FORECASTING REAL ESTATE BUSINESS: EMPIRICAL EVIDENCE FROM THE CANADIAN MARKET

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ABSTRACT

In this paper, we compare the out-of-sample forecasting ability of three ARIMA family models: ARIMA, ARIMAX, and ARIMAX-GARCH. The models are tested to forecast turning points and trends in the Canadian real estate index using monthly data from April 2002 to March 2011. The results indicate that the ARIMAX model, which includes exogenous macroeconomic variables such as the gross domestic product, the consumer price index, the difference in long-term and short-term interest rates, and the exchange rate of the Canadian dollar against the US dollar and their lags, provides the best out-of-sample forecasts. Overall, the models are suitable only for short-term forecasts.

JEL: R3, G01, O51, C53

KEYWORDS: Real Estate, Financial Crisis, Canada, ARIMAX, GARCH

INTRODUCTION

Since the 2008 financial crisis, the world markets have gone through much uncertainty, and even after four years of crisis, the markets are unstable. The crisis led many economists to probe the nature and causes: low interest rates, high interest rates, mortgage-backed securities, asset-backed securities, credit default swaps, bad regulations, cheating, etc. However, the real estate market played a central role, bringing real estate issues before policymakers. The real estate industry is unique in terms of its contribution to a country's gross domestic product (GDP) and the overall impact on economy. At the same time, the real estate market is inefficient and illiquid, and faces regular intervention by governments across the world. Hence, the movement of the real estate business becomes a key ingredient in planning for the layperson, investors, and policymakers.

Although much research is available for the US market, research on the Canadian real estate market is unavailable. Though the Canadian market is very similar to the US market in most cases, the Canadian real estate market has several different features. The Canadian real estate market was not hurt by the financial crisis compared to the US real estate market, which is still struggling to recover. In contrast, the Canadian real estate market has increased since the beginning of 2009. In terms of broader differences, the average Canadian saw his or her income grow, and the Canadian banking structure imposes uniform and stable interest rates. These factors suggest that other factors played a role in the real estate market. This study tests a simple and widely available model to assist the common forecaster. In particular, the study uses the time series auto regressive integrated moving average (ARIMA), and then uses the auto regressive integrated moving average with exogenous variables (ARIMAX) and the auto regressive integrated moving average with exogenous variables including generalized auto regressive conditional heteroskedastic (ARIMAX-GARCH) models to test their forecasting capability.

To understand the nature of the Canadian real estate market, this study uses a times series model with a macroeconomic variable in line with other studies such as those Brooks and Tsolocas (1999), De Wit and Van Dijk (2003), and Karakozova (2004), who found the effect of the macroeconomic variable on real estate. This paper contributes significantly to the existing real estate literature by adding knowledge of

Canadian real estate and its connection with macroeconomic variables and presenting a simple tool for forecasters.

Researchers have applied various models to explain the real estate market, from simple linear regression to advanced models such as the Vector Error Correction model (VECM), the Kalman filter, and so on. However, in the end simple models were found efficient compared to more complex models (Wilson, Ellis, Okunew and Higgins, 2000, Crawford and Fratantoni, 2003, Stevenson and Young, 2007). Thus, this paper focuses on the performance of univariate models. Moreover, the purpose of this study is to provide a simple tool to forecasters.

This study finds that it is very difficult to do precise long-term forecasting for the Canadian real estate index using the ARIMA family models, but these models worked very well in short-term forecasting. Specifically, out of the three models tested, the ARIMA, ARIMAX and ARIMAX-GARCH models, the ARIMAX model works best in all circumstances by giving minimum mean absolute percentage error. Other models work best in one circumstance but fail drastically in other circumstances. The performance of the ARIMAX model also demonstrates that macroeconomic variables have high information content in terms of future development in the real estate market.

The remainder of the paper is organized as follows: In the second section, we present our literature review, in the third section we present our data and methodology, in the fourth section we present our results and discussion, and in the fifth section we present our concluding comments.

LITERATURE REVIEW

In the context of this study, the literature related to real estate forecasting involving univariate models is reviewed.

Mei and Liu (1994) used rolling regressions for out-of-sample excess return forecasts for 10 years. These authors used the predictions of the models estimated for alternative real estate stock return series to construct active and passive buy and hold portfolios. Their analysis showed that active portfolios with a long and short trading strategy would have returned US$238.20 for homebuilder stocks over and above a passive strategy.

Tse (1997) employed ARIMA models in forecasting real-estate prices in Hong Kong. The price index used in this study was simply compiled by calculating a weighted average of the index for a property class or grade. To avoid the effect of government intervention, the study uses only Hong Kong office and industrial properties in its calculations. Quarterly data for the period 1980 Q1 to 1995 Q2 is used. The study finds that for office and industrial property, the ARIMA (2,1,1) model is appropriate for forecasting. This model was able to predict trends and turning points in the data.

Brooks and Tsolacos (2000) investigated UK retail rents using LaSalle Investment Management series and CB Hiller Parker series. These authors used four models, an auto regressive (AR) model, a long-term-mean model, a random-walk model, and a Vector Autoregressive (VAR) model. They find the AR(2) model fits best in estimation and when an ex-post forecast is produced up to eight quarters ahead; the AR(2) model outperforms all other models.

Wilson *et al.* (2000) studied the securitized real estate indices of the US, the UK, and Australia. These authors applied an exponential smoothing model, an ARIMA model, and spectral techniques for forecasting. They find that the exponential smoothing model works better than other models when a stable trend is present. Both the ARIMA and spectral regression modeling processes are capable of forecasting turning points only when data has historical causal factors that are potentially repeatable.

Fullerton, Laaksonen, and West (2000, 2001) examine housing supply in Florida using single-family and multi-family data, respectively. These papers compared the forecast accuracy of structural equation models, ARIMA, and random walk models. In both studies, the random walk model outperforms other models.

Clapp and Giaccotto (2002) use an autoregressive process to model the city-wide house price index of Dade County, Florida. They proposed a battery of tests to compare prediction errors for one-quarter ahead forecasts for individual properties. They compared their forecasts with two forecasting models, hedonic and repeat sales. Overall, they found that the hedonic model is more efficient than the repeat sales model.

Stevenson and McGarth (2003) study the London office market by employing ordinary least square (OLS), auto regressive integrated moving average (ARIMA), and Bayesian Vector Autoregressive (BVAR) models, and a simultaneous equation model. They used CB Hillier Parker London Office index data over the period 1977–1996. Their emphasis was to compare the model for their long-term forecast. Hence, they generated three-year forecasts from their models for comparison. They found that BVAR provides the best forecasts, while the ARIMA model generated the worst forecasts. The ARIMA model fails to capture a large upswing after mid-1997. The authors argue that the main reason behind the failure of the ARIMA model is that the final model selected in the study is a pure AR(1) model with no moving average (MA) terms.

Crawford and Fratantoni (2003) use ARIMA, GARCH, and regime switching univariate models to forecast the real estate market in various parts of the US. They used state-level repeat transactions data for California, Florida, Massachusetts, Ohio, and Texas. Annualized growth rates at a quarterly frequency are computed from each of these indices from 1979:1 to 2001:4. The study found that ARIMA models are generally more suitable for out-of-sample forecasting and point forecasts.

Studying the Helsinki office market, Karakozova (2004) finds that the ARIMAX model forecasts better than the regression and error correction models. This study compared out-of-sample forecasts from 2002 to 2005. In the case of the ARIMAX model, the author finds that past values of capital growth, growth in service sector employment, and growth in the gross domestic product are relevant in explaining the variation in office market returns in the Helsinki area.

Guirguis, Giannikos and Anderson (2005) studied the US housing market using quarterly data from 1975:01 to 1998:02 by using real house prices and various other macroeconomic indicators. The key attraction of this paper is that it used six different estimation techniques, the vector error correction model (VECM), the auto regressive (AR) model, the generalized auto regressive conditional heteroskedastic (GARCH) model, the Kalman filter with a random walk, the Kalman filter with an AR model, and exponential smoothing, in which estimated parameters are allowed to vary over time. The authors claimed that the Kalman filter with the AR model and the GARCH model provides the best out-of-sample forecasts.

Stevenson and Young (2007) applied the OLS, ARIMA, and VAR models to forecasting housing supply in the Irish market, using quarterly data from 1978 through 2003. They found that the ARIMA model has better forecasting ability over others for the period 1998–2001, because the Irish market had a sustained housing boom beginning in the mid-1990s that ignored the fundamentals. In the absence of fundamentals, ARIMA models perform well in predicting trends.

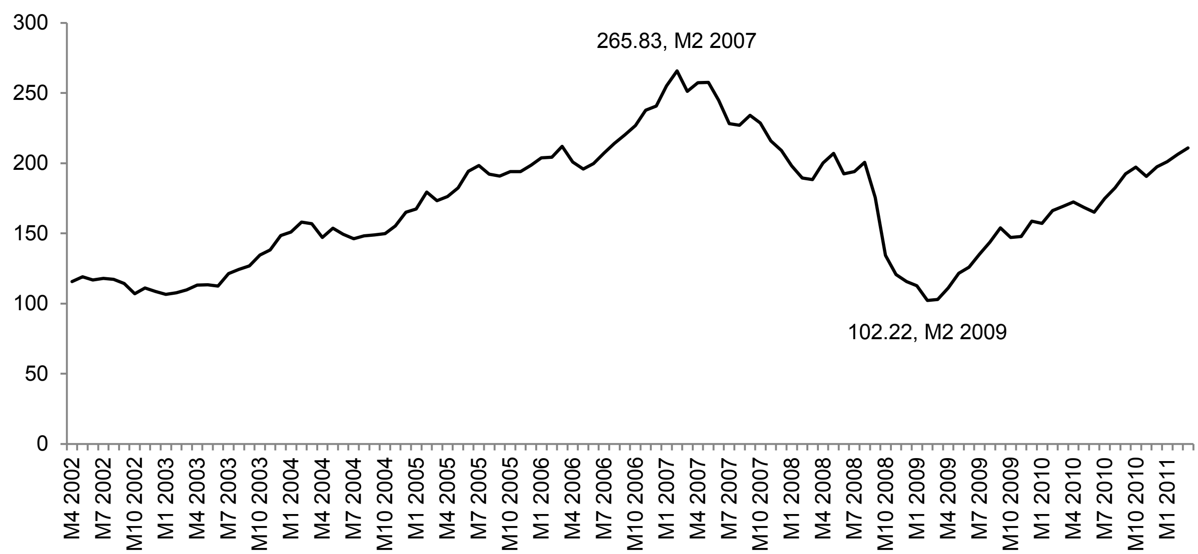
Gupta and Das (2010) used a Bayesian approach in predicting downturns in the US housing market in the period 2007:Q1–2008:Q1. Their result shows that the BVAR model, in any form, spatial and non-spatial (univariate and multivariate), is the best-performing model as well as doing a fair job in predicting the downturn against unrestricted the classical VAR model.

DATA AND METHODOLOGY

This study uses monthly data from the S&P/TSX Capped Real Estate Index as a proxy for the real estate market in Canada (REI) and macroeconomic variables such as the GDP, inflation, long-term and short-term Treasury bond rates, and the exchange rate of the Canadian dollar against the US dollar. The real estate index was obtained from the Yahoo Canada website, and the macroeconomic variables were obtained from the Statistics Canada website. Due to the availability of data, this study restricts the sample of study from April 2002 to March 2011.

Figure 1 shows that the Canadian real estate sector grew rapidly until February 2007, with the index going as high as 265.83. In April 2002, the index was only 115.73; this is almost 130% growth. After the market crash in February 2007, the real estate market kept sliding downward until February 2009 when the market turned up again.

Figure 1: S&P/TSX Capped Real Estate Index



*This figure shows S&P/TSX Capped Real Estate Index **(REI)** from April 2002 to March 2011.*

The choice of the macroeconomic variable in this study is guided by previous studies in a related area. The GDP is used as a determinant based on the Chen, Roll, and Ross (1986) and Karolyi and Sanders (1998) studies that find stock prices and industrial production have explanatory power for each other. Gardiner and Henneberry (1988, 1991) used the GDP in their rent forecasting models. Higher inflation leads to decreased demand for housing according to Feldstein (1992) and Kearl (1979). However, Quan and Titman (1999) argue that inflation may increase demand for housing because housing is seen as a hedge against the inflation. The consumer price index (CPI) is used as the variable for inflation.

The financial literature suggests that the difference between long-term and short-term interest rates has predictive power about the state of economy (Fama and French, 1992, Stock and Watson, 1989). The higher the difference, the higher the premium for holding assets, which leads to increased demand for real assets. The difference in the long-term government bond (10 years) and the short-term interest rate (three-month T-bill) is termed SPREAD. Ajayi and Mougoue (1996) and Granger, Huang and Yang (2000) find that the exchange rate and stock prices influence each other. Thus, this study uses the CAD/US exchange rate as another determinant in the model.

To understand the nature of the Canadian real estate market and its connection with major macroeconomic variable and provide valuable forecasts, this study follows Brooks and Tsolacos (1999), De Wit and Van Dijk (2003), Karakozova (2004), Crawford and Fratantoni (2003), Stevenson and Young (2007) and employs the auto regressive integrated moving average (ARIMA), the auto regressive integrated moving average with exogenous variables (ARIMAX), and the auto regressive integrated moving average with exogenous variables including generalized auto regressive conditional heteroskedastic (ARIMAX-GARCH) models. The ARIMA models have constant mean and constant variance while the ARIMAX model includes exogenous variables to explain the data-generating process. The ARIMAX-GARCH model has all the features of the ARIMAX model plus time-varying variance.

A general ARIMA (p,d,q) model can be represented as:

$$Z_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Z_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \tag{1}$$

Where Z_t is a variable of interest, p denotes the order of auto regression, q denotes the order of moving average, and d denotes the order of integration. Where ε_t follows $[\sim N(0, h_t)]$.

A general ARIMAX(p,d,q) model can be represented

$$Z_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Z_{t-i} + \sum_{i=1}^{k} \gamma_i X_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \tag{2}$$

Where Z_t is a variable of interest, p denotes the order of auto regression, q denotes the order of moving average, d denotes the order of integration, and X_t is a vector of exogenous variables with k lags. Where ε_t follows $[\sim N(0, h_t)]$.

Bollerslev (1986) developed the generalized auto regressive conditional heteroskedastic – GARCH (p,q) model that allows the conditional variance to be modeled as an ARMA process. Thus, in our paper we extend our ARIMAX model from equation (2) to model its conditional variance as the GARCH(p,q) process. Thus, our model (ARIMAX-GARCH) can be re-written as:

$$Z_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Z_{t-i} + \sum_{i=1}^{k} \gamma_i X_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \text{ where error process be } \varepsilon_t = v_t \sqrt{h_t}$$

Where $v_t =$ white-noise process such that $\sigma_v{}^2 = 1$ and $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i h_{t-i}$ (3)

where ε_t is shock $[\sim N(0, h_t)]$, αs are the ARCH coefficients with q lags, and γs are the GARCH coefficients with p lags. A non-negativity constraint is imposed on αs and γs during estimation.

The estimation process of all three models requires that the series used in the model are stationary. Hence, the log level series is tested for stationarity; if required, the log difference of series is used to make the process stationary. The Dickey fuller test (Dickey and Fuller, 1979) and the augmented Dickey fuller (ADF) test are used to check for the stationary process. The Dickey fuller test can be represented as $\Delta Z_t = a_0 + \psi Z_t + \varepsilon_t$, and the ADF test can be represented as $\Delta Z_t = a_0 + \psi Z_t + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \varepsilon_t$. The ADF test helps in determining the unit root process beyond AR(1). After each series is made stationary, an ARIMA model is built based on Box-Jenkins (1976) three-step process of identification, estimation and diagnostic checking. First, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are examined to decide the order of the AR and MA process. Further, based on minimization of Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC), the AR and MA terms are decided in the model. These criteria may give different results; in such cases, the model with the smallest standard error and the Ljung-Box *Q* (Ljung and Box, 1978) value is estimated. After the model is estimated, its residuals are examined again to test for leftover auto correlation using the ACF and the PACF.

The ARIMAX model is built on the ARIMA model. After the order of the AR and MA terms is chosen, exogenous variables are introduced in the model. The AR and MA terms chosen for the ARIMA model from the previous exercise may not be suitable with the introduction of (X) exogenous variables. Hence, various combinations of AR and MA terms are tested with the lags of the exogenous variable, and the one with the smallest standard error and Ljung-Box *Q* statistics is chosen for the ARIMAX estimation.

The GARCH process is fitted using equation (3) on the errors generated by the ARIMAX model from the previous exercise that created the ARIMAX-GARCH process. To keep the model parsimonious, only GARCH(1,1) is estimated in this study.

Since the basic aim of this study is to provide a model that is simple to estimate and efficient in forecasting, more emphasis is on forecasting of these models in different circumstances, and much of the paper is devoted to the forecasting abilities of the model. As suggested by Crawford and Fratantoni (2003), models can fit well compared to others but can be still poor forecasters.

To test the forecast accuracy of the models, we estimated them for a certain period and then subsequently made them forecast for a certain period. While deciding about the estimation period and the forecasting period, the models were forced to test key features about the index, such as in-sample forecast performance, out-of-sample forecast performance, downward trend in the series, upward trend in the series, downward turning point in the forecasting period, and upward turning point in the forecasting period.

For each set of estimation and forecasting periods, two kinds of forecasts were generated: dynamic and static forecasts. Dynamic forecasting feeds forward forecasts of the early periods to forecast the next period. A static forecast computes the forecast as a series of one-step-ahead forecasts using only actual values for lagged dependent variable terms. Forecasts from different models are compared based on three forecast error statistics, Root Mean Squared Error, Mean Absolute Error, and Mean Absolute Percentage Error. These can be represented as Root Mean Squared Error: $\sqrt{\sum_{t=T+1}^{T+h} (\hat{Z}_t - Z_t)^2 / h}$, Mean Absolute Error: $\sum_{t=T+1}^{T+h} \left| \hat{Z}_t - Z_t \right| / h$, and Mean Absolute Percentage Error: $100 \sum_{t=T+1}^{T+h} \left| \frac{\hat{Z}_t - Z_t}{Z_t} \right| / h$ where the forecast sample is j= T+1, T+2,….., T+h, and Z_t and $\hat{Z}_t$ denote the actual and forecasted value in period t, respectively.

RESULTS

As described in the Methodology section, the process starts with testing for unit root process in each series used, the Canadian real estate index (REI), the gross domestic product (GDP), the consumer price index (CPI), the difference in the long-term and short-term interest rates (SPREAD), and the exchange rate of the Canadian dollar against the US dollar (CAD/US). After log transformation, each variable is tested for stationarity using the DF and ADF tests. All are non-stationary. In the next step, the log difference of each variable is tested for stationarity, and the results indicate that all the variables become stationary after the first difference. Thus, the order of integration becomes one (d=1) for all the models used in this study. As a result, the log difference of the Canadian real estate index (RREI), the log difference of the gross domestic product (RGDP), the log difference of the consumer price index (RCPI), the log difference of the difference in the long-term and short-term interest rates (RSPREAD), and the log difference of the exchange rate of the Canadian dollar against the US dollar are used in all the models (RCAD/US).

The summary statistics of the full sample are reported in Table 1. It shows that over the entire sample the Canadian real estate index had an average return of approximately 0.6% with a standard deviation of 5%. The exchange rate of the CAD/US saw an average growth rate of -0.5%, which is due to the appreciation of the Canadian dollar against the US dollar. The average difference between long-term government and short-term bonds was negative. In addition, for the entire sample low inflation and low GDP growth are observed. Following Box-Jenkins (1976), ACF and PACF diagrams are used to decide the order of the AR and MA; the AIC picks the ARIMA(1,1,1) model, and the SBC picks the ARIMA(5,1,1) model. After these models were estimated using eq. (1), standard errors and Ljung-Box *Q* statistics were found to be smallest for the ARIMA (5,1,1) model. After the described diagnostic check for the model was conducted, the ARIMA (5,1,1) model was chosen for forecasting.

Table 1: Summary Statistics

	RREI	RCAD/US	RCPI	RSPREAD	RGDP
Mean	0.006	-0.005	0.002	-0.208	0.002
Std. Dev.	0.050	0.022	0.002	1.035	0.004
Observations	107	107	107	107	107

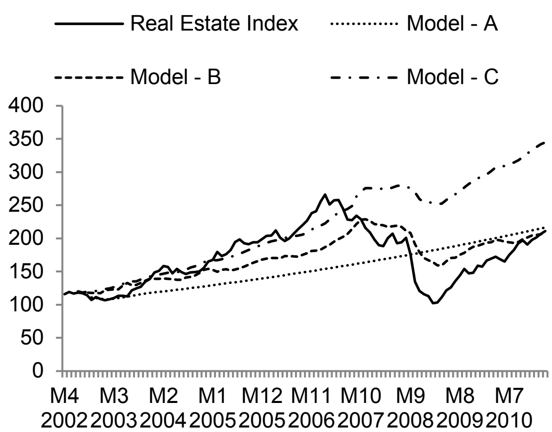
This table shows the summary statistics of the variables in the sample used for the study from April 2002 to March 2011. RREI is the log difference of the S&P/TSX Capped Real Estate Index. RCAD/US is the log difference of the exchange rate of the Canadian dollar against the US dollar. RCPI is the log difference of the consumer price index. RSPREAD is the log difference of the difference in long-term (10 years) and short-term interest rate (3 month) government bonds. RGDP is the log difference of the gross domestic product. Monthly data is used for all variables.

However, based on the smallest standard errors, AIC, and SBC criteria, the ARIMAX model, which was found suitable, was with AR(1) and MA(1) with RREI as the dependent variable and RGDP, RCPI, RSPREAD, RCAD/US, RGDP(-1), RCPI(-1), RSPREAD(-1), and RCAD/US (-1) as the exogenous variables, where (-1) stands for the lag of a variable. Equation (2) is used to estimate this for various time periods and forecasting. Further, the residuals from this model are fitted into the GARCH (1,1) process as described in eq. (3), which will be the ARIMAX-GARCH model for this study.

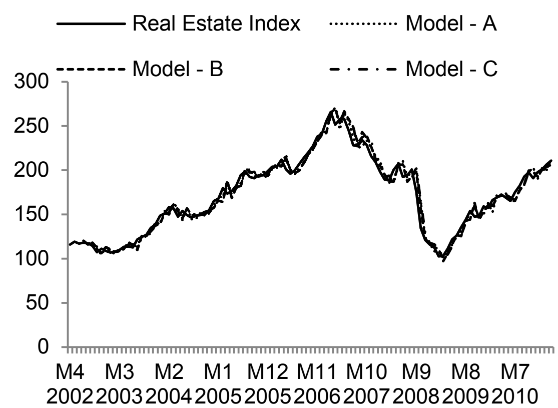
As suggested by Crawford and Fratantoni (2003), models can fit well over other but can be still poor forecasters. The forecasting results are presented in Figure 2 and Table 2, where * denotes the best model among that category. The first set of results is based on the estimation of models for the period M4 2002 to M3 2011, and forecasting is done for period M4 2002 to M3 2011. It is in-sample forecasting for the whole data set. In the next set, the models are estimated from M4 2002 to M3 2007 with the forecasting period from M3 2007 to M8 2007. It has a downward trend beginning from M2 2007. The third set of the result estimates the model from M4 2002 to M7 2007, which covers four extra months from the downward turning point of M2 2007 to give more information for data learning to the models used for forecasting from M7 2007 to M12 2007. The fourth set of estimation is done on the period M4 2002 to M1 2007, which is just before the downward turning point of M2 2007, and the forecast is produced for M1 2007 to M1 2008, which covers the turning point. The fifth set of results is from the estimation period of M4 2002 to M12 2008, which is just before the upward turning point of M2 2009 in the index, and the forecast is produced for the period of M12 2008 to M8 2009, which has an upward turning point and upward rally then onwards. The sixth set has an estimation period from M4 2002 to M10 2009, which has eight more observations from the upward turning point of M2 2009. The final set of the results has M4 2002 to M6 2010 as the estimation period, which covers one upward trend, one downward trend and two turning points in the series.

Overall, the results indicate that none of the models have good dynamic forecasts; they missed trends as well as turning points. However, the static forecasts have significantly better forecasts with very low MAPE. Thus, for practical purposes it is not wise to rely on dynamic forecasts. Another trend in the results indicates that including macroeconomic factors definitely improves the performance of the forecasts, except for the results for Set II. In all other cases, ARIMAX(1,1,1) or ARIMAX-GARCH(1,1) significantly improves the performance of forecasts over the ARIMA(5,1,1) model.

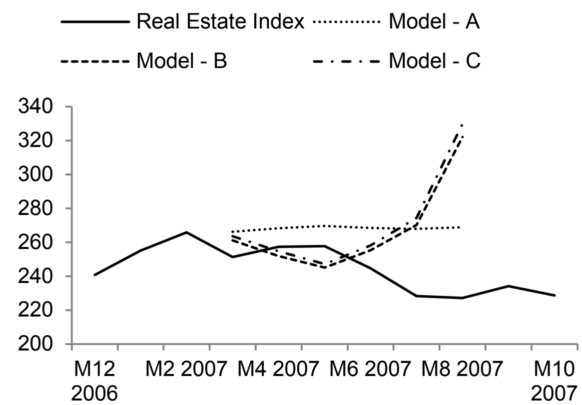
Figure 2: Dynamic and Static Forecasts



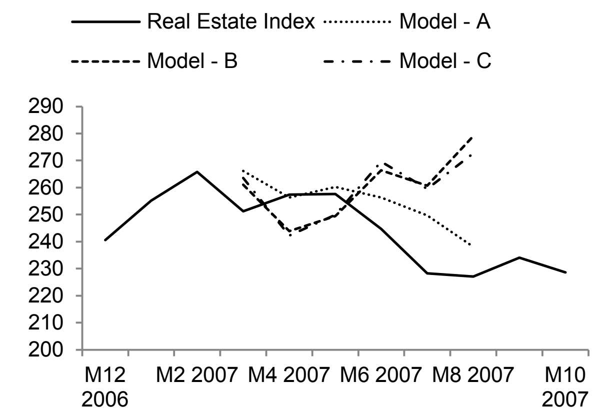
Set I - Model Estimation M4 2002 - M3 2011,
Dynamic Forecast M4 2002 - M3 2011



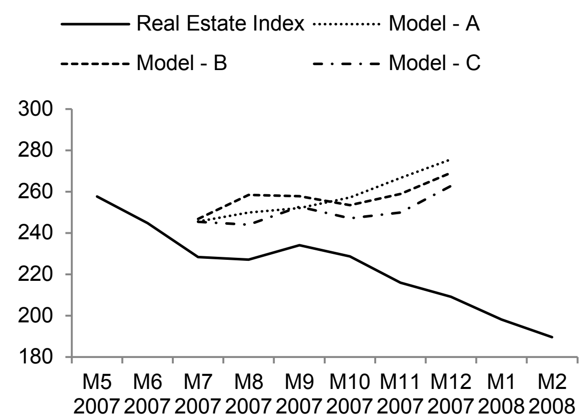
Set I - Model Estimation M4 2002 - M3 2011,
Static Forecast M4 2002 - M3 2011



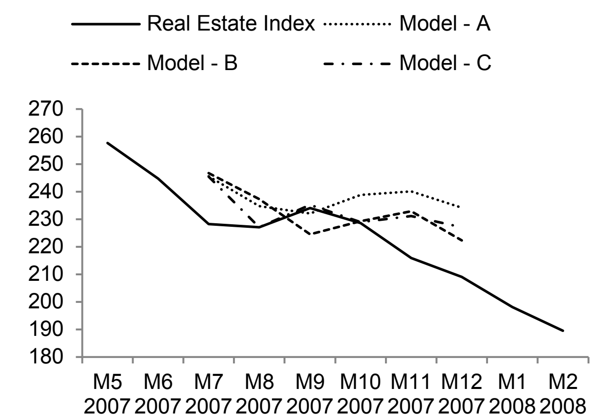
Set II - Model Estimation M4 2002 - M3 2007,
Dynamic Forecast M3 2007 - M8 2007



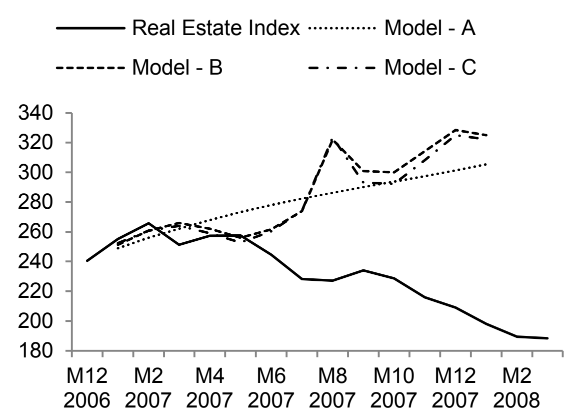
Set II - Model Estimation M4 2002 - M3 2007,
Static Forecast M3 2007 - M8 2007



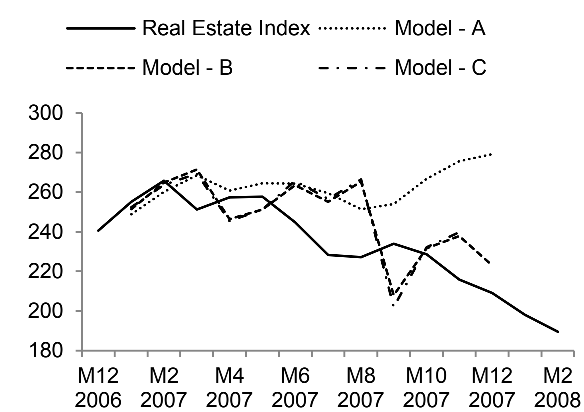
Set III - Model Estimation M4 2002 - M7 2007,
Dynamic Forecast M7 2007 - M12 2007



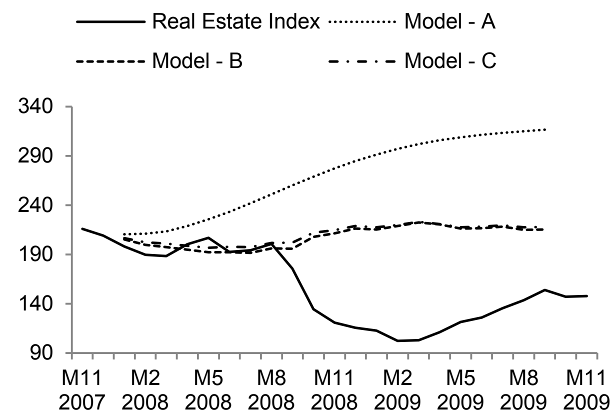
Set III - Model Estimation M4 2002 - M7 2007,
Static Forecast M7 2007 - M12 2007



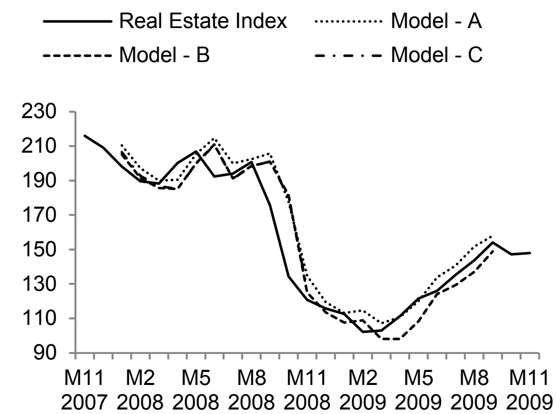
Set IV - Model Estimation M4 2002 - M1 2007,
Dynamic Forecast M1 2007 - M1 2008



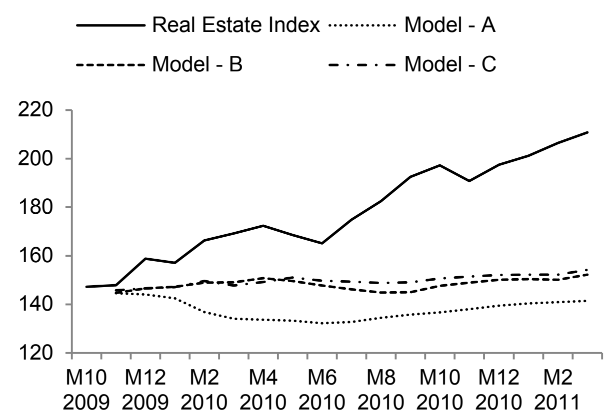
Set IV - Model Estimation M4 2002 - M1 2007,
Static Forecast M1 2007 - M1 2008



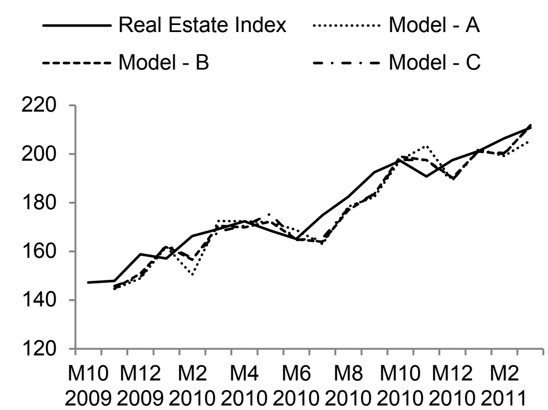
Set V - Model Estimation M4 2002 - M12 2008,
Dynamic Forecast M12 2008 - M8 2009



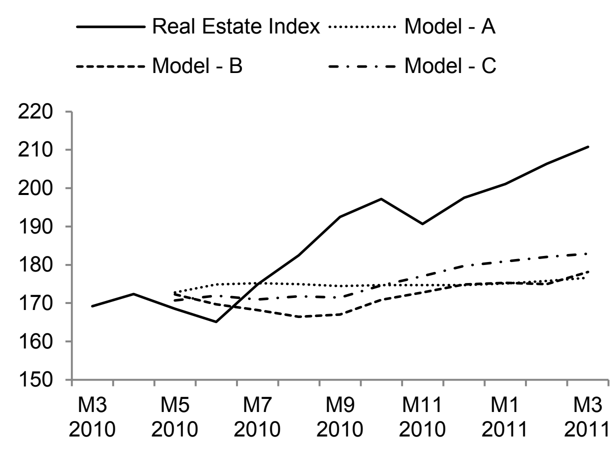
Set V - Model Estimation M4 2002 - M12 2008,
Static Forecast M12 2008 - M8 2009



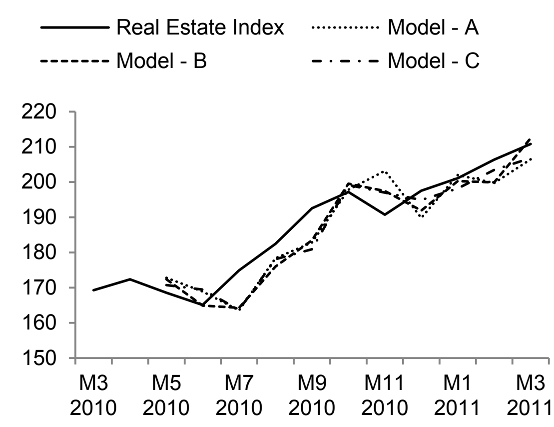
Set VI - Model Estimation M4 2002 - M10 2009,
Dynamic Forecast M10 2009 - M3 2011



Set VI - Model Estimation M4 2002 - M10 2009,
Static Forecast M10 2009 - M3 2011



Set VII - Model Estimation M4 2002 - M6 2010,
Dynamic Forecast M6 2010 - M3 2011



Set VII - Model Estimation M4 2002 - M6 2010,
Static Forecast M6 2010 - M3 2011

These figures are graphical representation of three alternative techniques: Model A: The ARIMA (5,1,1), Model B: The ARIMAX (1,1,1), and Model C: The ARIMAX (1,1,1)-GARCH (1,1) model.

Sets III, VI, and VII are the trend results; i.e., in actual data, the forecast period for Set III is downward trending, and Sets VI and VII are upward trending. In addition, in these cases, the turning point is introduced in the model's estimation period. An interesting observation for all these cases is that macroeconomic factors as well as conditional volatility play a role. ARIMAX-GARCH (1, 1) performs the best in the three cases on a statistical basis, but the ARIMAX forecasts are also very close.

Sets IV and V test the model for forecasting a turning point without including the turning point date in estimation period. Set IV is for downward crash, and Set V is for an upward rally. Interestingly, the ARIMAX model predicted a downward turning point very well after M2 2007. However, the simple ARIMA model performs better than the ARIMAX model for predicating an upward turning point in set V on a statistical basis, although the difference is less than a percent.

Table 2: Comparison of Forecasting Accuracy of Models

Set	Model Estimation	Forecast Period	Model	Dynamic			Static		
				RMSE	MAE	MAPE	RMSE	MAE	MAPE
I	M4 2002 – M3 2011	M4 2002 – M3 2011	A	49.352	41.601	23.663	7.777	5.819	3.397
			B	31.468*	25.428*	15.192*	7.485*	5.684*	3.355*
			C	77.948	54.526	34.663	7.841	5.764	3.403
II	M4 2002 -M3 2007	M3 2007- M8 2007	A	26.931*	23.796*	10.034*	12.572*	10.443*	4.392*
			B	43.083	29.192	12.556	27.583	22.930	9.713
			C	46.738	31.273	13.480	26.171	22.809	9.616
III	M4 2002-M7 2007	M7 2007 – M12 2007	A	38.662	33.991	15.523	16.716	14.390	6.571
			B	12.783*	9.627	4.465	9.910	7.815	3.596
			C	13.031	8.747*	4.090*	9.823*	7.045*	3.285*
IV	M4 2002 -M1 2007	M1 2007- M1 2008	A	44.912*	36.581*	15.837*	26.667	21.155	9.168
			B	68.648	51.564	23.612	18.646*	15.150*	6.548*
			C	66.09	49.240	22.576	21.190	17.243	7.357
V	M4 2002 -M12 2008	M12 2008- M8 2009	A	136.341	115.675	91.305	14.115	9.435*	6.334*
			B	71.638*	56.524*	46.424*	14.041*	9.486	6.503
			C	73.101	57.994	47.527	17.913	12.475	7.661
VI	M4 2002 -M10 2009	M10 2009-M3 2011	A	46.194	42.235	22.656	7.633	6.170	3.469
			B	36.152	31.716	16.825	5.895*	4.853	2.738
			C	34.356*	30.152*	15.994*	5.926	4.767*	2.716*
VII	M4 2002 -M6 2010	M6 2010- M3 2011	A	20.321	17.424	8.844	7.060	5.970	3.178
			B	26.822	21.726	11.481	6.618	5.340	3.128
			C	17.586*	15.522*	7.906*	5.909*	4.930*	2.640*

This table compares the forecasting accuracy for the three alternative techniques: Model A: The ARIMA (5,1,1), Model B: The ARIMAX (1,1,1), and Model C: The ARIMAX (1,1,1)-GARCH (1,1) model. The models are compared based on the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percent error (MAPE), which can be represented as follows: Root Mean Squared Error: $\sqrt{\sum_{t=T+1}^{T+h}(\hat{Z}_t - Z_t)^2 / h}$*, Mean Absolute Error:* $\sum_{t=T+1}^{T+h}\left|\hat{Z}_t - Z_t\right| / h$*, and Mean Absolute Percentage Error:* $100\sum_{t=T+1}^{T+h}\left|\frac{\hat{Z}_t - Z_t}{Z_t}\right| / h$ *where the forecast sample is j= T+1, T+2,….., T+h, and* Z_t *and* $\hat{Z}_t$ *denote the actual and forecasted value in period t, respectively. * denotes the best model in a set.*

Overall, the results suggest that whenever the ARIMA model outperforms the ARIMAX model or the ARIMAX-GARCH model outperforms ARIMAX model, the ARIMAX model is very close to the best model in that set. At the same time, the ARIMA and ARIMAX-GARCH forecasts always remain far apart. This suggests the strength of the ARIMAX model in forecasting and ease of modeling compared to other complex models. In two extremes of models with ARIMA on one side and ARIMAX-GARCH on one side, the inclination of the results from the ARIMAX model should be seen as the correct trend investors can use as a guide. If one has to pick one model for one-step forecasting in all circumstances, then ARIMAX models are the best. Similar to Karakozova (2004), our results also emphasize the importance of macroeconomic variables in ARIMAX models.

CONCLUDING COMMENTS

The main purpose of this paper is to provide a simple model that helps in forecasting turning points and trends in the Canadian real estate sector. Thus, a very comprehensive time series from the S&P/TSX Capped Real Estate Index from April 2002 to March 2011 is used for this study. This time series shows an upward rally from April 2002 to February 2007, a downward turning point in February 2007, a downward rally from February 2007 to February 2009, an upward turning point in February 2009, and an upward rally from February 2009 onwards. The real estate market, which is known to follow trends and changes due to economic impacts, is perfect for a study using ARIMA-family models. Thus, the forecasting ability of three models is compared in this paper: ARIMA, ARIMAX and ARIMAX-GARCH. The ARIMA model has constant mean and constant variance while the ARIMAX model includes exogenous variables to explain the data-generating process. The ARIMAX-GARCH model has all the features of the ARIMAX model, plus time-varying variance.
This study confirms the results of Tse (1997), Karakozova (2004), and Stevenson and Young (2007), that ARIMA-family models are suitable for short-term forecasting. Hence, one-step ahead forecasts are trustworthy for practical purposes. The results indicate that the ARIMAX model did a good job of predicting trends and turning points in static forecasts. In the best performance for one-step ahead forecasts, the ARIMAX model produced a mean absolute percentage error of 3.12%, and in the worst performance, the model produced a mean absolute percentage error of only 9.713%. These results further emphasize the importance of macroeconomic variables and their lags in the forecasting process.

This study has at least two forecasting limitations. First, none of the models can foresee systematic shocks. Thus, future forecasting always has some degree of riskiness. Secondly, it is difficult to get true future macro-economic variables ahead of time to perform future forecasting. Hence, it is difficult to do any long-term forecasting in the true sense when the economic environment is unstable.

This paper provides a simple tool for forecasting, but there are many complicated forecasting models available. Hence, this study can be extended in various forms, like using additional exogenous variables as explanatory variables, using multivariate forms of models, incorporating long memory in the models, and use of time varying coefficients for the model, among others. However, the ultimate choice of the investor or policy maker should depend on forecasting properties of the model.

REFERENCES

Ajayi, R.A. and M. Mougoue (1996) "On the Dynamic Relation between Stock Prices and Exchange Rates," *Journal of Financial Research*, vol. 19, p. 193-207.

Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics*, vol. 31, p. 307-327.

Box, G. and G. Jenkins (1976) "Time Series Analysis, Forecasting, and Control," San Francisco: Holden Day.

Brooks, C. and S. Tsolacos (1999) "The Impact of Economic and Financial Factors on UK Property Performance," *Journal of Property Research*, vol. 16, p. 139-152.

Brooks, C. and S. Tsolacos (2000) "Forecasting Models of Retail Rents," *Environment and Planning A*, vol. 32 (10) p. 1825-1839.

Clapp, J. and C. Giaccotto (2002) "Evaluating House Price Forecasts," *Journal of Real Estate Research*, vol. 24, p. 1-26.

Chen, N.-F., R. Roll and S. Ross (1986) "Economic Forces and the Stock Market," *Journal of Business*, vol. 59, p. 383-403.

Crawford, G.W. and M.C. Fratantoni (2003) "Assessing the Forecasting Performance of Regime-Switching, ARIMA and GARCH Models of House Prices," *Real Estate Economics*, vol. 31, p. 223-244.

De Wit, I. and R. Van Dijk (2003) "The Global Determinants of Direct Office Real Estate Returns," *Journal of Real Estate Finance & Economics*, vol. 26(1) p. 27.

Dickey, D.A. and W.A. Fuller (1979) "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," *Journal of the American Statistical Association*, vol. 76 (366) p. 427-431.

Fama, E.F. and K.R. French (1992) "The Cross-section of Expected Stock Returns," *Journal of Finance*, vol. 47, p. 427-465.

Feldstein, M.S. (1992) Comment on James M. Poterba's paper, Tax reform and the housing market in the late 1980s: who knew what, and when did they know it?, in L. Browne and E. S. Rosegren (eds.), Real Estate and Credit Crunch, *Federal Reserve Bank of Boston Conference Series*, vol. 36, p. 252-257.

Fulleron, T. M., M. M. Laaksonen and C. T. West (2000) "Regional single-family housing start forecast Accuracy," *Journal of Housing Research*, vol. 11, p. 109-120.

Fulleron, T. M., M. M. Laaksonen and C. T. West (2001) "Regional multi-family housing start forecast Accuracy," *International Journal of Forecasting*, vol. 17, p. 171-180.

Gardiner, C. and J. Henneberry (1988) "The Development of a Simple Regional Model of Office Rent Prediction*," Journal of Property Valuation and Investment*, vol. 7, p. 36-52.

Gardiner, C. and J. Henneberry (1991) "Predicting Regional Office Rents Using Habit-Persistence Theories," *Journal of Property Valuation and Investment*, vol. 9, p. 215-226.

Granger, C.W.J., B. Huang and C.W. Yang (2000) "A Bivariate Causality between Stock Prices and Exchange Rates: Evidence from Recent Asian Flu," *The Quarterly Review of Economics and Finance*, vol. 40, p. 337-354.

Guirguis, H. S., C. I. Giannikos and R. I. Anderson (2005) "The US Housing Market: Asset Pricing Forecasts Using Time Varying Coefficients," *Journal of Real Estate Finance and Economics*, vol. 30(3), p. 33-53.

Gupta, R. and S. Das (2010) "Predicting Downturn in the US Housing Market: A Bayesian Approach," *Journal of Real Estate Finance and Economics*, vol. 41(3), p. 294-319.

Karakozova, O. (2004) "Modelling and Forecasting Office Returns in the Helsinki Area," *Journal of Property Research*, vol. 21(1), p. 51-73.

Karolyi, G.A. and A.B. Sanders (1998) "The Variation of Economic Risk Premiums in Real Estate Returns," *Journal of Real Estate Finance and Economics*, vol. 17, p. 245-262.

Kearl, J.H. (1979) "Inflation, Mortgages, and Housing," *Journal of Political Economy*, vol. 87, p. 1-29.
Ljung, G. and G. Box (1978) "On a Measure of Lack if Fit in Time Series Models," *Biometrica*, vol. 65, p. 297-303.

Mei, J. and C.H. Liu (1994) "The predictability of real estate returns and market timing", *Journal of Real Estate Finance and Economics*, vol. 8, p. 115-135.

Quan, D.C. and S. Titman (1999) "Do Real Estate Prices and Stock Prices Move Together? An International Analysis," *Real Estate Economics*, vol. 27, p. 183-207.

Stevenson, S. and O. McGrath (2003) "A comparison of alternative rental forecasting models: empirical tests on the London office market," *Journal of Property Research*, vol. 20, p. 235-260.

Stevenson, S. and J. Young (2007) "Forecasting Housing Supply: Empirical Evidence from the Irish Market," European *Journal of Housing Policy*, vol. 7, p. 1-17.

Stock, J.H. and M.W. Watson (1989) "New Indexes of Coincident and Leading Indicators," in Olivier Blanchard and Stanley Fischer (eds.), *NBER Macroeconomics Annual*, Cambridge, MA: The MIT Press.

Tse, R.Y.C. (1997) "An Application of the ARIMA Model to Real-estate Prices in Hong Kong," *Journal of Property Finance*, vol. 8(2), p. 155-163.

Wilson, P.J., C. Ellis, J. Okunew and D.M. Higgins (2000) "Comparing Univariate Forecasting Techniques in Property Markets," *Journal of Real Estate Portfolio Management*, vol. 6(3), p. 283-306.

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