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PREDICTIVE ABILITY OF COMPETING MODELS FOR SOUTH AFRICA'S FIXED BUSINESS NON-RESIDENTIAL INVESTMENT SPENDING

Abstract. *The study evaluates the forecasting ability of models of South Africa's real fixed business non-residential investment spending growth over the recent 2003:1–2011:4 out-of-sample period. The forecasting models are based on the Accelerator, Neoclassical, Cash-Flow, Average Q, Stock Price and Excess Stock Return Predictors models of investment spending. The Average Q, Stock Price and Return Predictors models appear more important in forecasting the behaviour of South Africa's business investment spending growth over the recent 2003:1–2011:4 out-of-sample period. The results from this study point to the important role of the stock market in promoting investment growth in South Africa, underscoring the need for stock market development. Also, stock market variables seem to play an increasingly important role in predicting investment spending behaviour in recent times.*

Key words: *business fixed investment spending; out-of-sample forecasts; mean squared forecast error; forecast encompassing*

JEL classification codes: C22, C53, E22, E27

1. Introduction

Investment spending is an important component of GDP. Households, governments, and businesses invest when they set aside a share of their current income in order to acquire capital assets whose returns promise to increase their incomes in the future (Kopcke and Bauman, 2001). Although, the proportion of

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investment spending in GDP is much smaller than consumption, it is the most volatile component. Therefore, fluctuation in investment spending is a prime contributor to fluctuations in long-run growth and aggregate activity at business cycle horizons (Chirinko, 1993; Rapach and Wohar, 2007). In the long run, the average magnitude of investment spending determines the size of the capital stock. Business investment spending often has a cyclical relationship with the overall economy. This is because greater business investment would generate more employment, which would mean more workers receiving wages, which in turn would increase the overall demand for goods and services, thus further stimulating businesses to increase investment spending yet again (Mankiw, 2011).

Given its crucial role, investment behaviour has been an important topic in the economic research agenda. In most applied econometric studies, the common practice is to have one or several models that explain investment behaviour. Although, there may be no 'true' investment specification that explains actual investment patterns, it can be agreed that the absence of a consensus empirical model inhibits investment policy formulation, complicates forecasts, and adversely affects the usefulness of theoretical and empirical macroeconomic models whose interpretations hinge on the precise form of the equations explaining net capital formation (Feldstein, 1982; Bernanke *et al*., 1988). The most popular models of investment behaviour are the Accelerator (Clark, 1917; Chenery, 1952; Koyck, 1954), Neoclassical (Jorgenson, 1963; Hall and Jorgenson, 1967; Jorgenson, 1971), Tobin's *Q* (Tobin, 1969), and Cash-Flow (Meyer and Kuh, 1957; Duesenberry, 1958; Grunfeld, 1960).[1] A number of empirical studies have run 'horse races' designed to identify the model (or models) that best explains business fixed investment spending over a particular period. These studies include Jorgenson and Siebert (1968), Jorgenson *et al.* (1970a, 1970b), Bischoff (1971), Clark (1979), Bernanke *et al.* (1988), Barro (1990), Blanchard *et al.* (1993), Oliner *et al.* (1995), Kopcke and Bauman (2001), Tevlin and Whelan (2003) and Rapach and Wohar (2007). Many of these studies compared the out-of-sample forecasting ability of competing models. This is due to the popular belief that tests of out-of-sample predictive power are the most stringent tests of a model's reliability (Rapach and Wohar, 2007). Furthermore, given the interest of policymakers in forecasting business fixed investment spending, out-of-sample tests constitute a relevant test design for the examination of forecasting models (Bernanke, 2003; Poole, 2003; Rapch and Wohar, 2007).

Despite the cardinal position and role of investment, we are not aware of any study that has attempted to identify the best forecasting model (or models) of fixed private business non-residential investment behaviour in South Africa.

[1] See Kopcke and Bauman (2001) and Chirinko (1993) for useful surveys of models of business fixed investment spending.

Therefore, our paper contributes to the literature by running out-of-sample horse races involving a number of forecasting models of South Africa's fixed business non-residential investment spending over the recent 2003:1–2011:4 period. This period witnessed both investment 'booms' as well as investment 'busts' that respectively contributed to the economic expansion and recession in South Africa. It is thus interesting to compare forecasting models of South Africa's business fixed investment spending over this period.

Following Rapach and Wohar (2007), we employ six forecasting models of South Africa's fixed private business non-residential investment spending growth at forecast horizons of 1–4, 6, and 8 quarters, with each model utilizing a different explanatory variable (or variables). The forecasting models are the Accelerator, Neoclassical, Tobin's *Q* or simply average *Q*, Cash-Flow, Barro's (1990) Stock Price model, and Excess Stock Return Predictors models. In the latter model equity risk premium is represented by the term spread, default spread, and relative short-term interest rate – which Lettau and Ludvigson, (2002) found to have predictive ability with respect to US business fixed investment spending.

In order to have a comprehensive picture of the forecasting performance of the six different models, the forecast accuracy of each model over the recent 2003:1–2011:4 out-of-sample period is evaluated using a number of different econometric procedures. These include the mean squared error (MSE) metric, the Mincer and Zarnowitz (1969) test of unbiased forecast, the Blair, Poon, and Taylor (2001) forecast volatility test, the Diebold and Mariano (1995) pair-wise tests for significant differences in the MSE (with the Harvey *et al.*, 1997 modification), the pair-wise forecast encompassing test of Harvey *et al.* (1998), and the multiple forecast encompassing test of Harvey and Newbold (2000).

The rest of the paper is organized as follows. The next section discusses the econometric methodology. The empirical results are reported in the third section. The last section concludes.

2. Econometric methodology

2.1 Model specifications

The use of non-stationary real business fixed investment spending or its variants as dependent variables does not allow reliable inferences as the standard asymptotic results on which inferences are based typically do not hold in the presence of non-stationary variables. As a result, we tested for unit roots in the levels (and log-levels) of South Africa's real business fixed investment spending. Using the unit root tests of Ng and Perron (2001) with good size and power, we cannot reject the unit root null hypothesis for this variable. Hence, following Barro (1990) and Rapach and Wohar (2007), we use the first differences of the log levels of real business fixed investment spending as the dependent variable in our forecasting models. The investment series is plotted in Figure 1.

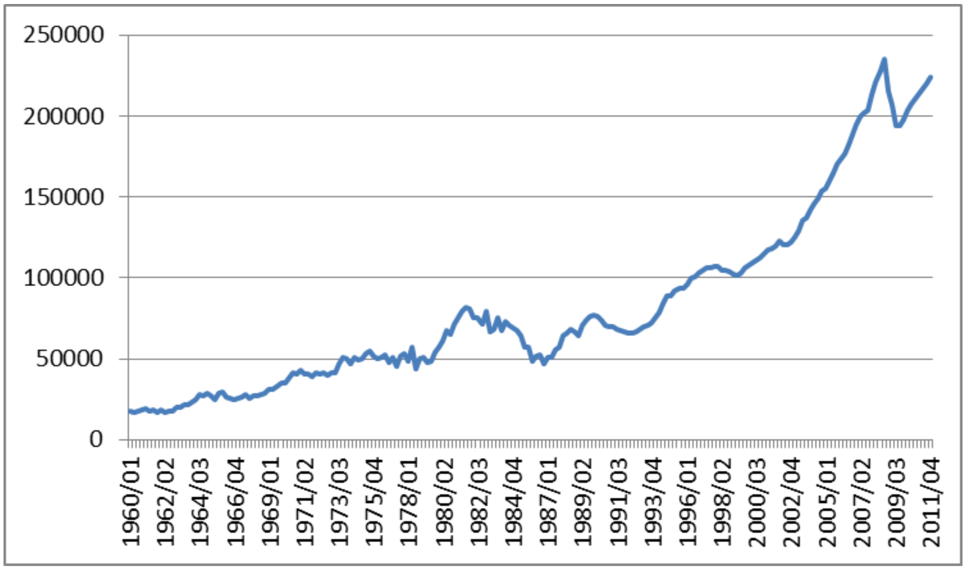

Figure 1. Real private fixed non-residential business investment (R millions)

We employ an autoregressive distributed lag (ARDL) structure for our forecasting models following Barro (1990) and Rapach and Wohar (2007). Letting $\Delta i_t = i_t - i_{t-1}$, where i_t is the log-level of real fixed private business non-residential investment spending at time t, and, $y_{t+h} = \sum_{j=1}^{h} \Delta i_{t+j}$ our forecasting models take the following form:

$$y_{t+h} = \alpha_m + \sum_{j=0}^{q_{m,1}-1} \beta_{m,j} \Delta i_{t-j} + \sum_{j=0}^{q_{m,2}-1} \gamma_{m,j} \Delta x_{m,t-j} + \varepsilon_{m,t+h} \tag{1}$$

where $\Delta x_{m,t}$ is a variable characterizing a particular investment model m $(m = 1,\ldots,M)$, h is the forecast horizon, and $\varepsilon_{m,t+h}$ is a disturbance term. The Ng and Perron (2001) unit root tests indicate that $i_t \sim I(1)$, so that $\Delta i_t, y_{t+h} \sim I(0)$ in equation (1). We also use the Ng and Perron (2001) unit root test results to specify each of the $x_{m,t}$ variables that characterize the different investment models such that $x_{m,t} \sim I(1)$ and $\Delta x_{m,t} \sim I(0)$. This ensures that equation (1) contains only stationary variables. The $x_{m,t}$ for the first five forecasting models are defined as follows[2]:

[2] The sources and construction of the data series are described in the Data Appendix.

• Accelerator model: $x_{1,t}$ = log-level of real business output

• Neoclassical model: $x_{2,t}$ = log-level of the ratio of real business output to the real user cost of capital

• Average Q: $x_{3,t}$ = log-level of the ratio of the market value of capital to its replacement cost

• Cash-Flow: $x_{4,t}$ = log-level of real profits

• Stock Price: $x_{5,t}$ log-level of real stock prices

Any evidence of a stable long-run relationship between i_t and $x_{m,t}$ would require an inclusion of an error-correction term in equation (1). Therefore, we also tested for cointegration between i_t and each of the $x_{m,t}$ variables. However, we found no evidence of cointegration, so we do not include an error-correction term in any of the forecasting models.

The sixth forecasting model takes a slightly different form from equation (1). This model employs three of the excess stock return predictors considered by Lettau and Ludvigson (2002). Following the specification in Lettau and Ludvigson (2002) and Rapach and Wohar (2007), we include a single lag of each variable in the forecasting model, so that the 'Return Predictors' model takes the form:

$$y_{t+h} = \alpha_6 + \beta_{6,0}\Delta i_t + \gamma_{6,1} rrel_t + \gamma_{6,2} term_t + \gamma_{6,3} def_t + \varepsilon_{m,t+h} \tag{2}$$

where $rrel_t$ is the relative short-term interest rate (the difference between the 3-month Treasury bill yield and a 1-year backward-looking moving average), $term_t$ is the term spread (the difference between the 10-year government bond yield and the 3-month Treasury bill yield), and def_t is the default spread (the difference between low- and high-grade corporate bond yields). We analyze the ability of each of the six (non-nested) models to forecast South Africa's fixed private non-residential investment spending growth over the recent 2003:1–2011:4 out-of-sample period. A recursive scheme which simulates the situation of a forecaster in real time is used in forming the out-of-sample forecasts.[3]

[3] Details of the procedure can be found in Rapach and Wohar (2007).

2.2 Forecast evaluation

The most popular measure of forecast accuracy, the MSE, which corresponds to the forecasts at horizon h generated by model m is used and is defined as

$$MSE_{m,h} = (T - R - h + 1)^{-1} \sum_{t=R}^{T-h} u^2{}_{m,t+h} \quad (3)$$

To assess whether the forecasts at horizon h generated by model m are unbiased, we use the Mincer and Zarnowitz (1969) regression

$$y_{t+h} = a + b\hat{y}_{m,t+h} + e_{t+h} \quad (4)$$

where y_{t+h} is actual investment spending growth from period t to $t+h$, $\hat{y}_{t+h}$ is the forecast of investment spending growth period t to $t+h$. The forecasts are considered unbiased if $a = 0$ and $b = 1$. We estimate the parameters of equation (4) using OLS and compute the t-statistics. We also calculate an F-statistic corresponding to a test of the joint null hypothesis that $a = 0$ and $b = 1$ in equation (4).[4] Further, we compare the degree of variation in the forecast errors at horizon h from model m with the actual volatility in y_{t+h} following Blair, Poon, and Taylor (2001). The measure is given as

$$P_{m,h} = 1 - \frac{\sum_{t-R}^{T-h} \left(y_{t+h} - \hat{y}_{m,t+h}\right)^2}{\sum_{t-R}^{T-h} \left(y_{t+h} - \bar{y}_h\right)^2} \quad (5)$$

The $P_{m,h}$ statistic will be close to unity when the forecast errors are small. However, $P_{m,h}$ can be negative unlike the R^2 measure. This occurs when the forecast errors are more volatile than the variable itself which is an undesirable property for a forecasting model.

To test for significant differences in forecasting ability between a pair of competing models, the procedure in Diebold and Mariano (1995) and West (1996) is employed. More specifically, we test $H0: MSE_{i,h} = MSE_{j,h}$ against

[4] See Rapach and Wohar (2007) for details of estimation and computation of the test statistics.

$H1: MSE_{i,h} \neq MSE_{j,h}$ for a pair of competing models i and j. The test statistic is based on the loss differential, $\hat{d}_{t+h} = \hat{u}^2_{i,t+h} - \hat{u}^2_{j,t+h} (t = R,...,T-h)$, and takes the form

$$DM_h = [\hat{V}(\bar{d}_h)^{-1/2}]\bar{d}_h \qquad (6)$$

where $\hat{V}(\bar{d}_h) = n_h^{-1}(\hat{\phi}_0 + 2\sum_{k=1}^{h-1}\hat{\phi}_k)$, $\hat{\phi}_k = (1/n_h)\sum_{t=R+k}^{T-h}(\hat{d}_{t+h} - \bar{d}_h)(\hat{d}_{t-k+h} - \bar{d}_h)$, and $n_h = T - R - h + 1$. West (1996) shows that the DM_h statistic is distributed asymptotically standard normal when comparing forecasts from non-nested models as is done in this study.[5] In order to improve the finite-sample performance of the DM_h statistic, Harvey *et al.* (1997) recommend using a modified DM_h statistic:

$$MDM_h = \left[\frac{n_h + 1 - 2h + n_h^{-1}h(h-1)}{n_h}\right]DM_h \qquad (7)$$

and the t_{n_h-1} distribution in place of the standard normal for inference. Therefore, to test for equal forecast accuracy in our applications, we employ the MDM_h statistic and the t_{n_h-1} distribution.[6]

Forecasts from two competing models can also be compared using the notion of forecast encompassing. Consider forming an optimal composite forecast of y_{t+h} as a convex combination of the forecasts from the pair of competing models i and j:

$$\hat{y}_{t+h} = (1-\lambda)\hat{y}_{i,t+h} + \lambda\hat{y}_{j,t+h} \qquad (8)$$

where $0 \leq \lambda \leq 1$. If $\lambda = 0$, then the forecasts generated by model i are said to encompass the forecasts generated by model j, as model j does not contribute any useful information – apart from that already contained in model i – to the formation of an optimal composite forecast. On the other hand, if $\lambda > 0$, then the

[5] Note that the parameter uncertainty involved in estimating equation (1) and forming the out-of-sample forecasts does not affect the asymptotic distribution of the DM_h statistic when equation (1) is estimated using OLS. However, in general, parameter uncertainty affects the asymptotic distributions of statistics used to analyze forecast performance; see West (1996), West and McCracken (1998), McCracken (2000), and McCracken and West (2002).

[6] We also compute the West and Cho (1995) chi-squared statistic that tests the joint null hypothesis, $H0: MSE_{1,h} = ... = MSE_{M,h}$.

forecasts generated by model i do not encompass the forecasts generated by model j, so that model j does contain information that is useful (beyond that already contained in model i) to the formation of an optimal composite forecast. Harvey *et al.* (1998) develop a statistic to test the null hypothesis that the forecasts generated by model i encompass the forecasts generated by model j $(H_0 : \lambda = 0)$ against the alternative hypothesis that the model i forecasts do not encompass the model j forecasts $(H_1 : \lambda > 0)$. The statistic, which we denote as HLN_h following Rapach and Wohar (2007), takes the same form as the DM_h statistic in equation (7), with the exception that $\hat{d}_{t+h} = (\hat{u}_{i,t+h} - \hat{u}_{j,t+h})\hat{u}_{i,t+h}$. As in Harvey *et al.* (1997), Harvey *et al.* (1998) suggest using a modified version of HLN_h:

$$MHLN_h = \left[\frac{n_h + 1 - 2h + n_h^{-1} h(h-1)}{n_h} \right] HLN_h \tag{9}$$

and the $t_{n_h - 1}$ distribution for inference. We use the $MHLN_h$ statistic and the $t_{n_h - 1}$ distribution to test for forecast encompassing in this study.

We also use the Harvey and Newbold (2000) procedure to test the null hypothesis that the forecasts generated by, say, model 1 jointly encompass the forecasts generated by the remaining $M - 1$ models. To understand the nature of the test, consider forming an optimal composite forecast involving the forecasts generated by each of the individual M models:

$$\hat{y}_{t+h} = (1 - \lambda_2 - \lambda_3 - \ldots - \lambda_M)\hat{y}_{1,t+h} + \lambda_2 \hat{y}_{2,t+h} + \ldots + \lambda_M \hat{y}_{M,t+h} \tag{10}$$

If $\lambda_2 = \ldots = \lambda_M = 0$, then the forecasts generated by model 1 jointly encompass the remaining forecasts, and the remaining models do not contain information that is useful (beyond that already contained in model 1) in the formation of an optimal composite forecast. Harvey and Newbold (2000) test the null hypothesis of multiple forecast encompassing using the MS_h^* statistic:

$$MS_h^* = (M-1)^{-1}(n_h - 1)^{-1}(n_n - M + 1)\bar{d}_h'[\hat{V}(\bar{d}_h)]^{-1}\bar{d}_h \tag{11}$$

where $\bar{d}_h = [\bar{d}_{2,h}, \ldots, \bar{d}_{M,h}]'$, $\bar{d}_{i,h} = (1/n_h)\sum_{t=R}^{T-h} \hat{d}_{i,t+h} (i = 2, \ldots, M)$, $\bar{d}_{i,t+h} = (\hat{u}_{1,t+h} - \hat{u}_{i,t+h})\hat{u}_{1,t+h} (i = 2, \ldots, M)$, and $\hat{V}(\bar{d}_h)$ is calculated using equation (14) in Harvey and Newbold (2000, p. 474). Harvey and Newbold (2000) recommend basing inference on the F_{M-1,n_h-M+1} distribution. In Monte Carlo experiments, they find that the MS_h^* statistic has good size properties and has limited power under some circumstances.

3. Empirical results

The simulated out-of-sample forecasts over the recent 2003:1–2012:4 period generated by the six forecasting models of fixed private non-residential investment spending growth is evaluated. The in-sample portion of the total sample covers the post-democracy period, 1994:1–2011:4, and we consider forecast horizons of 1–4, 6, and 8 quarters. Forecast horizons of 1–8 quarters are relevant for business cycle dynamics and are thus likely to be of keen interest to policymakers (Rapach and Wohar, 2007). Moreover, forecast horizons up to 8 quarters also helps to allow for lags in the investment spending process. Table 1 reports the MSE, Mincer and Zarnowitz (1969) regression results, and the Blair, Poon, and Taylor (2001) statistic for each of the six forecasting models and forecast horizons of 1-4, 6, and 8 quarters. A low MSE is a desirable forecasting property.

Table 1. Mean squared forecast errors, tests of unbiased forecasts, and measures of forecast explanatory power—real fixed business non-residential investment spending growth, 2003:1-2011:4 out-of-sample period

Model		Accelerator	Neoclassical	Average Q	Cash Flow	Stock Price	Return Predictors
$h=1$	MSE	5.81	6.54	**5.72**	6.32	5.87	6.33
	$\hat{a}$	0.34 (0.51)	0.59 (0.82)	0.28 (0.44)	-0.50 (-0.45)	0.19 (0.28)	0.49 (0.67)
	$\hat{b}$	0.92 (0.23)	0.67 (0.79)	0.91 (0.32)	1.76 (1.17)	0.96 (0.10)	0.76 (0.63)
	F	0.18 [0.84]	0.36 [0.70]	0.10 [0.91]	3.28* [0.05]	0.06 [0.94]	0.23 [0.79]
	$P_{m,h}$	0.20	0.10	0.21	0.13	0.19	0.13
$h=2$	MSE	19.69	21.57	19.17	20.55	**18.86**	22.52
	$\hat{a}$	1.12 (0.69)	1.51 (0.89)	0.87 (0.57)	-0.81 (-0.21)	0.35 (0.19)	1.82 (0.87)
	$\hat{b}$	0.8 (0.47)	0.58 (0.93)	0.80 (0.62)	1.70 (0.56)	0.99 (0.03)	0.51 (0.92)
	F	0.25 [0.78]	0.46 [0.63]	0.20	2.19	0.06	0.43

				[0.82]	[0.12]	[0.94]	[0.65]
	$P_{m,h}$	0.13	0.04	0.15	0.09	0.16	-0.00
$h=3$	MSE	43.00	56.98	**27.16**	40.93	40.27	50.09
	$\hat{a}$	2.63 (1.12)	2.62* (2.19)	-1.49 (-0.37)	-0.10 (-0.02)	1.42 (0.48)	4.59 (1.33)
	$\hat{b}$	0.55 (1.01)	-0.13 (-2.88)	1.11 (0.22)	1.41 (0.36)	0.77 (0.49)	0.09 (1.51)
	F	0.67 [0.52]	4.17* [0.02]	0.54 [0.59]	1.60 [0.22]	0.13 [0.88]	1.14 [0.33]
	$P_{m,h}$	0.01	-0.32	0.37	0.05	0.07	-0.16
$h=4$	MSE	83.38	83.61	**39.50**	63.71	67.72	85.11
	$\hat{a}$	6.98* (2.38)	10.15** (2.68)	-2.73 (-0.47)	2.21 (0.31)	5.09 (1.06)	8.37* (2.20)
	$\hat{b}$	-0.08** (-2.76)	-0.61* (-2.28)	1.15 (0.28)	0.90 (0.09)	0.24 (1.11)	-0.34* (-2.47)
	F	4.19* [0.02]	3.59* [0.04]	1.67 [0.20]	0.47 [0.63]	0.63 (0.54)	3.15† [0.06]
	$P_{m,h}$	-0.32	-0.32	0.38	-0.00	-0.07	-0.34
$h=6$	MSE	171.67	168.42	**52.05**	220.50	269.90	162.57
	$\hat{a}$	10.56** (3.14)	10.64** (3.23)	-1.12 (-0.20)	10.41** (3.19)	9.59** (2.66)	11.79** (3.08)
	$\hat{b}$	-0.16** (-3.53)	-0.17** (-3.45)	1.04 (0.11)	-0.26** (-4.02)	-0.01** (-7.44)	-0.34** (-3.22)
	F	9.82** [0.00]	9.70** [0.00]	0.23 [0.79]	15.88** [0.00]	31.67** [0.00]	6.93** [0.00]
	$P_{m,h}$	-0.73	-0.70	0.48	-1.22	-1.72	-0.64
$h=8$	MSE	236.07	210.02	**80.62**	286.98	219.68	203.62
	$\hat{a}$	13.88** (3.36)	13.25** (3.29)	1.53 (0.24)	12.43** (3.47)	9.95* (2.54)	14.21** (3.55)
	$\hat{b}$	-0.36** (-4.34)	-0.32** (-3.82)	0.90 (0.29)	-0.38** (-4.86)	0.13** (6.57)	-0.45** (-3.68)
	F	11.94** [0.00]	10.56** [0.00]	0.05 [0.95]	23.70** [0.00]	21.79** [0.00]	10.19** [0.00]
	$P_{m,h}$	-1.00	-0.78	0.32	-1.44	-0.87	-0.73

Notes: A bold entry signifies the model with the lowest MSE. *,** indicate significance at the 5%, and 1% levels, respectively. MSE is the mean squared forecast error; $\hat{a}$ and $\hat{b}$ are the OLS estimates of a and b, respectively, in the Mincer and Zarnowitz (1969) regression model. T-statistics corresponding to $a = 0$ (for $\hat{a}$) and $b = 1$ (for $\hat{b}$) are given in parentheses. F is the Wald statistic corresponding to a test of the joint null hypothesis that $a = 0$ and $b = 1$; p-values are given in brackets. $P_{m,h}$ is the Blair, Poon, and Taylor (2001) ratio of the variation in the forecast errors to the actual volatility.

The Average *Q* model has the lowest MSE at all horizons except at a 2-quarter horizon where the Stock Price model has the lowest MSE. In general, the results in Table 1 point to the importance of stock market models (Average Q, Stock Price and Return Predictors) in forecasting investment over the recent 2003:1–2011:4 out-of-sample period as these models turn out to have either the lowest or second lowest MSE at all horizons, except for a 1-quarter horizon, where the traditional Accelerator model has the second lowest MSE value. The Mincer and Zarnowitz (1969) regression results reveal that only the Cash flow model and Neoclassical models produce biased forecasts at 1-quarter and 3-quarter horizons respectively. At a 2-quarter horizon, all models produced unbiased forecasts. For all of the forecast horizons, only the Average *Q* model produced unbiased forecasts while the rest produced biased forecasts at 4, 6 and 8-quarters. In general, the $P_{m,h}$ statistic for all forecasting models is very small with the highest being 0.48. The Average *Q* model has the highest $P_{m,h}$ statistic and remained positive at all horizons except at the 2-quarter horizon where the stock price model has the highest value. At 4, 6 and 8-quarters, the $P_{m,h}$ statistic for all other models is negative indicating the deteriorating quality of the forecasts from these models at longer horizons.

The MSE ratio and MDM_h statistic for all pairs of forecasting models are reported in Table 2. A ratio greater than (less than) unity indicates that the MSE for the forecasting model given in the first row (column) of the table is less than the MSE for the forecasting model given in the first column (row) of the table. Further, a negative (positive) MDM_h statistic indicates that the MSE for the forecasting model given in the first row (column) of the table is less than that of the forecasting model given in the first column (row) of the table. There is one rejection of the null hypothesis of equal MSE at 1, 3, and 4-quarter horizons each in favour of the Accelerator, Stock price and Average *Q* models respectively. At a 6-quarter horizon, there are five rejections of equal MSE of the Average *Q* model with the other five forecasting models. Again, at an 8-quarter horizon, there are four rejections of the null hypothesis in favour of the Average *Q*. However, at this horizon, the equality of Average *Q* and Stock Price MSEs could not be rejected.[7]

[7] The West and Cho (1995) chi-squared statistic used to test $H0: MSE_{1,h} = ... = MSE_{M,h}$ (see footnote 5) is significant at

Table 3 reports the $MHLN_h$ statistics corresponding to all model pairs. The statistics correspond to a test of the null hypothesis that the forecasts for the model given in the first row of the table encompass the forecasts for the model given in the first column of the table. The MS_{h^*} statistic for a test of the null hypothesis that the forecasts for the model given in the first row of the table jointly encompass the forecasts for the other five models are also reported in Table 3. Table 3 shows that 9 (8) of the 30 $MHLN_h$ statistics at the 1-quarter (2-quarter) horizon are significant, thus rejecting the null hypothesis of forecast encompassing at conventional significance levels, indicating that there are situations where the forecasts generated by a particular model contain information useful for forecasting investment spending growth beyond the information contained in another model. At the 1-quarter (2-quarter) horizon, the forecasts from the Accelerator and Average *Q* (Neoclassical) are able to forecast encompass the forecasts from each of the other five models in both pair-wise and joint tests. However, at the 1-quarter horizon Average *Q* and Stock Price models also forecast encompass the Accelerator model whereas none of the other five models is able to forecast encompass the Average *Q* model. Therefore, Average *Q* (Neoclassical) model stand out as the best forecasting model at the 1-quarter (2-quarter) horizon according to the encompassing tests, as none of the five other models contain information useful for forecasting South Africa's real business investment spending growth beyond the information contained in the Average *Q* (Neoclassical), and the Average *Q* (Neoclassical) model contains information useful for forecasting investment spending beyond that contained in the other five models.[8]

Table 2. MSE ratios and modified Diebold and Mariano (1995) statistics for tests of equal forecast MSE: real fixed private non-residential investment spending growth, 2003:1–2011:4 out-of-sample period

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price
$h=1$					
Neoclassical	0.89 (-0.89) [0.38]				
Average Q	1.01 (0.37)	1.14 (0.90) [0.37]			

forecast horizons of 3, 4, 6 and 8 quarters, thus projecting the best performance of the Average *Q* and Stock Price models.

[8] The inability to reject multiple forecast encompassing for the other models at the 1-quarter and 2-quarter horizons is likely due to the low power of these tests relative to the pair-wise encompassing tests.

	[0.71]				
Cash-Flow	0.92 (-0.45) [0.66]	1.03 (0.12) [0.90]	0.91 (-0.60) [0.55]		
Stock Price	0.99 (-0.22) [0.83]	1.11 (0.75) [0.46]	0.97 (-1.11) [0.27]	1.08 (0.47) [0.64]	
Return Predictors	0.92 (-1.71†) [0.10]	1.03 (0.32) [0.75]	0.90 (-1.64) [0.11]	1.00 (0.00) [1.00]	0.93 (-1.33) [0.19]
$h = 2$					
Neoclassical	0.91 (-0.79) [0.44]				
Average Q	1.03 (0.58) [0.56]	1.12 (0.75) [0.46]			
Cash-Flow	0.96 (-0.22) [0.83]	1.05 (0.18) [0.86]	0.93 (-0.47) [0.64]		
Stock Price	1.04 (0.69) [0.49]	1.14 (0.83) [0.41]	1.02 (0.60) [0.55]	1.09 (0.60) [0.55]	
Return Predictors	0.87 (-1.42) [0.17]	0.96 (-0.30) [0.76]	0.85 (-1.27) [0.21]	0.91 (-0.53) [0.60]	0.84 (-1.64) [0.11]
$h = 3$					
Neoclassical	0.75 (-1.61) [0.12]				
Average Q	1.58 (0.92) [0.36]	2.10 (1.21) [0.23]			
Cash-Flow	1.05 (0.24) [0.81]	1.39 (0.97) [0.34]	0.66 (-1.45) [0.16]		
Stock Price	1.07 (1.44) [0.17]	1.41 (1.64) [0.11]	0.67 (-0.85) [0.40]	1.02 (0.09) [0.93]	
Return Predictors	0.86 (-1.35) [0.18]	1.14 (0.69) [0.49]	0.54 (-1.23) [0.23]	0.82 (-0.93) [0.36]	0.80 (-1.75†) [0.09]
$h = 4$					
Neoclassical	1.00 (-0.02)				

	[0.99]				
Average Q	2.11 (1.28) [0.21]	2.12 (1.15) [0.26]			
Cash-Flow	1.31 (0.82) [0.42]	1.31 (0.70)[0.49]	0.62 (-2.03*) [0.05]		
Stock Price	1.23 (1.23) [0.23]	1.23 (1.25) [0.22]	0.58 (-1.05) [0.30]	0.94 (-0.24) [0.81]	
Return Predictors	0.98 (-0.24) [0.81]	0.98 (-0.09) [0.93]	0.46 (-1.51) [0.14]	0.75 (-1.12) [0.27]	0.80 (-1.55) [0.13]
$h = 6$					
Neoclassical	1.02 (0.93) [0.36]				
Average Q	3.30 (1.86†) [0.07]	3.24 (1.79†) [0.08]			
Cash-Flow	0.78 (-0.60) [0.56]	0.76 (-0.64) [0.53]	0.24 (-2.77**) [0.01]		
Stock Price	0.64 (-0.91) [0.37]	0.62 (-0.92) [0.36]	0.19 (-2.67**) [0.01]	0.82 (-0.68) [0.50]	
Return Predictors	1.06 (0.16) [0.88]	1.04 (0.11) [0.92]	0.32 (-2.39*) [0.02]	1.36 (1.19) [0.24]	1.66 (1.40) [0.17]
$h = 8$					
Neoclassical	1.12 (0.81) [0.43]				
Average Q	2.21 (1.98*) [0.06]	1.98 (3.27**) [0.00]			
Cash-Flow	0.74 (-0.46) [0.65]	0.67 (-0.74) [0.47]	0.34 (-1.91†) [0.07]		
Stock Price	1.26 (1.56) [0.13]	1.13 (0.49) [0.63]	0.57 (-1.25) [0.22]	1.70 (0.75) [0.46]	
Return Predictors	1.05 (0.15) [0.88]	0.94 (-0.20) [0.84]	0.48 (-3.99**) [0.00]	1.42 (0.86) [0.40]	0.83 (-0.36) [0.72]

Note: †, *, ** indicate significance at the 10%, 5%, and 1% levels, respectively. The top figure is the ratio of the mean squared error for the model given in the first row to the mean squared error for the model given in the first column. The figure in parentheses is the modified Diebold and Mariano (1995) statistic corresponding to a test of the null hypothesis that the forecast mean squared errors from two models are equal against the two-sided alternative hypothesis that they are not equal; p-values are given in brackets.

Table 3. Harvey *et al.* (1998) statistics for tests of forecast encompassing: real fixed private non-residential investment spending growth, 2003:1–2011:4 out-of-sample period

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price	Return Predictors
$h=1$						
Accelerator		1.31† [0.10]	0.32 [0.38]	1.37† [0.09]	0.47 [0.32]	2.18* [0.02]
Neoclassical	-0.44 [0.67]		-0.41 [0.66]	0.82 [0.21]	-0.32 [0.63]	0.42 [0.34]
Average Q	1.07 [0.15]	1.37† [0.09]		1.60† [0.06]	2.01* [0.03]	2.04* [0.02]
Cash-Flow	0.49 [0.31]	0.92 [0.18]	0.51 [0.31]		0.45 [0.33]	0.81 [0.21]
Stock Price	0.07 [0.47]	1.14 [0.13]	0.00 [0.50]	1.39† [0.09]		1.70* [0.05]
Return Predictors	-1.20 [0.88]	1.15 [0.13]	-1.17 [0.87]	0.92 [0.18]	-0.93 [0.82]	
MS_{h^*}	0.84 [0.53]	0.67 [0.65]	1.38 [0.26]	1.24 [0.32]	1.07 [0.39]	1.15 [0.36]
$h=2$						
Accelerator		1.12 [0.14]	0.47 [0.32]	1.03 [0.15]	-0.25 [0.60]	1.75* [0.04]
Neoclassical	-0.45 [0.67]		-0.23 [0.59]	0.68 [0.25]	-0.48 [0.68]	0.74 [0.23]
Average Q	2.08* [0.02]	1.22 [0.12]		1.66* [0.05]	3.63** [0.00]	1.68* [0.05]
Cash-Flow	0.60 [0.28]	0.94 [0.18]	0.76 [0.23]		0.25 [0.40]	1.10 [0.14]
Stock Price	1.08 [0.14]	1.15 [0.13]	1.28† [0.10]	1.43† [0.08]		1.85* [0.04]
Return Predictors	-0.97 [0.83]	0.45 [0.33]	-0.71 [0.76]	0.20 [0.42]	-1.38 [0.91]	
MS_{h^*}	0.61 [0.69]	0.50 [0.77]	0.99 [0.44]	1.14 [0.36]	0.51 [0.76]	0.88 [0.51]

$h = 3$						
Accelerator		1.95* [0.03]	0.05 [0.48]	0.42 [0.34]	-0.98 [0.83]	1.56† [0.06]
Neoclassical	-0.33 [0.63]		-0.58 [0.72]	-0.22 [0.59]	-0.90 [0.81]	0.38 [0.35]
Average Q	1.54† [0.07]	1.61† [0.06]		2.87** [0.00]	1.34† [0.09]	1.64† [0.06]
Cash-Flow	0.75 [0.23]	1.56† [0.06]	0.04 [0.49]		0.41 [0.34]	1.12 [0.14]
Stock Price	1.70* [0.05]	2.06* [0.02]	-0.09 [0.54]	0.67 [0.25]		1.83* [0.04]
Return Predictors	-0.98 [0.83]	1.70* [0.05]	-0.54 [0.70]	-0.66 [0.74]	-1.61 [0.94]	
MS_{h^*}	2.02† [0.10]	1.72 [0.16]	2.20† [0.08]	2.83* [0.03]	1.73 [0.16]	1.39 [0.26]
$h = 4$						
Accelerator		0.98 [0.17]	-0.48 [0.68]	-0.32 [0.62]	-0.83 [0.79]	1.08 [0.14]
Neoclassical	0.64 [0.26]		-0.38 [0.65]	-0.28 [0.61]	-0.82 [0.79]	0.58 [0.28]
Average Q	1.65* [0.05]	1.60† [0.06]		3.53** [0.00]	1.62† [0.06]	1.96* [0.03]
Cash-Flow	1.18 [0.12]	1.10 [0.14]	0.21 [0.42]		0.53 [0.30]	1.25 [0.11]
Stock Price	1.50† [0.07]	1.62† [0.06]	-0.10 [0.54]	0.08 [0.47]		1.53† [0.07]
Return Predictors	0.98 [0.17]	1.06 [0.15]	-0.44 [0.67]	-0.95 [0.82]	-1.54 [0.93]	
MS_{h^*}	2.42† [0.06]	2.32† [0.07]	2.15† [0.09]	3.51** [0.01]	2.03† [0.10]	1.47 [0.23]
$h = 6$						
Accelerator		-0.04 [0.52]	-0.83 [0.79]	0.82 [0.21]	1.14 [0.13]	0.40 [0.35]
Neoclassical	1.25 [0.11]		-0.93 [0.82]	0.84 [0.20]	1.16 [0.13]	0.45 [0.33]
Average Q	2.49** [0.01]	2.30** [0.01]		2.47** [0.01]	2.45** [0.01]	2.68**[0.01]
Cash-Flow	-0.11 [0.54]	-0.15 [0.56]	-0.67 [0.74]		1.64† [0.06]	-0.79 [0.78]
Stock Price	-0.08 [0.53]	-0.15 [0.56]	-0.41 [0.66]	0.42 [0.34]		0.44 [0.33]
Return Predictors	0.88 [0.19]	0.96 [0.17]	-0.98 [0.83]	1.36† [0.09]	1.46† [0.08]	
MS_{h^*}	3.87** [0.01]	2.13† [0.09]	0.52 [0.76]	2.63* [0.05]	2.76* [0.04]	1.81 [0.15]

$h=8$						
Accelerator		-0.04 [0.52]	-1.38 [0.91]	0.79 [0.22]	2.31** [0.01]	0.36 [0.36]
Neoclassical	1.48† [0.08]		-5.69 [1.00]	0.89 [0.19]	2.23* [0.02]	0.50 [0.31]
Average Q	2.25* [0.02]	2.95** [0.00]		2.13* [0.02]	4.99** [0.00]	3.36**[0.00]
Cash-Flow	0.11 [0.46]	-0.45 [0.67]	-1.25 [0.89]		14.59** [0.00]	-0.46 [0.68]
Stock Price	2.91** [0.00]	1.15 [0.13]	0.79 [0.22]	0.93 [0.18]		0.86 [0.20]
Return Predictors	1.03 [0.16]	0.56 [0.29]	-1.82 [0.96]	1.01 [0.16]	2.00* [0.03]	
MS_{h^*}	2.06 [0.11]	2.87* [0.04]	1.29 [0.30]	3.74** [0.01]	12.15** [0.00]	2.38† [0.07]

Note: †, *, ** indicate significance at the 10%, 5%, and 1% levels, respectively. The statistics correspond to a test of the null hypothesis that the forecasts for the model given in the first row of the table encompass the forecasts for the model given in the first column of the table; p-values are given in brackets. MS_{h^*} is the Harvey and Newbold (2000) statistic corresponding to a test of the null hypothesis that the forecasts for the model given in the first row of the table jointly encompasses the forecasts for the other models.

At horizon 3, the Average *Q* contains useful forecast information beyond that contained in any of the five models in the pair-wise test but the null of forecast encompassing is rejected for Average Q in the joint tests. At the same horizon, the Stock Price model forecast encompasses all other models in pair-wise except Average *Q* and the multiple forecast encompassing is also not rejected. Moreover, none of the other five (four) models is able to forecast encompass the Average *Q* (Stock Price) model. Thus, in terms of the forecast encompassing tests, Average *Q* and Stock Price are the best performing models at horizon 3. The Average Q also is the best performing model at the 4, 6 and 8-quarter horizons with the Return Predictors following closely at the 6-quarter horizon.

The different forecast evaluators employed in this study appear to produce consistent results both in terms of statistical significance and selection of the best performing forecasting model at all horizons except horizon 2. Overall, when we consider the results in Tables 1 to 3 together, the stock market models (Average *Q* and Stock Price) often offer important forecasting gains relative to other competing models over the 2003:1–2011:4 out-of-sample period.[9]

[9] We also performed alternative out-of-sample forecasts using the entire data set available on the relevant variables for South Africa (i.e. 1963-2011). Our results show that the stock market has gained importance in recent times when compared to earlier periods, as the traditional models appear to perform better in the earlier periods. This could be as a result of multiple structural breaks in the investment spending series as indicated by the Bai and Perron (2003) tests performed on the series.

4. Conclusion

In this study, we run horse races involving a number of forecasting models of South Africa's real fixed private business non-residential investment spending growth over the recent 2003:1–2011:4 out-of-sample period. The in-sample period covers 1994:1-2011:4, a period corresponding to the post-democracy era. The forecasting models are based on the Accelerator, Neoclassical, Average *Q*, Cash-Flow, Stock Price and Excess Stock Return Predictors models of investment spending. The different forecast evaluators appear to produce consistent results at almost all horizons. The Average *Q* followed by the Stock Price and Return Predictors models typically generates the most accurate forecasts, and forecast-encompassing tests indicate that these models contains most of the information useful for forecasting investment spending growth relative to the other models. These results point to an important predictive role for the stock market with respect to the business fixed investment spending growth in South Africa. Therefore, the need for appropriate and timely policy intervention for the development and stability of the stock market in South Africa cannot be undermined.

Data appendix

The appendix describes the data used in the present study. Except otherwise stated, all data used in this study are obtained from South African Reserve Bank (SARB) Quarterly Bulletin.

Real fixed private non-residential investment spending

Real fixed private non-residential investment spending is the difference between the gross fixed capital formation: Private business enterprises and gross fixed capital formation: Residential buildings (both expressed in constant 2005 prices and seasonally adjusted).

Real business output

Real business output is the seasonally adjusted gross value added at basic prices of Finance, insurance, real estate and business services.

Real user cost of capital

We measure the real user cost of capital following Rapach and Wohar (2007), who use the Hall and Jorgenson (1967) formula:

$$C_t = [R_t + \delta - (\dot{P}_t / P_t)][(1 - ITC_t - \tau_t \cdot DEP_t)/(1-\tau_t)]$$

where C_t is the real user cost of capital, R_t is the real interest rate, δ is the depreciation rate, P_t is the price of capital relative to the price of business output, $\dot{P}_t / P_t$ is an expected 'capital gains' term, ITC_t is the investment tax credit, τ_t is the marginal corporate income tax rate, and DEP_t is the present value of depreciation allowances. The real interest rate is the nominal government bond yield minus expected inflation, where expected inflation is measured as a 3 year moving average of change in the business output deflator derived from nominal business output and real business output. We set the depreciation rate equal to 0.2. The price of capital relative to business output is the price deflator for fixed private non-residential investment spending divided by the output price deflator. The price deflator for fixed private non-residential investment spending is constructed from the nominal and real fixed private non-residential investment spending series. The real investment series is described above, and the nominal investment spending series is the difference between the current seasonally adjusted gross fixed capital formation: Private business enterprises and current seasonally adjusted gross fixed capital formation: Residential buildings. The 'capital gains' term is measured as a 3-year moving average of the percentage change in P_t. The investment tax credit and depreciation allowance are set equal to zero due to data unavailability. The marginal corporate income tax rates are tax payable by companies as percentage of total revenue.

Average Q

Average Q is defined as the ratio of the market value of capital to its replacement cost following Hayashi, (1982) and Mirakhor (1996)

$$\text{Average Q} = \frac{V}{C}$$

Assuming that there are no debt instruments and the firm is equity financed only, V is the market value of equity measured as the product of the number of shares outstanding and the share price on the last day of the month preceding capital investment announcement. We use the stock market capitalization from Global Financial Data. C is the current-rand value of fixed capital stock for the Finance, insurance, real estate and business services sector from the SARB.

Real profits

Real profits are measured as seasonally adjusted net operating surplus deflated by the output deflator.

Real stock prices

Real stock prices are the JSE All share price index deflated using the output deflator.

Relative short-term interest rate

The relative bill rate is the 3-month Treasury bill yield minus a 1-year backward-looking moving average. The 3-month Treasury bill yield is from the IMF's International Financial Statistics.

Term spread

The term spread is the difference between the 10-year government bond yield and the 3-month Treasury bill yield. The 10-year government bond yield is from the IMF's International Financial Statistics.

Default spread

Rapach and Wohar (2007) calculated the default spread as the difference between the corporate Baa bond yield and corporate Aaa bond yield. However, the relevant data is not available for South Africa, hence we set default spread equal to zero.

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