1429	0.1065	0.1641	0.0554	-0.1580	0.0743
loghp{1}	0.0622	0.0692	0.1605	0.0420	0.0525	0.0422	0.1562	0.0677
logexist{1}	0.0316	0.0404	-0.0069	0.0284	0.0203	0.0204	-0.0202	0.0422
mort30y{1}	-0.0011			-0.0019	-0.0034	-0.0040		
fed{1}		-0.0011	-0.0013				-0.0007	-0.0012
ur{1}			-0.0016		-0.0001		0.0019	-0.0009
rredel{1}			-0.0006			0.0009	0.0005	
D_logRREloans{1}	0.1559	0.1024		0.0645	0.0432	0.1697		0.0462
D_loggdp{1}	-0.1257	-0.1240		-0.1190	-0.0798	-0.1418		-0.0088
D_loghp{1}	0.0264	-0.0244		-0.0030	0.0242	0.0851		-0.0426
D_logexist{1}	-0.0219	-0.0174		-0.0261	-0.0223	-0.0595		-0.0231
D_mort30y{1}	-0.0034			-0.0016	-0.0004	0.0011		
D_fed{1}		-0.0006						-0.0003
D_ur{1}					0.0044			0.0046
D_rredel{1}						0.0026		
T_1990:1				-0.0008	-0.0004			-0.0009
T_1999:1				0.0017	0.0017	0.0005	-0.0017	0.0013
T_2006:2				-0.0026	-0.0025	-0.0015	-0.0005	-0.0016
D_T_1990:1				0.0026	0.0024			0.0028
D_T_1999:1				0.0022	0.0010	0.0027	0.0046	-0.0011
D_T_2006:2				-0.0002	-0.0003	0.0002	0.0031	0.0005
Lag(s)	2	2	1	2	2	2	1	2
Rank(s)	1	1	4	3	5	5	3	5
AIC	-4905	-4623	-3510	-5107	-5647	-3405	-3568	-5390
SBC	-4533	-4251	-3357	-4756	-5299	-3274	-3425	-5045

Notes: 1. The specifications above are modelled in their Error-Correction form.

2. R_Trend specifies a model with linear trends in the variables and in the cointegrating relations.

* indicates the optimal model: minimizing the AIC/SBC

TABLE 2.2: CRE Models- Full Sample Estimation
Dependent Variable: D_logCREloans

	Models[1]								
	[A]	[B]*	[C]	[D]	[E]	[F]*	[G]	[H]	[I]
Variables									
Constant	-0.9515	-1.0504	-1.9863	-0.9644	-0.9346	-0.2549	-1.7115	1.1465	-2.8929
R_Trend[2]		-0.0004	-0.0009	-0.0005	-0.0007		-0.0106		
logCREloans{1}	-0.1307	-0.1480	-0.1161	-0.0935	-0.1804	-0.1638	-0.1054	-0.1389	-0.0774
logservice{1}	0.0760	0.0485	0.0980	0.0418	-0.0245	-0.1356	-0.1234	-0.1577	0.1779
logcreret{1}	0.0811	0.0896	0.0592	0.0652	0.0935	0.0635	0.0106	0.1114	0.0830
logcpi{1}	-0.3852	-0.3185	-0.0202	-0.0956	-0.1252	-0.3607	-0.0781	-0.3710	0.0442
loggdp{1}	0.2583	0.2799	0.1618	0.1354	0.2772	0.4784	0.6687	0.2996	0.0706
crevac{1}	0.0011	0.0016	0.0021	0.0013	0.0019	0.0013	0.0015	0.0020	0.0019
fed{1}		0.0011	0.0019				-0.0005		
tenyr{1}				0.0029				0.0033	
credel{1}			-0.0002	-0.0015	0.0004		-0.0015	-0.0037	-0.0038
D_logCREloans{1}	0.2336	0.2126			0.2371	0.1986			0.0715
D_logservice{1}	0.4287	0.1399			-0.0549	0.0253			0.7454
D_logcreret{1}	-0.2044	-0.2136			-0.1234	-0.1781			-0.0938
D_logcpi{1}	0.7198	0.5699			0.4004	0.6397			0.1896
D_loggdp{1}	-0.4606	-0.4316			-0.1683	-0.5295			0.0384
D_crevac{1}	-0.0055	-0.0050			-0.0053	-0.0044			-0.0043
D_fed{1}		0.0016							
D_tenyr{1}									
D_credel{1}					0.0007				-0.0021
T_1989:2						-0.0021			
T_1992:4						0.0012	0.0052	-0.0004	-0.0022
T_2008:2						-0.0018	0.0019	0.0011	0.0037
D_T_1989:2						-0.0037			
D_T_1992:4						-0.0063	-0.0055	-0.0053	-0.0157
D_T_2008:2						0.0057	0.0155	0.0232	0.0120
Lag(s)	2	2	1	1	2	2	1	1	2
Rank(s)	2	4	6	5	6	4	6	6	3
AIC	-5489	-5799	-4647	-4603	-4529	-5643	-4803	-4707	-4529
SBC	-5256	-5573	-4496	-4452	-4395	-5425	-4661	-4563	-4402

Notes: 1. The specifications above are modelled in their Error-Correction form.

2. R_Trend specifies a model with linear trends in the variables and in the cointegrating relations.

* indicates the optimal model: minimizing the AIC/SBC

3.2

3.3 Forecasting

3.3.1 Residential Real Estate (RRE):

Table 3.2 displays the results of the forecasting exercise for the RRE market. The findings indicate that the model excluding structural breaks forecasts with a lower RMSE on average than the model that includes the breaks. Furthermore, Model A also appears to forecast better both in the short run and the long run. As shown in the table below, Model A's forecast is superior to Model E since RMSE is minimized both at the 1-step-ahead and 4-step-ahead forecast[7].

TABLE 3.1: RRE In-Sample Forecast Exercise

	Model A (excluding SB)		Model E (including SB)	
	Rolling Forecast	Recursive Forecast	Rolling Forecast	Recursive Forecast
1-step-ahead	0.0050	0.0041 *	0.0048	0.0062
2-steps-ahead	0.0073 *	0.0078	0.0088	0.0109
3-steps-ahead	0.0111 *	0.0133	0.0146	0.0167
4-steps-ahead	0.0176 *	0.0200	0.0205	0.0229

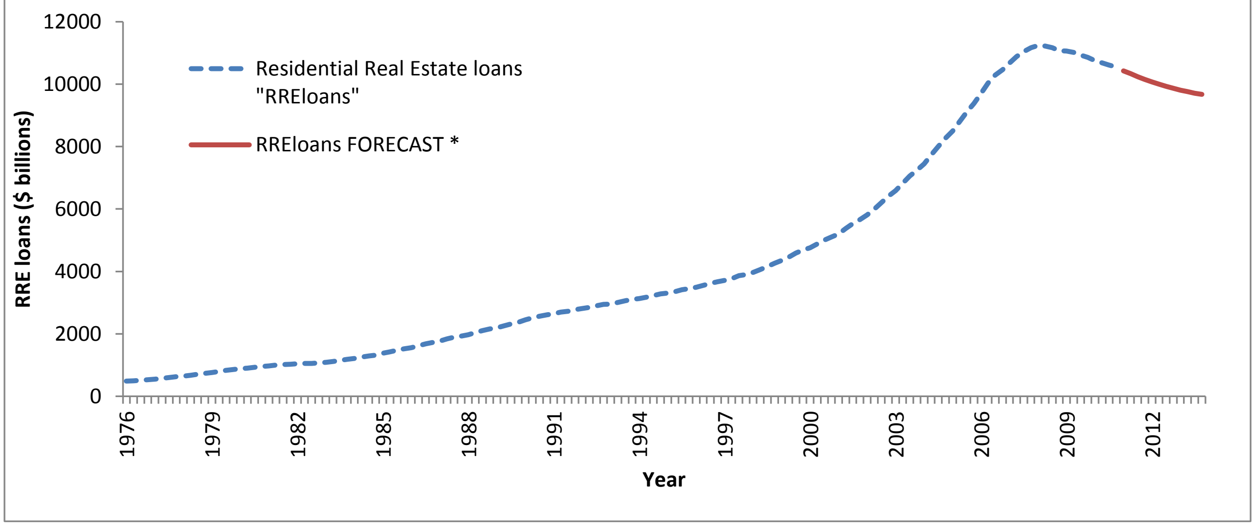
Notes: The Root Mean Square Errors (RMSEs) are used to assess forecast accuracy
* indicates the best model (minimizing the RMSE) for each step-ahead forecast

The forecasting exercise determines that the model which excludes the structural breaks forecasts with a minimum RMSE on average throughout the full sample. This model is then forecasted out 3 years 2011-2013. Figure 2 suggests that residential real estate loans will slightly decrease with a growth rate of -2.51% per year. This is a

[7] Results shown in Table 3.2 also include 2- and 3-steps-ahead forecast errors. The findings are consistent with the conclusion that model 3 forecasts with a lower RMSE on average than model 4.

negative outlook given that RRE loans had been declining with a rate of 2.117% per year from its peak in 2008:1 to 2010:4.

FIGURE 2: Residential Real Estate Loans- FORECAST



The forecast error variance decomposition analysis indicates what proportion of the 15-steps-ahead forecast error variance of variable *i* is explained by shocks to variable *j*. It is typical for a variable to explain the majority of its forecast error variance in the short-run and smaller fractions in the long-run. The proportion of error variance of 'logRREloans' that is explained by its own shocks at 4-steps-ahead is 68.61, and at 12-steps ahead is 17.54. The proportion that is explained by shocks to 'loghp' at 4-steps-ahead is 16.27, and at 12-steps-ahead is 52.81. The proportion that is explained by shocks to 'mort30y' at 4-steps-ahead is 10.07, and at 12-steps-ahead is 16.29[8]. This analysis shows that shocks to the house price index will affect RRE loans in the short-run, but they will have even more of an impact in the long-run. This can be seen in the recent

[8] The proportion of error variance of 'logRREloans' that is explained by shocks to the remaining variables is less than 10.00; the shocks to other variables are not going to considerable affect RRE loans in the short-run or the long-run. The Appendix shows the decomposition of variance for the series from steps 1 to 15.

housing bubble as evidenced by the sudden increase in house prices that led to a rapid increase in RRE loans over the past decade.

3.3.2 Commercial Real Estate (CRE):

Table 2.2 displays the results of the forecasting exercise for the CRE market. The findings indicate that the model including structural breaks forecasts with a lower RMSE on average than the model that excludes the breaks. Furthermore, Model F also appears to forecast better both in the short run and the long run. As shown in the table below, Model F's forecast is superior to Model B since RMSE is minimized both at the 1-step-ahead and 4-step-ahead forecast[9].

TABLE 3.2: CRE In-Sample Forecast Exercise

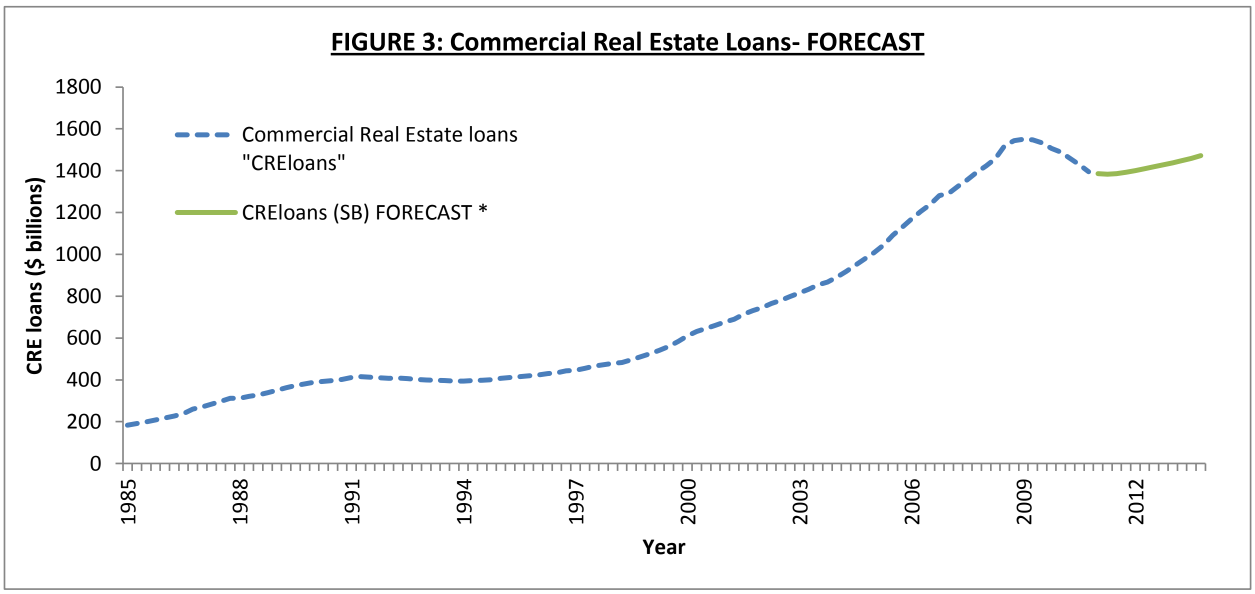
	Model B (excluding SB)		Model F (including SB)	
	Rolling Forecast	Recursive Forecast	Rolling Forecast	Recursive Forecast
1-step-ahead	0.0101	0.0100	0.0086 *	0.0099
2-steps-ahead	0.0157	0.0140	0.0134	0.0132 *
3-steps-ahead	0.0258	0.0257	0.0226	0.0222 *
4-steps-ahead	0.0317	0.0349	0.0277	0.0267 *

Notes: The Root Mean Square Errors (RMSEs) are used to assess forecast accuracy
* indicates the best model (minimizing the RMSE) for each step-ahead forecast

The forecasting exercise determines that the model which includes the structural breaks forecasts with a minimum RMSE on average throughout the full sample. This model is then forecasted out from 2011-2013. Figure 3 suggests that commercial real estate loans will slightly increase with a growth rate of 1.99% per year. This is a positive outlook given that CRE loans have been declining at a rate of 5.290% per year from its

[9] Results shown in Table 2.2 also include 2- and 3-steps-ahead forecast errors. The findings are consistent with the conclusion that model 2 forecasts with a lower RMSE on average than model 1.

peak in 2009:1 to 2010:4. However, this forecast is inconsistent with the view that CRE and RRE loans move together. Since both sectors are driven by common fundamentals, such as similar demand cycles, these markets should display a tendency to move together in the long-run. A possible reason that the markets are moving in opposite directions is the financial assistance program for banks and bank holding companies, Troubled Asset Relief Program (TARP), that expired October 2010 (February Oversight Report, 2010). The problems in the CRE sector and its impact on the economy, such as rising loan default rates and declines in CRE investments, will be felt over the next few years. Since the data in this study ends in 2010:4 and the expiration of the program is quite recent, its effect on the CRE sector is not detected in this analysis.



The forecast error variance decomposition analysis indicates that the proportion of error variance of ‘logCREloans’ that is explained by its own shocks at 4-steps-ahead is 69.76, and at 12-steps ahead is 16.65. The proportion that is explained by shocks to ‘logservice’ at 4-steps-ahead is 11.03, and at 12-steps-ahead is 24.97. The proportion that is explained by shocks to ‘loggdp’ at 4-steps-ahead is 12.68, and at 12-steps-ahead is

42.29[10]. This analysis shows that shocks to service employment and gdp are going to affect CRE loans in the short-run, but they will even more of an impact in the long-run.

4. CONCLUSION

The purpose of this study is to forecast commercial and residential real estate loans. Since these series are non-stationary and seem to move together in the long-run, the Johansen test is implemented to develop cointegrated VAR models for both real estate sectors (commercial and residential). This method analyses whether real estate loans and other endogenous real estate and macroeconomic variables, such as investment returns, interest rates, and employment, display a tendency to move together in the long run. Once the models are specified, with the inclusion and exclusion of structural breaks, the Akaike and Schwartz-Bayesian information criteria statistics are minimized to decide which model is superior in each sub-category. Out-of-sample forecasting exercise, which includes rolling and recursive schemes, is then carried out for the 4 models that remain to determine whether including the structural breaks in the models improves forecasting accuracy on average throughout the sample. Results show that including the structural breaks in the commercial real estate sector model improves forecast accuracy for both forecasting methods. On the contrary, excluding the structural breaks in the best residential real estate model improves forecast accuracy for both forecasting methods. The final forecasting results obtained for both commercial and residential real estate loans leads to the conclusion that both real estate sectors will move in opposite directions from 2011-2013; forecasts suggest that CRE loans will increase, but RRE

[10] The proportion of error variance of 'logCREloans' that is explained by shocks to the remaining variables is less than 10.00; the shocks to other variables are not going to considerable affect CRE loans in the short-run or the long-run. The Appendix shows the decomposition of variance for the series from steps 1 to 15.

loans will decrease.

Areas of further research could extend into improvements in model specifications and forecast accuracy. To specify models that best describe the real estate loan market, certain variables may not be strictly endogenous. A weakly exogenous variable is one that does not adjust to the disequilibrium error. In this case, that variable could be included in the cointegrated VAR model as an exogenous variable; set as an independent variable with no lag parameters included. Additionally, improved methods of forecasting could be used to minimize forecast error. Pesaran & Pick (2008) found that in the presence of structural breaks, rolling window averaging from model could result in lower mean square forecast errors; this is supported by empirical evidence[11].

[11] Bhattacharya & Thomakos (2011) found that rolling window averaging outperformed the best window forecasts for exchange rates, inflation, and output growth more than 50% of the time across all rolling windows.

APPENDIX: Variance Decomposition Analysis

Decomposition of Variance for Series LOGCRELOANS

Step	Std Error	logCREloans	logservice	logcreret	logcpi	loggdp	crevac
1	0.007	100.000	0.000	0.000	0.000	0.000	0.000
2	0.010	95.872	1.497	0.000	2.614	0.004	0.013
3	0.012	86.056	5.583	1.582	2.563	3.927	0.289
4	0.014	69.757	11.025	3.801	1.806	12.682	0.929
5	0.017	54.262	15.765	5.537	1.332	21.327	1.779
6	0.019	42.448	19.134	6.772	1.028	27.930	2.687
7	0.022	34.025	21.339	7.623	0.807	32.630	3.576
8	0.025	28.080	22.748	8.165	0.648	35.944	4.415
9	0.027	23.834	23.658	8.462	0.539	38.308	5.199
10	0.029	20.736	24.261	8.571	0.470	40.031	5.931
11	0.031	18.420	24.674	8.540	0.431	41.315	6.620
12	0.033	16.645	24.970	8.408	0.411	42.293	7.273
13	0.035	15.254	25.191	8.206	0.401	43.052	7.897
14	0.036	14.138	25.363	7.958	0.395	43.649	8.497
15	0.038	13.225	25.501	7.683	0.390	44.122	9.079

Decomposition of Variance for Series LOGRRELOANS

Step	Std Error	logRREloans	loggdp	loghp	logexist	mort30y
1	0.006	100.000	0.000	0.000	0.000	0.000
2	0.009	93.578	0.450	1.696	0.030	4.246
3	0.012	82.926	0.799	7.837	1.479	6.959
4	0.016	68.612	1.047	16.274	3.997	10.070
5	0.020	55.048	1.277	24.630	6.426	12.620
6	0.026	44.192	1.480	31.742	8.258	14.328
7	0.032	36.054	1.646	37.451	9.494	15.356
8	0.038	30.042	1.774	41.973	10.284	15.927
9	0.046	25.568	1.872	45.573	10.774	16.213
10	0.053	22.186	1.945	48.475	11.066	16.328
11	0.061	19.580	2.000	50.847	11.232	16.341
12	0.070	17.536	2.042	52.812	11.316	16.294
13	0.079	15.903	2.075	54.462	11.346	16.214
14	0.088	14.579	2.100	55.864	11.343	16.115
15	0.097	13.490	2.119	57.066	11.318	16.008

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