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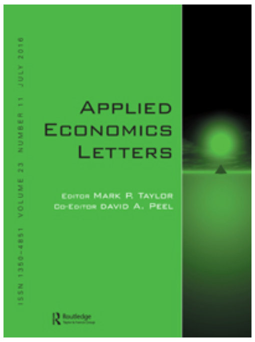

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Forecasting Canadian mortgage rates

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ABSTRACT
Mortgage rates are one of the important drivers of the housing market. While there is a literature looking at the pass-through effect from Central Bank rates to mortgage rates, there is less known about how useful Central Bank rates are for forecasting mortgage rates. This article uses a selection of models (ARIMA, ARIMAX, BATS, state space error, trend seasonal (ETS), Holt Winter, random walk, simple exponential smoothing (SES), OLS and VAR) to forecast Canadian 5-year conventional mortgage rates. Based on RMSE, regression-based approaches like ARIMAX or OLS that use Central Bank rates to forecast mortgage rates are preferred when it comes to forecasting Canadian mortgage rates 6 or 12 months into the future, respectively.

KEYWORDS
Forecasting; mortgage rates; bank rate; Canada

JEL CLASSIFICATION
E43; E47; R31

I. Introduction

Mortgage rates are one of the important drivers of the housing market, and movements in Central Bank rates are the prime factor affecting movements in mortgage rates. Complete interest rate pass-through occurs when there is a one-to-one relationship between changes in Central Bank rates and changes in mortgage rates. Interest rate pass-through from Central Bank rates to mortgage rates may, however, not be complete due to information asymmetries and adjustment costs (Stiglitz and Weiss 1981). Scholnick (1999) found evidence of complete pass-through to the 30-year US mortgage rate. Payne (2006a, 2006b) found evidence of incomplete pass-through. Payne (2007) found evidence of incomplete pass-through to US adjustable rate mortgages. Further studies that find evidence of incomplete pass-through include Heffernan (1997), Hofmann and Mizen (2004) and Fuertes, Heffernan, and Kalotychou (2010). Whether or not pass-through is complete or incomplete, Central Bank rates still exert a powerful force over mortgage rates. This article complements the existing literature on mortgage rates by investigating the usefulness of Central Bank rates in forecasting mortgage rates.

II. Data and methods

The data set consists of the conventional 5-year Canadian mortgage rate and the bank rate. The bank rate is the minimum rate the Bank of Canada charges on 1-day loans to financial institutions and is set at 0.25% above the Bank of Canada overnight target rate. The data are collected from the CANSIM database. The sample period consists of 510 monthly observations from January 1973 to June 2015.

Forecasts are generated from ARIMA, ARIMAX, BATS, state space error, trend seasonal (ETS), Holt Winter, random walk, simple exponential smoothing (SES), OLS and VAR. Most of these are well-known time-series forecasting techniques and are discussed in Athanasopoulos and Hyndman (2014). BATS is an exponential smoothing state space model with Box–Cox transformation, ARIMA errors, trend and seasonal components (De Livera, Hyndman, and Snyder 2011). This choice of forecasting methods provides a good mix between univariate and multivariate forecasting models.

Out-of-sample forecasts are generated using a fixed width rolling window. A rolling window approach is useful in accounting for structural changes, asymmetries and outliers. The estimation window is fixed at 96 observations (8 years of monthly data) and rolled from the beginning of the sample to the end of the sample producing a sequence of h month forecasts. An 8-year window is a long enough time to cover most business cycles and include enough observations to ensure good parameter fit for the forecasting methods. Forecast

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horizons, denoted h, include 1, 3, 6 and 12 months. For example, in the case of 1-month forecasts, the first 96 observations are used to estimate the methods and then a 1-month mortgage rate forecast is made. The estimation window is then rolled forward through the data set producing a sequence of 414 1-month forecasts. The forecasting results are not sensitive to small changes (±24 observations) in the estimation window.

For the OLS regression, mortgage rates (m) are regressed on an h period lag of the bank rate (b). The bank rate at time period t is then used to forecast mortgage rates h steps ahead.

$$m_t = \alpha + \beta b_{t-h} + \varepsilon_t$$

The random error term ε is assumed independent and identically distributed. Setting $h = 0$ yields the current period pass-through relationship. For the entire data set, the estimate of β is 0.78 with an associated t-value of 78.79, indicating a pass-through effect less than unity. The R^2 from this regression is 0.92. The estimated β of 0.78 indicates incomplete pass-through and is larger than other studies like Payne (2007), who finds β estimates between 0.47 and 0.51 for the US. A high R^2 and statistically significant estimated coefficients from an in-sample estimation does not, however, guarantee a good forecasting model.

The ARIMAX model combines a standard ARIMA model for mortgage rates with the bank rate lagged h periods as an explanatory variable. This is essentially the OLS specification with auto-regressive and moving-average terms added in for the mortgage rate.

Preliminary research indicated that the mortgage rate and bank rate are cointegrated. In response to this finding, a VAR model was set up in the spirit of Toda and Yamamoto (1995). They recommend using a conventional information criteria (SIC is used in this analysis) to select the lag length for the VAR. Then add one additional lag length to the VAR to accommodate the cointegration. This VAR is used to forecast h steps ahead.

All methods are refit each time the estimation window is rolled forward. All estimation is done using R (R Core Team 2015). Optimal parameter values for ARIMA, ARIMAX, BATS, ETS, Holt Winter and SES are determined using grid search algorithms associated with the R functions for these methods.

Forecasts are evaluated using RMSE. Other measures like mean error (ME), mean percentage error (MPE) and mean absolute percentage error (MAPE) are presented for completeness. The Diebold and Mariano (1995) (DM) test is used to compare models to the benchmark random walk.

III. Results

Forecast accuracy tests, ranked by RMSE, are shown in Table 1. For each forecast horizon, the random walk ranks no lower than third. For h = 1, BATS ranks best, while for h = 3, SES ranks best. For h = 6 and h = 12, ARIMAX and OLS rank best, respectively, indicating the usefulness of the bank rate for forecasting mortgage rates at longer horizons. The forecast accuracy measures for the random walk and SES are very similar because the optimal α value for the SES is in most cases very close to unity. Negative MPE values indicate that, on average, most of the models forecast mortgage rates above their actual values.

Table 2 reports DM tests for predictive accuracy where each model is compared to the benchmark random walk. The test is two sided, with a null hypothesis that the two methods have the same forecast accuracy against the alternative hypothesis they differ. ETS, SES and VAR are the only methods that do not reject the null hypothesis at 5% across all four forecast horizons. Based on the DM test, the random walk, ETS, SES and VAR have the same forecast accuracy. For h = 1, 3 or 6, ARIMAX does not produce forecasts statistically different than the random walk. For h = 6 or 12, OLS does not produce forecasts statistically different than the random walk. In practice, however, one may be more interested in economic significance and RMSE rankings over statistical significance.

IV. Conclusion

This article reports the findings of comparing several popular forecasting methods in their ability to forecast Canadian mortgage rates. The results from this forecasting exercise demonstrate the usefulness of the bank rate in forecasting conventional 5-year Canadian mortgage rates. No method consistently

Table 1. Forecast accuracy measures for 1-, 3-, 6- and 12-month forecasts.

	$h = 1$						$h = 3$				
	ME	RMSE	MAE	MPE	MAPE		ME	RMSE	MAE	MPE	MAPE
BATS	−0.0328	0.3900	0.2528	−0.4545	2.7037	SES	−0.0803	0.8267	0.5300	−1.1560	5.4509
VAR	−0.0544	0.3940	0.2640	−0.7871	2.8487	Random walk	−0.0803	0.8267	0.5300	−1.1553	5.4514
Random walk	−0.0274	0.3985	0.2391	−0.3713	2.5286	ETS	−0.0875	0.8660	0.5369	−1.1959	5.4892
SES	−0.0275	0.3986	0.2392	−0.3721	2.5302	ARIMA	−0.1079	0.8800	0.5650	−1.4647	5.7995
ARIMA	−0.0310	0.4041	0.2622	−0.4134	2.7675	ARIMAX	−0.1009	0.8825	0.5867	−1.8257	6.1208
ETS	−0.0299	0.4042	0.2416	−0.3832	2.5417	VAR	−0.1715	0.9022	0.5848	−2.5498	6.1395
ARIMAX	−0.0392	0.4207	0.2665	−0.5724	2.8529	BATS	−0.0827	0.9375	0.6245	−1.1366	6.5967
Holt Winter	−0.0046	0.4971	0.3235	0.0233	3.4412	Holt Winter	−0.0859	0.9936	0.6304	−0.7461	6.5335
OLS	−0.2751	0.9706	0.7100	−4.5926	7.9197	OLS	−0.3458	1.0670	0.7863	−5.3557	8.6861
			$h = 6$						$h = 12$		
ARIMAX	−0.2490	1.0991	0.7538	−3.7384	8.0987	OLS	−0.8388	1.4466	1.0912	−10.330	12.4683
SES	−0.1720	1.1570	0.7275	−2.3382	7.5026	SES	−0.4016	1.4748	0.9811	−4.8867	10.5129
Random walk	−0.1719	1.1570	0.7276	−2.3376	7.5037	Random walk	−0.4015	1.4748	0.9811	−4.8860	10.5128
OLS	−0.4632	1.1781	0.8682	−6.5499	9.5909	ETS	−0.4306	1.6039	1.0102	−5.0496	10.6761
ETS	−0.1863	1.2019	0.7421	−2.4117	7.5788	BATS	−0.4790	1.6246	1.0861	−5.9551	11.7463
ARIMA	−0.2286	1.2520	0.7962	−2.9567	8.2201	ARIMAX	−0.5147	1.6269	1.1427	−6.1448	12.7076
VAR	−0.3576	1.2925	0.8700	−4.9656	9.1354	VAR	−0.7588	1.6734	1.1845	−9.3568	13.0153
BATS	−0.2028	1.3141	0.8453	−2.7953	8.8253	ARIMA	−0.5153	1.7217	1.1470	−6.1124	12.3568
Holt Winter	−0.1574	1.3771	0.8860	−1.3615	9.0337	Holt Winter	−0.3199	2.0647	1.3057	−2.8216	13.6896

Notes: Forecasts computed using a rolling fixed width window of 96 monthly observations. Complete data set covers the period January 1973 to June 2015.

Table 2. Diebold–Mariano test.

	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
	DM	*p*-Value	DM	*p*-Value	DM	*p*-Value	DM	*p*-Value
ARIMA	−0.8155	**0.4153**	−2.4303	0.0155	−2.4769	0.0137	−2.0237	0.0437
BATS	1.0811	**0.2803**	−2.1112	0.0354	−2.2908	0.0225	−1.5690	**0.1174**
ETS	−1.1754	**0.2405**	−0.9975	**0.3191**	−1.0059	**0.3151**	−0.9956	**0.3200**
HW	−3.4286	0.0007	−1.7518	**0.0806**	−2.2546	0.0247	−1.8212	**0.0693**
OLS	−8.0819	0.0000	−2.1746	0.0302	−0.1700	**0.8651**	0.1351	**0.8926**
SES	−1.9464	**0.0523**	0.5470	**0.5847**	1.2225	**0.2222**	0.6418	**0.5214**
VAR	0.3842	**0.7010**	−1.8627	**0.0632**	−1.4661	**0.1434**	−1.5447	**0.1232**
ARIMAX	−0.7605	**0.4474**	−1.0263	**0.3054**	0.6657	**0.5060**	−2.1415	0.0328

Notes: Benchmark method is the random walk. Bold denotes *p*-values greater than 0.05.

ranks best across all forecast horizons, indicating the importance of comparing methods. According to the RMSE, VAR is ranked second for forecasting 1 month into the future, while ARIMAX and OLS are ranked first for forecasting 6 and 12 months into the future, respectively.

Disclosure statement

No potential conflict of interest was reported by the author.

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