Forecasting the Recent Behavior of U.S. Business Fixed Investment Spending: An Analysis of Competing Models

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February 15, 2005 (Revised)

Abstract

In this paper, we evaluate the performance of a number of forecasting models of U.S. business fixed investment spending growth over the recent 1995:1-2004:2 out-of-sample period at multiple forecast horizons. The forecasting models are based on the conventional Accelerator, Neoclassical, Average Q, and Cash-Flow models of investment spending, as well as empirical models developed more recently by Barro (1990) using real stock prices and Lettau and Ludvigson (2002) using excess stock return predictors. None of the forecasting models stands out above the others at forecast horizons of 1-2 quarters. However, at forecast horizons beyond 2 quarters, forecast encompassing tests indicate that the Barro (1990) real stock price model contains most of the information useful for forecasting U.S. business fixed investment spending growth for 1995:1-2004:2 relative to the other models. This points to an important role for the stock market in tracking the recent course of U.S. business fixed investment spending.

JEL classification codes: C22, C53, E22, E27

Key words: Business fixed investment spending; Out-of-sample forecasts; Mean squared forecast error; Forecast encompassing

*Corresponding author. We thank seminar participants at the 2004 Midwest Econometrics Group Meetings, 2004 Midwest Macro Meetings, 2004 Missouri Economics Conference, Federal Reserve Bank of Saint Louis, IUPUI, and Saint Louis University, as well as Steve Fazarri, Jonathan Wright, and especially Todd Clark, Allan Timmermann (Departmental Editor), and two anonymous referees for very helpful comments. The usual disclaimer applies. This is a significantly revised version of our previous paper, "Forecasting U.S. Business Fixed Investment Spending." The results reported in this paper were generated using GAUSS 6.0. The GAUSS programs are available at http://pages.slu.edu/faculty/rapachde/Research.htm.

1. Introduction

Empirical models of U.S. business fixed investment spending have a long tradition. This is not surprising, given the crucial role of investment spending in determining both long-term growth and fluctuations in aggregate activity at business-cycle horizons. The empirical literature has considered a number of different models of investment spending. Among the most popular models 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 common approach in the empirical literature is to include one or more of these conventional models in a 'horse race' designed to identify the model (or models) that best explains U.S. business fixed investment spending over a particular period. A partial list of empirical studies that run horse races includes Jorgenson and Seibert (1968), Jorgenson, Hunter, and Nadiri (1970a,b), Bischoff (1971), Clark (1979), Bernanke, Bohn, and Reiss (1988), Barro (1990), Blanchard, Rhee, and Summers (1993), Oliner, Rudebusch, and Sichel (1995), Kopcke and Brauman (2001), and Tevlin and Whelan (2003). Many of these papers feature horse races comparing the out-of-sample forecasting ability of competing models, owing to the widely held belief that tests of out-of-sample predictive power are the most stringent tests of a model's reliability, especially insofar as out-of-sample tests guard against structural instabilities and data mining. Furthermore, given the interest of policymakers in forecasting U.S. business fixed investment spending,[2] out-of-sample tests constitute a relevant test design for the examination of forecasting models (Poon and Granger, 2003).

Out-of-sample horse races have been run over different periods in the extant literature, ranging from the 1960s to the mid-1990s. In the present paper, we run out-of-sample horse races involving a number of forecasting models of U.S. business fixed investment spending over the more recent 1995:1-2004:2 out-of-sample period. This period witnessed an investment 'boom' that was at the center of the longest economic expansion in U.S. history, as well as an investment 'bust' that contributed significantly

[1] See Kopcke and Brauman (2001) and Chirinko (1993) for useful surveys of models of business fixed investment spending.
[2] See Bernanke (2003) and Poole (2003) with respect to monetary policy.

to the economic recession of 2001. We view this volatile period of investment spending as a useful laboratory for comparing different forecasting models of U.S. business fixed investment spending, so that the present paper represents an important update of the horse race literature on U.S. business fixed investment spending.

We consider six forecasting models of U.S. fixed private nonresidential investment spending growth at forecast horizons of 1-4, 6, and 8 quarters, with each model utilizing a different explanatory variable (or variables). Each of the first four forecasting models uses a variable suggested by one of the conventional models cited in the opening paragraph: real business output (Accelerator); real business output divided by the real user cost of capital (Neoclassical); the market value of capital relative to its replacement cost or average Q (Tobin's Q); real profits (Cash-Flow). The fifth forecasting model follows Barro (1990) and uses real stock prices in place of average Q, as Barro (1990) argues that stock prices are a potentially better measure of the market's assessment of the future profitability of investment projects than average Q. The sixth forecasting model of U.S. fixed private nonresidential investment spending growth is motivated by the recent work of Lettau and Ludvigson (2002). Building on the modern Q theory of investment spending [see Abel (1982) and Abel and Blanchard (1986)], Lettau and Ludvigson (2002) argue that variables demonstrating predictive ability with respect to the equity risk premium (excess stock returns) should also have predictive ability with respect to business fixed investment spending. The sixth forecasting model includes three of the excess stock return predictors—the term spread, default spread, and relative short-term interest rate—that Lettau and Ludvigson (2002) find to have in-sample predictive ability with respect to U.S. business fixed investment spending growth.[3]

We use a number of different econometric procedures to evaluate the forecasts generated by competing models over the 1995:1-2004:2 out-of-sample period. We first measure the accuracy of the forecasts generated by each model using the familiar root mean squared error (RMSE) metric. We then

[3] Lettau and Ludvigson (2002) also consider the dividend yield and the consumption-wealth ratio (Lettau and Ludvigson, 2001). However, they find that the dividend yield is not a reliable predictor of excess stock returns over the 1990s and that the consumption-wealth ratio only predicts investment spending at horizons beyond the 8-quarter horizon.

assess whether the forecasts generated by each model are unbiased by estimating Mincer and Zarnowitz (1969) regressions. We also conduct pair-wise tests for significant differences in the forecast mean squared error (MSE) across models by applying the popular Diebold and Mariano (1995) statistic [with the Harvey, Leybourne, and Newbold (1997) modification]. In addition to testing for equal forecast MSE across models, we conduct pair-wise tests of forecast encompassing using the Harvey, Leybourne, and Newbold (1998) statistic. Forecast encompassing allows us to examine whether the forecasts generated by a given model contain information useful for forecasting U.S. business fixed investment spending growth beyond the information already contained in the forecasts generated by a competing model. We also test whether the forecasts generated by a given model jointly encompass the forecasts generated by all of the other competing model using the multiple forecast encompassing test of Harvey and Newbold (2000). By analyzing the forecasts generated by competing models using a number of different econometric procedures, we should have a more complete picture of the forecasting performance of the different models over the 1995:1-2004:2 out-of-sample period.

The rest of the paper is organized as follows: Section 2 discusses econometric issues relating to the specification of the forecasting models and outlines the procedures we use to evaluate the forecasts generated by the different models; Section 3 reports the empirical results; Section 4 summarizes our main findings.

2. Econometric Methodology

2.1. Specification of the Forecasting Models

Early studies, such as Jorgenson, Hunter, and Nadiri (1970a,b), typically estimate conventional models of investment spending with the level of real business fixed investment spending serving as the dependent variable. A number of other studies, such as Oliner, Rudesbusch, and Sichel (1995) and Tevlin and Whelan (2003), estimate conventional models with the ratio of the level of real business fixed investment spending to the lagged capital stock serving as the dependent variable. Still other studies, such as Clark (1979) and Bernanke, Bohn, and Reiss (1988), use the ratio of the level of real business fixed investment spending to real potential output as the dependent variable. From the perspective of modern time-series econometrics, the use of these dependent variables is potentially problematic, as unit root tests clearly indicate that the levels (or log-levels) of these variables are non-stationary.[4] Importantly, the use of non-stationary dependent variables calls into question the reliability of the inferences made in existing studies, as the standard asymptotic results on which inferences are based typically do not hold in the presence of non-stationary variables.[5] It also provides an explanation for the considerable serial correlation often detected in models of investment spending in the extant literature [see, for example, Bernanke, Bohn, and Reiss (1988)].

In an effort to specify forecasting models with a stationary dependent variable, we follow Barro (1990) and use the first differences of the log-levels (approximately equal to the growth rate) of real U.S. business fixed investment spending as the dependent variable in our forecasting models. We further follow Barro (1990) by adopting an autoregressive distributed lag (ARDL) structure for our forecasting models. This structure has also been used recently by Stock and Watson (2003) in their extensive analysis of the ability of a host of variables to forecast real output growth and inflation in the G7 countries. Letting $\Delta i_t = i_t - i_{t-1}$, where i_t is the log-level of real fixed private nonresidential investment spending at time *t*, and $y_{t+h} = \sum_{j=1}^{h} \Delta i_{t+j}$, our forecasting models take the following form:

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

where $\Delta x_{m,t}$ is a variable characterizing a particular investment model *m* ($m = 1,...,M$), *h* is the forecast horizon, and $\varepsilon_{m,t+h}$ is a disturbance term. The Ng and Perron (2001) unit root tests with good size and

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[4] Using data from the Bureau of Economic Analysis (BEA) and Tevlin and Whelan (2003), we tested for unit roots in the levels (and log-levels) of U.S. real business fixed investment spending, the ratio of real business fixed investment spending to the lagged capital stock, and the ratio of real business fixed investment spending to real business output. Using the unit root tests of Ng and Perron (2001) with good size and power, we cannot reject the unit root null hypothesis for these variables. The complete unit root test results, as well as all other unreported results, are available at http://pages.slu.edu/faculty/rapachde/Research.htm.

[5] Of course, the relationship among the levels of non-stationary variables contains important information if the variables are cointegrated. As we discuss below, we fail to find evidence of cointegrating relationships among the levels of the variables that appear in the models of U.S. business fixed investment spending we consider in the present paper.

power clearly 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 $x_{m,t} \sim I(1)$ [$\Delta x_{m,t} \sim I(0)$]. This ensures that equation (1) contains only stationary variables. The first five forecasting models are defined as follows:

- 'Accelerator' model: $x_{1,t} \equiv$ log-level of real business output
- 'Neoclassical' model: $x_{2,t} \equiv$ log-level of the ratio of real business output to the real user cost of capital
- 'Average Q': $x_{3,t} \equiv$ log-level of the ratio of the market value of capital to its replacement cost
- 'Cash-Flow': $x_{4,t} \equiv$ log-level of real profits
- 'Stock Price': $x_{5,t} \equiv$ log-level of real stock prices[6]

We also tested for cointegration between i_t and each of the $x_{m,t}$ variables, as it would be appropriate to include an error-correction term in equation (1) if there is a stable long-run relationship between i_t and $x_{m,t}$. We found no evidence of cointegration, so we do not include an error-correction term in any of the forecasting models.[7]

Our 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), we include a single lag of each variable in the forecasting model, so that the 'Return Predictors' model takes the form,

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

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 long-

[6] The sources and construction of the data are described in the Data Appendix.
[7] Note that even if a cointegrating relationship actually exists, including the error-correction term in the forecasting model typically only improves forecasting performance at longer horizons (Engle and Yoo, 1987; Clements and Hendry, 1995; Hoffman and Rasche, 1996).

and short-term government bond yields), 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 U.S. fixed private nonresidential investment spending growth over the 1995:1-2004:2 out-of-sample period.

In order to form out-of-sample forecasts for a given model *m*, we use the following recursive scheme that (apart from data availability and revisions) simulates the situation of a forecaster in real time. We first divide the total sample of *T* observations into in-sample and out-of-sample portions, where the in-sample portion spans the first *R* observations and the out-of-sample portion the last $T-R$ observations. The first out-of-sample forecast for model *m* is generated in the following manner. We estimate equation (1) via OLS using data available through period *R*.[8] Using the OLS parameter estimates and the observations for Δi_{R-j} and $\Delta x_{m,R-j}$, we construct a forecast for y_{R+h} based on model *m* using the fitted equation $\hat{y}_{m,R+h} = \hat{\alpha}_{m,R} + \sum_{j=0}^{q_{m,1}-1} \hat{\beta}_{m,R,j} \Delta i_{R-j} + \sum_{j=0}^{q_{m,2}-1} \hat{\gamma}_{m,R,j} \Delta x_{m,R-j}$, where $\hat{\alpha}_{m,R}$, $\hat{\beta}_{m,R,j}$, and $\hat{\gamma}_{m,R,j}$ are the OLS estimates of α_m, $\beta_{m,j}$, and $\gamma_{m,j}$, respectively, in equation (1) using data available through period *R*.[9] Denote the forecast error by $\hat{u}_{m,R+h} = y_{R+h} - \hat{y}_{m,R+h}$. In order to generate a forecast for y_{R+1+h} based on model *m*, we update the above procedure one period by using data available through period $R+1$. We repeat this process through the end of the available sample, leaving us with a set of $T-R-h+1$ recursive out-of-sample forecasts corresponding to model *m*, $\{\hat{u}_{m,t+h}\}_{t=R}^{T-h}$.

2.2. Evaluation of Forecasts

In order to analyze the forecasts at horizon *h* generated by model *m*, we first compute the RMSE, the most popular measure of forecast accuracy. The MSE corresponding to the forecasts at horizon *h* generated by model *m* is defined as

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[8] We select $q_{m,1}$ and $q_{m,2}$ in equation (1) using the SIC and the in-sample observations. We consider $q_{m,1}$ values from 0-8. To ensure that $x_{m,t}$ appears in equation (1), we consider $q_{m,2}$ values from 1-8.

[9] This procedure is modified in obvious ways to generate simulated out-of-sample forecasts for the Return Predictors model given by equation (2).

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

while $RMSE_{m,h} = MSE_{m,h}^{0.5}$. We also test whether the forecasts at horizon *h* generated by model *m* are unbiased using the Mincer and Zarnowitz (1969) regression,

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

where 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 $\hat{a} / se(\hat{a})$ and $(\hat{b} - 1) / se(\hat{b})$, where $\hat{a}$ ($\hat{b}$) is the OLS estimate of *a* (*b*) and $se(\hat{a})$ [$se(\hat{b})$] is its estimated standard error. Given that the forecast errors at horizon *h* from an optimal forecasting model follow a moving average process of order $h-1$, we calculate the standard errors using the Newey and West (1987) heteroskedastic and autocorrelation consistent (HAC) covariance estimator. We also calculate an *F*-statistic corresponding to a test of the joint null hypothesis that $a = 0$ and $b = 1$ in equation (4), where we again compute the test statistic using the HAC covariance estimator.

In addition to computing $RMSE_{m,h}$ and estimating equation (3), we follow Blair, Poon, and Taylor (2001) and compare the amount of variation in the forecast errors at horizon *h* from model *m* with the actual volatility in y_{t+h} using the following measure:

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

where $\bar{y}_h = (T-R-h+1)^{-1} \sum_{t=R}^{T-h} y_{t+h}$. When the forecast errors are small, $P_{m,h}$ will be close to unity. Observe that, unlike the R^2 measure, $P_{m,h}$ can be negative. This occurs when the forecast errors are more volatile than the variable itself, clearly an undesirable property for a forecasting model.

We also test for significant differences in forecasting ability between the forecasts generated by a pair of competing models. In particular, we use the popular test due to Diebold and Mariano (1995) and West (1996) to test $H_0 : MSE_{i,h} = MSE_{j,h}$ against $H_1 : MSE_{i,h} \neq MSE_{j,h}$ for the pair of competing models

i and j. The 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,

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

where $\bar{d}_h = (1/n_h)\sum_{t=R}^{T-h}\hat{d}_{t+h}$, $\hat{V}(\bar{d}_h) = n_h^{-1}(\hat{\phi}_0 + 2\sum_{k=1}^{h-1}\hat{\phi}_k)$, $\hat{\phi}_k = (1/n_h)\sum_{t=R+k}^{T-h}(\hat{d}_{t+h} - \bar{d}_h)(\hat{d}_{t-k+h} - \bar{d}_h)$, 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 we do).[10] In order to improve the finite-sample performance of the DM_h statistic, Harvey, Leybourne, and Newbold (1997) recommend using a modified DM_h statistic,

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

and the t_{n_h-1} distribution in place of the standard normal for inference. We use the MDM_h statistic and the t_{n_h-1} distribution to test for equal forecast accuracy in our applications in Section 3 below.[11]

Forecasts from two competing models can also be compared using the notion of forecast encompassing.[12] 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:

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

where $0 \le \lambda \le 1$. 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 $\lambda > 0$,

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[10] 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).

[11] We also compute the West and Cho (1995) chi-squared statistic that tests the joint null hypothesis, $H_0 : MSE_{1,h} = ... = MSE_{M,h}$.

[12] See Clements and Hendry (1998) for a textbook treatment of forecast encompassing.

then the 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, Leybourne, and Newbold (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, 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, Leybourne, and Newbold (1997), Harvey, Leybourne, and Newbold (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 our applications in Section 3 below.[13] It is useful to include encompassing tests in our analysis, as encompassing tests may be more powerful in detecting significant differences in forecasting ability between competing models than the Diebold and Mariano (1995) test of equal MSE.[14]

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:

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

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[13] West (2001) shows that the parameter uncertainty inherent in forming the forecasts does affect the asymptotic distribution of the HLN_h statistic, so that the HLN_h statistic does not have a standard normal asymptotic distribution. However, West (2001) finds that the size distortions for the $MHLN_h$ statistic and the $t_{n_h - 1}$ distribution are small in Monte Carlo experiments when the ratio of the number of out-of-sample forecasts to the number of in-sample observations (n_h / R) is approximately 0.25 or less and n_h is less than approximately 40. In our applications in Section 3 below, n_h / R is near 0.25 and n_h is less than 40, so that parameter uncertainty is unlikely to lead to important size distortions in our use of the $MHLN_h$ statistic and $t_{n_h - 1}$ distribution.

[14] See, for example, Rapach and Weber (2004).

If $\lambda_2 = ... = \lambda_M = 0$, 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:

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

where $\bar{d}_h = [\bar{d}_{2,h},...,\bar{d}_{M,h}]^{'}$, $\bar{d}_{i,h} = (1/n_h)\sum_{t=R}^{T-h}\hat{d}_{i,t+h}$ ($i = 2,...,M$), $\hat{d}_{i,t+h} = (\hat{u}_{1,t+h} - \hat{u}_{i,t+h})\hat{u}_{1,t+h}$ ($i = 2,...,M$), 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.[15]

3. Empirical Results

We evaluate the simulated out-of-sample forecasts over the 1995:1-2004:2 period generated by the six forecasting models of fixed private nonresidential investment spending growth described in Section 2.1 above. The in-sample portion of the total sample covers 1963:1-1994:4, and we consider forecast horizons of 1-4, 6, and 8 quarters. This gives us a reasonably long period with which to estimate the ARDL model used to construct the first out-of-sample forecast for each model and still leaves us with a reasonable number of out-of-sample observations. Forecast horizons of 1-8 quarters are relevant for business cycle dynamics and are thus likely to be of keen interest to policymakers. Considering forecast horizons out to 8 quarters also helps to allow for lags in the investment spending process.

Table 1 reports the RMSE, Mincer and Zarnowitz (1969) regression results, and the Blair, Poon, and Taylor (2001) $P_{m,h}$ statistic for each of the six forecasting models and forecast horizons of 1-4, 6, and 8 quarters. For all of the forecast horizons, the Mincer and Zarnowitz (1969) regression results reveal that only the Accelerator model produces biased forecasts, and it does so at horizons of 1-4 and 6 quarters at

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[15] Their Monte Carlo experiments also suggest that the MS_h^* statistic has limited power under some circumstances.

significance levels of 10% or lower. At the 1-quarter horizon, the RMSE values for the different models are all fairly close, ranging from 1.52-1.68, with the Average Q (Cash-Flow) model having the lowest (highest) RMSE. The Average Q model also has the highest $P_{m,h}$ statistic (0.50) at the 1-quarter horizon. At forecast horizons of 2-4 and 6 quarters, the Stock Price model displays the lowest RMSE, while the Average Q model has the next lowest RMSE at these horizons. The Stock Price model also has the highest $P_{m,h}$ statistic at horizons of 2-4 and 6 quarters, where the $P_{m,h}$ statistics are equal to 0.51, 0.54, and 0.47 at forecast horizons of 2, 3, and 4 quarters, respectively. (The Average Q model also has a $P_{m,h}$ statistic of 0.51 at the 2-quarter horizon.) At the 8-quarter horizon, the Stock Price model continues to have the lowest RMSE, but the $P_{m,h}$ statistics all become negative at this horizon, indicating a noticeable deterioration in the quality of the forecasts at the 8-quarter horizon.

Table 2 reports the MDM_h statistics corresponding to all pairs of forecasting models. Note that 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. None of the *p*-values indicate that the MDM_h statistic is significant for any pair of models at conventional levels at forecast horizons of 1-4 and 6 quarters in Table 2, so that there are not significant differences in forecast MSE across models at these horizons. There are three rejections of the null hypothesis of equal MSE at the 8-quarter horizon.[16] Overall, the small number of rejection in Table 2 may be due in part to the low power of the MDM_h statistic to detect differences in forecasting ability in the present setting, and so we turn to the forecast encompassing test results.

The $MHLN_h$ statistics corresponding to all model pairs are reported in Table 3. 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. Table 3 also reports the

[16]The West and Cho (1995) chi-squared statistic used to test the null hypothesis that $H_0 : MSE_{1,h} = ... = MSE_{M,h}$ (see footnote 11) is insignificant at forecast horizons of 1-4 and 6 quarters; it is significant at the 1% level at the 8-quarter horizon.

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. We see from Table 3 that there are quite a large number of rejections of the null hypothesis of forecast encompassing at conventional significance levels, indicating that there are numerous situations where the forecasts generated by a particular model contain information useful for forecasting U.S. real business fixed investment spending growth beyond the information contained in another model. At the 1-quarter (2-quarter) horizon, 21 (18) of the 30 $MHLN_h$ statistics are significant at the 10% level, and there is no case where the forecasts from a particular model are able to encompass the forecasts from each of the other five models in pair-wise tests at horizons of 1 and 2 quarters. We can also reject the null hypothesis of multiple forecast encompassing for the Accelerator and Return Predictors (Accelerator, Neoclassical, Cash-Flow, and Return Predictors) models at the 1-quarter (2-quarter) horizon.[17]

Two of the forecasting models begin to distinguish themselves at horizons of 3 and 4 quarters according to the encompassing tests in Table 3. At the 3-quarter horizon, both the Stock Price and Average Q models are able to forecast encompass the other five models in both pair-wise and joint tests. In addition, the Accelerator, Neoclassical, Cash-Flow, and Return Predictors models cannot forecast encompass the Average Q or Stock Price models in pair-wise tests. The Average Q and Stock Price models thus stand out as the 'best' forecasting models at the 3-quarter horizon according to the encompassing tests, as none of the other models contain information useful for forecasting U.S. real business investment spending growth beyond the information contained the Average Q and Stock Price models, and each of these two models contains information useful for forecasting investment spending beyond that contained in the other four models. At the 4-quarter horizon, only the forecasts generated by the Stock Price model encompass the forecasts generated by the remaining five models in both pair-wise and joint tests. Furthermore, none of the other five models can forecast encompass the Stock Price model at the 4-quarter horizon. In terms of the forecast encompassing tests, the Stock Price model ranks as the

[17] 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.

'best' model at the 4-quarter horizon over the 1995:1-2004:2 out-of-sample period. At horizons of 6 and 8 quarters, the Stock Price model continues to forecast encompass the other five models in both the pair-wise and joint tests.

Figures 1a and 1b provide a visual comparison of the forecasts generated by each of the six models at each of the forecast horizons. At the 1-quarter horizon, the forecasts from the different models appear to move more or less together, and each of the models under-predicts investment spending growth around 1996 and over-predicts investment spending growth around 2001. At horizons of 2-4 quarters, the Average Q and Stock Price models appear to do a better overall job of tracking investment spending growth over the 1995:1-2004:2 out-of-sample period, and this is also reflected in the lower RMSEs for these models at these horizons in Table 1. Compared to the other models, the Average Q and Stock Price models are especially better able to track the sharp contraction in investment spending around 2001. Taking the results in Table 3 and Figure 1b together, the two forecasting models that explicitly incorporate stock market information—the Average Q and Stock Price models—appear to perform the best over the 1995:1-2004:2 out-of-sample period at forecast horizons of 2-4 quarters, suggesting that stock prices contained important information for forecasting U.S. business fixed investment spending over this period.[18] At forecast horizons of 6 and 8 quarters, we see from Figure 1c that all of the models have a more difficult time tracking investment spending growth, especially when it comes to the sharp downturn around 2001.

We briefly describe the results for some robustness checks that we performed. First, we analyzed the simulated forecasting performance of all of the models over the 1985:1-1994:4 out-of-sample period.

[18] In a previous version of this paper, we tested each of the forecasting models against autoregressive (AR) benchmarks, and we typically find that the forecasting models significantly outperform the AR benchmarks. Note that the Diebold and Mariano (1995) and Harvey, Leybourne, and Newbold (1998) statistics do not have standard asymptotic distributions when comparing forecasts from nested models, as is the case when comparing forecasts generated by equation (1) to forecasts generated by an AR benchmark; see Clark and McCracken (2001) and McCracken (2004). We also computed forecasts of the structures and equipment components of U.S. real fixed private nonresidential spending growth using each of the forecasting models above, as well as a forecasting model based on the Tevlin and Whelan (2003) disggregated model. In general, the forecasting models perform more poorly in forecasting the structures component of U.S. real fixed private nonresidential investment spending growth than in Table 1. With respect to forecasting the equipment component of U.S. real fixed private nonresidential investment spending growth, the results are somewhat similar to those reported in Tables 1-3, but none of the forecasting models tends to stand out like the Stock Price model at horizons of 3 and 4 quarters in Table 3.

The Accelerator model has the lowest RMSE at horizons of 1-3 quarters, while the Return Predictors model has the lowest RMSE at horizons of 4, 6, and 8 quarters. As in Table 2, the MDM_h statistics fail to reject the null hypothesis of equal MSE for almost all of the model pairs. As in Table 3, there are numerous rejections of the forecast encompassing null hypothesis according to the $MHLN_h$ statistics. Unlike in Table 3, the Average Q and Stock Price models do not stand out at horizons of 3 and 4 quarters over the 1985:1-1994:4 out-of-sample period, suggesting a more important role for the stock market in tracking investment spending over the recent 1995:1-2004:2 period.

Following Stock and Watson (2003), we also investigated the stability of the α_m and $\gamma_{m,j}$ coefficients in equation (1) for each of the forecasting models over the entire 1963:1-2004:2 in-sample period using the Quandt (1960) likelihood ratio (QLR) test for coefficient stability. We use 15% trimming at each end of the sample, so that likelihood ratio statistics are computed over all possible break dates in the middle 70% of the sample, and the QLR statistic is the maximum of these likelihood ratio statistics.[19] The QLR statistics, along with the least squares estimated break dates, are reported in Table 4. The QLR statistics are significant at all reported horizons for the Return Predictors model at conventional levels, with the estimated break dates occurring in the early to mid 1980s. The QLR statistics are also significant at horizons of 1-4 and 8 quarters for the Accelerator model. Note that the estimated break dates for the Accelerator model occur at 1995:4 at horizons of 3 and 4 quarters, and 1995:4 is very near the beginning of our out-of-sample period. This may help explain the biased forecasts produced by the Accelerator model in Table 1. The QLR statistics are significant at horizons of 1-3 quarters for the Stock Price model, with the breaks occurring in the mid 1980s. There is significant evidence of a break at the 4-quarter (1-quarter) horizon for the Neoclassical (Cash-Flow) model, while there is no significant evidence of a break at any reported horizon for the Average Q model. With the exception of the Accelerator and Return

[19] The likelihood ratio statistics are computed using the Newey and West (1987) HAC covariance estimator. We implemented the QLR test using the GAUSS programs available from Mark Watson's home page at http://www.wws.princeton.edu/~mwatson.

Predictors models and the Stock Price model at shorter horizons, the forecasting models appear relatively stable.[20]

4. Conclusion

In this paper, we run horse races involving a number of forecasting models of U.S. real fixed private nonresidential investment spending growth over the 1995:1-2004:2 out-of-sample period, a volatile period marked by an investment ‘boom’ and ‘bust’ cycle. The forecasting models we consider are based on the familiar Accelerator, Neoclassical, Average Q, and Cash-Flow models of investment spending, and we also consider two forecasting models suggested by the more recent work of Barro (1990) and Lettau and Ludvigson (2002). Our results indicate that none of the individual forecasting models stand out at horizons of 1-2 quarters over the 1995:1-2004:2 out-of-sample period. However, at the 3-quarter forecast horizon, the Average Q and Stock Price models contain all of the information useful for forecasting U.S. business fixed investment spending growth over the 1995:1-2004:2 period relative to the other forecasting models, while the Stock Price model contains all of the useful information at the 4-quarter forecast horizon. The Average Q and Stock Price models are the only two models that explicitly utilize information from stock prices, pointing to an important predictive role for the stock market with respect to the recent course of U.S. business fixed investment spending.

[20] For the models that evince instability, it would be interesting in future research to examine whether their forecasting performance could be significantly improved by estimating the forecasting models using an estimation window whose size is adjusted based on the results of tests for structural change using a procedure along the lines of Pesaran and Timmermann (2002).

Data Appendix

This appendix describes the data used in the present paper.

Real Fixed Private Nonresidential Investment Spending

Real fixed private nonresidential investment spending is the seasonally adjusted quantity index from the BEA, NIPA Table 5.3.3.

Real Business Output

Real business output is seasonally adjusted real gross value added by the business sector (quantity index) from NIPA Table 1.3.3.

Real User Cost of Capital

We measure the real user cost of capital following Tevlin and Whelan (2003), who use the Hall and Jorgenson (1967) formula:

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

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 the 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 Baa corporate bond yield minus expected inflation, where expected inflation is measured as the average inflation rate of the business output deflator over the previous five years and the business output deflator is derived from nominal business output (NIPA Table 1.3.5) and real business output. We also add a constant 'risk premium' that normalizes the real interest rate to 6.80%, which Tevlin and Whelan (2003) treat as the average rate of return on physical capital. We use the depreciation rate for structures (0.05648) from Bernanke, Bohn, and Reiss (1988) and the depreciation rates for computer equipment (0.31) and non-computer equipment (0.13) from Tevlin and Whelan (2003). To calculate the depreciation rate for the fixed private nonresidential capital stock, we take a weighted average of the structures, computer equipment, and non-computer equipment depreciation rates, where the weights are the average shares (over 1987-2003) of structures, computer equipment, and non-computer equipment in the capital stock. The capital stock data are from NIPA Table 2.1. The price of capital relative to business output is the price deflator for fixed private nonresidential investment spending divided by the business output price deflator. The price deflator for fixed private nonresidential investment spending is constructed from the nominal and real fixed private nonresidential investment spending series. The real investment series is described above, and the nominal investment spending series is from NIPA Table 5.3.5. The 'capital gains' term is measured as a 3-year moving average of the percentage change in P_t. The investment tax credit and marginal corporate income tax rates are from the Federal Reserve Board. DEP_t is computed using the 'sum of the year's digits' approach of Hall and Jorgenson [1967, equation (8)], where the service life is a weighed average of the service lives of a number of number of the components making up fixed private nonresidential investment spending.[21] The weights are the shares of each of the components in nominal investment.

Average Q

Average Q is calculated using the tax-adjusted formula from Bernanke, Bohn, and Reiss (1988) as described in Lettau and Ludvigson (2002, p. 64):

$$Q_t = \left(\frac{1}{1-\tau_t}\right)\left(\frac{V_t - B_t + D_t}{A_t} + ITC_t + \tau_t DEP_t - 1\right), \tag{A.2}$$

where V_t is the market value of equity, B_t is the present value of the depreciation allowances still to be taken on the existing capital stock, D_t is the value of total liabilities in non-farm, non-financial corporate business, and A_t is the current-dollar value of the stock of equipment, nonresidential structures, and inventories for non-farm, non-financial corporate businesses. V_t, D_t, and A_t are from the Federal Reserve Board's Flow of

[21] We thank Stacey Tevlin for kindly providing us with the investment tax credit, marginal corporate income tax rate, and service lives data.

Funds Accounts for the United States. B_t is calculated using $B_t = KTAX_t \tau_t \{\delta_t^T / [\delta_t^T + RB_t(1-\tau_t)]\}$, where $KTAX_t$ is the nominal stock of equipment and nonresidential structures in non-farm, non-financial corporate business that has not been depreciated for tax purposes, δ_t^T is the rate of tax depreciation, and RB_t is 10-year Treasury bond yield. To generate the $KTAX_t$ series, we begin with the nominal capital stock from the end of 1964 (from the BEA report, "Fixed Assets and Consumer Durable Goods for 1925-2001"[22]) and use the relation $KTAX_t = KTAX_{t-1} - CCA_t + IN_t$, where CCA_t is capital consumption allowances (NIPA Table 1.7.5) and IN_t is nominal fixed private nonresidential investment spending. Given $KTAX_t$, we can calculate the rate of tax depreciation using $\delta_t^T = CCA_t / KTAX_t$

Real Profits

Real profits are measured as seasonally adjusted nominal after-tax corporate profits with inventory valuation and capital consumption adjustments (NIPA Table 1.12) deflated by the business output deflator.

Real Stock Prices

Real stock prices are the S&P 500 stock price index deflated by the business output deflator. The S&P 500 index is from Global Financial Data.

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 Global Financial Data.

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[22] The report is available at http://www.bea.gov/bea/ARTICLES/2002/09September/0902FixedAssets.pdf.

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 Global Financial Data.

Default Spread

The default spread is the difference between the corporate Baa bond yield and corporate Aaa bond yield. The corporate bond yields are from Global Financial Data.

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Table 1: Root mean squared forecast errors, tests of unbiased forecasts, and measures of forecast explanatory power—real fixed private nonresidential investment spending growth, 1995:1-2004:2 out-of-sample period

Model	RMSE	$\hat{a}$	$\hat{b}$	F	$P_{m,h}$	RMSE	$\hat{a}$	$\hat{b}$	F	$P_{m,h}$
	$h=1$					$h=2$				
Accelerator	1.60	-1.17** (-3.05)	2.00** (4.00)	8.06** [0.00]	0.44	2.94	-2.20† (-1.91)	1.95** (3.00)	7.17** [0.00]	0.43
Neoclassical	1.63	-0.12 (-0.34)	1.07 (0.36)	0.7 [0.93]	0.42	2.97	-0.58 (0.57)	1.20 (0.83)	0.38 [0.68]	0.42
Average Q	1.52	0.21 (0.71)	0.86 (-0.98)	0.49 [0.62]	0.50	2.73	0.50 (0.57)	0.81 (-1.13)	0.90 [0.41]	0.51
Cash-Flow	1.68	-0.05 (-0.12)	1.04 (0.19)	0.02 [0.98]	0.38	2.98	-0.44 (-0.39)	1.15 (0.57)	0.20 [0.82]	0.41
Stock Price	1.60	0.21 (0.63)	0.80 (-1.40)	1.03 [0.37]	0.44	2.72	0.28 (0.32)	0.81 (-1.14)	1.55 [0.23]	0.51
Return Predictors	1.64	-0.65 (-1.39)	1.42 (1.56)	1.22 [0.31]	0.42	3.05	-1.20 (-0.87)	1.40 (1.01)	0.52 [0.60]	0.39
	$h=3$					$h=4$				
Accelerator	4.54	-3.69 (-1.39)	2.10* (2.07)	4.76* [0.02]	0.36	6.30	-5.29 (-1.22)	2.25† (1.81)	3.10† [0.06]	0.27
Neoclassical	4.46	-1.36 (-0.71)	1.28 (0.95)	0.48 [0.62]	0.38	6.27	-1.71 (-0.49)	1.36 (0.79)	0.42 [0.66]	0.28
Average Q	4.21	0.85 (0.47)	0.81 (-0.73)	0.37 [0.69]	0.44	5.47	-0.05 (-0.02)	1.15 (0.50)	0.46 [0.64]	0.45
Cash-Flow	4.73	-1.70 (-0.55)	1.42 (0.76)	0.55 [0.58]	0.30	6.44	-3.28 (-0.68)	1.50 (0.24)	1.51 [0.24]	0.24
Stock Price	3.83	0.09 (0.06)	-0.96 (-0.19)	0.05 [0.95]	0.54	5.38	-0.14 (-0.06)	1.08 (0.30)	0.17 [0.85]	0.47
Return Predictors	4.69	-2.09 (-0.69)	1.55 (0.91)	0.55 [0.58]	0.31	6.49	-3.85 (-0.70)	1.79 (0.93)	0.77 [0.47]	0.23

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. RMSE is the root 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, $y_{t+h} = a + b\hat{y}_{t+h} + e_{t+h}$, where y_{t+h} is actual investment spending growth from period t to $t+h$ and $\hat{y}_{t+h}$ is the forecast of investment spending growth period t to $t+h$; 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 $a=0$, $b=1$; p-values are given in brackets (0.00 indicates less than 0.05). $P_{m,h}$ is the Blair, Poon, and Taylor (2001) ratio of the variation in the forecast errors to the actual volatility in y_{t+h}.

Table 1 (continued)

Model	RMSE	$\hat{a}$	$\hat{b}$	F	$P_{m,h}$	RMSE	$\hat{a}$	$\hat{b}$	F	$P_{m,h}$
	$h = 6$					$h = 8$				
Accelerator	9.97	-6.81 (-0.69)	2.06 (0.91)	0.52 [0.60]	0.10	14.30	18.96* (2.05)	-1.29** (-2.82)	4.21* [0.02]	-0.17
Neoclassical	10.10	0.11 (0.01)	1.05 (0.07)	0.02 [0.98]	0.08	13.68	17.80† (1.70)	-0.84 (-1.42)	1.49 [0.24]	-0.07
Average Q	9.46	-2.26 (-0.34)	1.56 (0.83)	0.83 [0.45]	0.19	13.44	7.89 (0.59)	0.19 (-0.68)	0.24 [0.79]	-0.04
Cash-Flow	10.16	0.70 (0.08)	0.88 (-0.13)	0.02 [0.98]	0.07	13.43	8.83 (0.96)	0.05† (-1.75)	1.87 [0.17]	-0.04
Stock Price	9.31	-1.62 (-0.27)	1.43 (0.76)	0.85 [0.44]	0.22	13.30	5.55 (0.47)	0.49 (-0.54)	0.15 [0.86]	-0.02
Return Predictors	10.15	-1.60 (-0.14)	1.25 (0.21)	0.05 [0.96]	0.07	13.51	8.75 (0.71)	0.06 (-1.08)	0.87 [0.43]	-0.05

Table 2: Modified Diebold and Mariano (1995) statistics for tests of equal forecast MSE—real fixed private nonresidential investment spending growth, 1995:1-2004:2 out-of-sample period

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price
$h = 1$					
Neoclassical	-0.18 [0.86]				
Average Q	0.57 [0.58]	0.98 [0.33]			
Cash-Flow	-0.62 [0.54]	-0.53 [0.60]	-1.12 [0.27]		
Stock Price	0.02 [0.98]	0.22 [0.83]	-1.33 [0.19]	0.51 [0.61]	
Return Predictors	-0.31 [0.76]	-0.09 [0.93]	-0.79 [0.43]	0.32 [0.75]	-0.24 [0.81]
$h = 2$					
Neoclassical	-0.15 [0.89]				
Average Q	0.44 [0.66]	0.53 [0.59]			
Cash-Flow	-0.24 [0.81]	-0.13 [0.90]	-0.61 [0.55]		
Stock Price	0.49 [0.63]	0.65 [0.52]	0.01 [0.99]	0.70 [0.49]	
Return Predictors	-0.55 [0.59]	-0.33 [0.75]	-0.60 [0.55]	-0.27 [0.79]	-0.74 [0.47]

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The statistics correspond 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; a negative (positive) statistic indicates that the forecast mean squared error for the model given in the first row (column) of the table is less than that of the model given in the first column (row) of the table; *p*-values are given in brackets (0.00 indicates less than 0.05).

Table 2 (continued)

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price
$h = 3$					
Neoclassical	0.20 [0.84]				
Average Q	0.34 [0.74]	0.24 [0.81]			
Cash-Flow	-0.60 [0.55]	-0.50 [0.62]	-0.54 [0.59]		
Stock Price	1.01 [0.32]	0.78 [0.44]	0.62 [0.54]	1.25 [0.22]	
Return Predictors	-0.60 [0.55]	-0.43 [0.67]	-0.43 [0.67]	0.14 [0.89]	-1.11 [0.27]
$h = 4$					
Neoclassical	0.05 [0.96]				
Average Q	1.02 [0.32]	0.93 [0.36]			
Cash-Flow	-0.34 [0.74]	-0.22 [0.83]	-1.01 [0.32]		
Stock Price	1.07 [0.29]	0.93 [0.36]	0.73 [0.47]	1.09 [0.28]	
Return Predictors	-0.48 [0.63]	-0.29 [0.77]	-0.94 [0.36]	-0.20 [0.85]	-1.02 [0.31]

Table 2 (continued)

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price
$h = 6$					
Neoclassical	-1.17 [0.25]				
Average Q	0.52 [0.60]	0.83 [0.41]			
Cash-Flow	-0.18 [0.85]	-0.05 [0.96]	-0.46 [0.65]		
Stock Price	0.70 [0.49]	0.99 [0.33]	1.06 [0.30]	0.59 [0.56]	
Return Predictors	-0.56 [0.58]	-0.09 [0.93]	-0.64 [0.53]	0.02 [0.99]	-0.84 [0.41]
$h = 8$					
Neoclassical	0.26 [0.79]				
Average Q	2.34* [0.03]	0.10 [0.92]			
Cash-Flow	0.54 [0.60]	0.26 [0.80]	0.00 [1.00]		
Stock Price	3.85** [0.00]	0.15 [0.88]	2.56* [0.02]	0.08 [0.94]	
Return Predictors	0.62 [0.54]	0.18 [0.86]	-0.06 [0.95]	-0.13 [0.90]	-0.16 [0.88]

Table 3: Harvey, Leybourne, and Newbold (1998) statistics for tests of forecast encompassing—real fixed private nonresidential investment spending growth, 1995:1-2004:2 out-of-sample period

Model	Accelerator	Neoclassical	Average Q	Cash-Flow	Stock Price	Return Predictors
$h=1$						
Accelerator		1.78* [0.04]	1.96* [0.03]	2.20* [0.02]	2.40* [0.01]	1.57† [0.06]
Neoclassical	1.72* [0.05]		0.39 [0.35]	1.17 [0.12]	1.32† [0.10]	1.23 [0.11]
Average Q	3.36** [0.00]	2.09* [0.02]		2.05* [0.02]	1.79* [0.04]	2.60** [0.01]
Cash-Flow	1.17 [0.12]	0.56 [0.29]	0.64 [0.26]		1.39† [0.09]	0.88 [0.19]
Stock Price	3.39** [0.00]	1.76* [0.04]	-0.74 [0.77]	1.79** [0.04]		2.51** [0.01]
Return Predictors	1.11 [0.14]	1.41† [0.08]	1.50† [0.07]	1.58† [0.06]	1.94* [0.03]	
MS_h^*	2.23† [0.07]	1.34 [0.27]	1.11 [0.37]	1.57 [0.20]	1.48 [0.22]	2.12† [0.09]
$h=2$						
Accelerator		1.71* [0.05]	1.37† [0.09]	2.04* [0.02]	1.54† [0.07]	1.36† [0.09]
Neoclassical	1.52† [0.07]		0.78 [0.22]	1.70* [0.05]	0.83 [0.21]	1.02 [0.16]
Average Q	2.36* [0.01]	2.10* [0.02]		1.94* [0.03]	0.73 [0.24]	2.18* [0.02]
Cash-Flow	1.60† [0.06]	2.43* [0.01]	0.94 [0.18]		1.05 [0.15]	1.39† [0.09]
Stock Price	3.06** [0.00]	2.56** [0.00]	0.73 [0.24]	2.37* [0.01]		2.47** [0.01]
Return Predictors	1.05 [0.15]	0.60 [0.28]	1.06 [0.15]	1.07 [0.15]	1.10 [0.14]	
MS_h^*	2.97* [0.03]	2.60* [0.04]	1.14 [0.36]	2.05† [0.10]	0.99 [0.44]	2.73* [0.04]

Notes: †,*,** 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 (0.00 indicates less than 0.05). 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.

Table 3 (continued)

Model	Accelerator	Neoclassical	Average Q	Cash-flow	Stock Price	Return Predictors
$h = 3$						
Accelerator		1.21 [0.12]	0.96 [0.17]	1.63† [0.06]	0.89 [0.19]	1.44† [0.08]
Neoclassical	1.46† [0.08]		0.57 [0.29]	1.16 [0.13]	0.21 [0.42]	1.06 [0.15]
Average Q	1.92* [0.03]	1.50† [0.07]		1.88* [0.03]	0.29 [0.39]	1.75* [0.04]
Cash-Flow	0.61 [0.27]	0.72 [0.24]	0.91 [0.19]		0.59 [0.28]	0.61 [0.27]
Stock Price	2.35* [0.01]	1.49† [0.07]	1.14 [0.13]	2.11* [0.02]		1.88* [0.03]
Return Predictors	0.84 [0.20]	0.37 [0.36]	0.76 [0.23]	1.01 [0.16]	0.24 [0.41]	
MS_h^*	1.69 [0.17]	1.07 [0.39]	1.69 [0.17]	1.38 [0.26]	0.59 [0.71]	1.09 [0.39]
$h = 4$						
Accelerator		1.23 [0.11]	0.18 [0.43]	1.21 [0.12]	0.33 [0.37]	1.35† [0.09]
Neoclassical	0.99 [0.17]		0.01 [0.49]	0.86 [0.20]	0.03 [0.50]	0.79 [0.22]
Average Q	1.81* [0.04]	2.04* [0.02]		1.55* [0.07]	-0.01 [0.51]	1.32† [0.10]
Cash-Flow	0.42 [0.34]	0.76 [0.23]	0.10 [0.46]		0.07 [0.47]	1.24 [0.11]
Stock Price	2.17* [0.02]	2.14* [0.02]	1.60† [0.06]	1.70* [0.05]		1.52† [0.07]
Return Predictors	0.51 [0.31]	0.38 [0.35]	-0.10 [0.54]	1.13 [0.14]	-0.07 [0.53]	
MS_h^*	1.18 [0.34]	2.20† [0.08]	2.23† [0.08]	0.75 [0.60]	0.60 [0.70]	0.90 [0.49]

Table 3 (continued)

Model	Accelerator	Neoclassical	Average Q	Cash-flow	Stock Price	Return Predictors
$h = 6$						
Accelerator		1.88* [0.03]	-0.04 [0.51]	0.71 [0.24]	-0.08 [0.53]	1.54† [0.07]
Neoclassical	1.21 [0.12]		-0.35 [0.64]	0.69 [0.25]	-0.32 [0.62]	0.70 [0.25]
Average Q	0.94 [0.18]	1.21 [0.12]		0.94 [0.18]	-0.72 [0.76]	0.90 [0.19]
Cash-Flow	0.53 [0.30]	0.83 [0.21]	0.31 [0.38]		0.29 [0.39]	0.81 [0.21]
Stock Price	1.23 [0.11]	1.54† [0.07]	1.47† [0.08]	1.12 [0.14]		1.15 [0.13]
Return Predictors	0.82 [0.21]	1.22 [0.11]	-0.16 [0.56]	0.76 [0.23]	-0.23 [0.59]	
MS_h^*	2.61* [0.05]	4.75** [0.00]	1.05 [0.41]	1.14 [0.36]	0.41 [0.84]	1.72 [0.16]
$h = 8$						
Accelerator		0.08 [0.47]	-2.05 [0.98]	-0.25 [0.60]	-3.08 [1.00]	-0.27 [0.61]
Neoclassical	0.58 [0.28]		0.23 [0.41]	0.30 [0.38]	0.20 [0.42]	0.76 [0.23]
Average Q	2.51** [0.01]	0.42 [0.34]		0.32 [0.37]	-2.65 [0.99]	0.40 [0.35]
Cash-Flow	0.79 [0.22]	0.77 [0.23]	0.35 [0.36]		0.26 [0.40]	0.70 [0.24]
Stock Price	4.16** [0.00]	0.48 [0.32]	2.48** [0.01]	0.41 [0.34]		0.50 [0.31]
Return Predictors	0.97 [0.17]	0.87 [0.20]	0.47 [0.32]	1.13 [0.13]	0.36 [0.36]	
MS_h^*	6.49** [0.00]	2.71* [0.04]	2.77* [0.04]	2.30† [0.07]	1.56 [0.21]	5.86** [0.00]

Table 4: Maximum likelihood ratio statistics for tests of α_m and $\gamma_{m,j}$ coefficient stability in equation (1)—real fixed private nonresidential investment spending growth, 1963:1-2004:2 in-sample period

Model	$h=1$	$h=2$	$h=3$	$h=4$	$h=6$	$h=8$
Accelerator	25.54**	19.96*	15.45*	18.99**	6.84	18.15**
	[0.00]	[0.01]	[0.03]	[0.01]	[0.31]	[0.00]
	(1981:4)	(1981:3)	(1995:4)	(1995:4)		(1991:3)
Neoclassical	7.05	4.55	9.41	18.48**	8.00	16.37†
	[0.53]	[0.63]	[0.27]	[0.01]	[0.41]	[0.09]
				(1977:4)		(1977:4)
Average Q	2.87	3.06	4.03	3.52	5.55	4.43
	[0.99]	[0.98]	[0.92]	[0.96]	[0.63]	[0.65]
Cash-Flow	13.34*	6.45	11.70	6.81	11.53	6.93
	[0.02]	[0.35]	[0.23]	[0.56]	[0.25]	[0.30]
	(1992:2)					
Stock Price	14.96*	20.32**	18.91**	10.73	3.60	5.45
	[0.03]	[0.00]	[0.00]	[0.18]	[0.79]	[0.49]
	(1984:2)	(1983:4)	(1983:4)			
Return Predictors	16.20†	22.86**	26.40**	31.88**	33.85**	38.54**
	[0.05]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	(1980:2)	(1984:2)	(1984:2)	(1984:2)	(1984:1)	(1984:1)

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The statistics are computed using 15% trimming at the beginning and end of the sample; *p*-values are given in brackets (0.00 indicates less than 0.05); least squares estimated break date is given in parentheses.

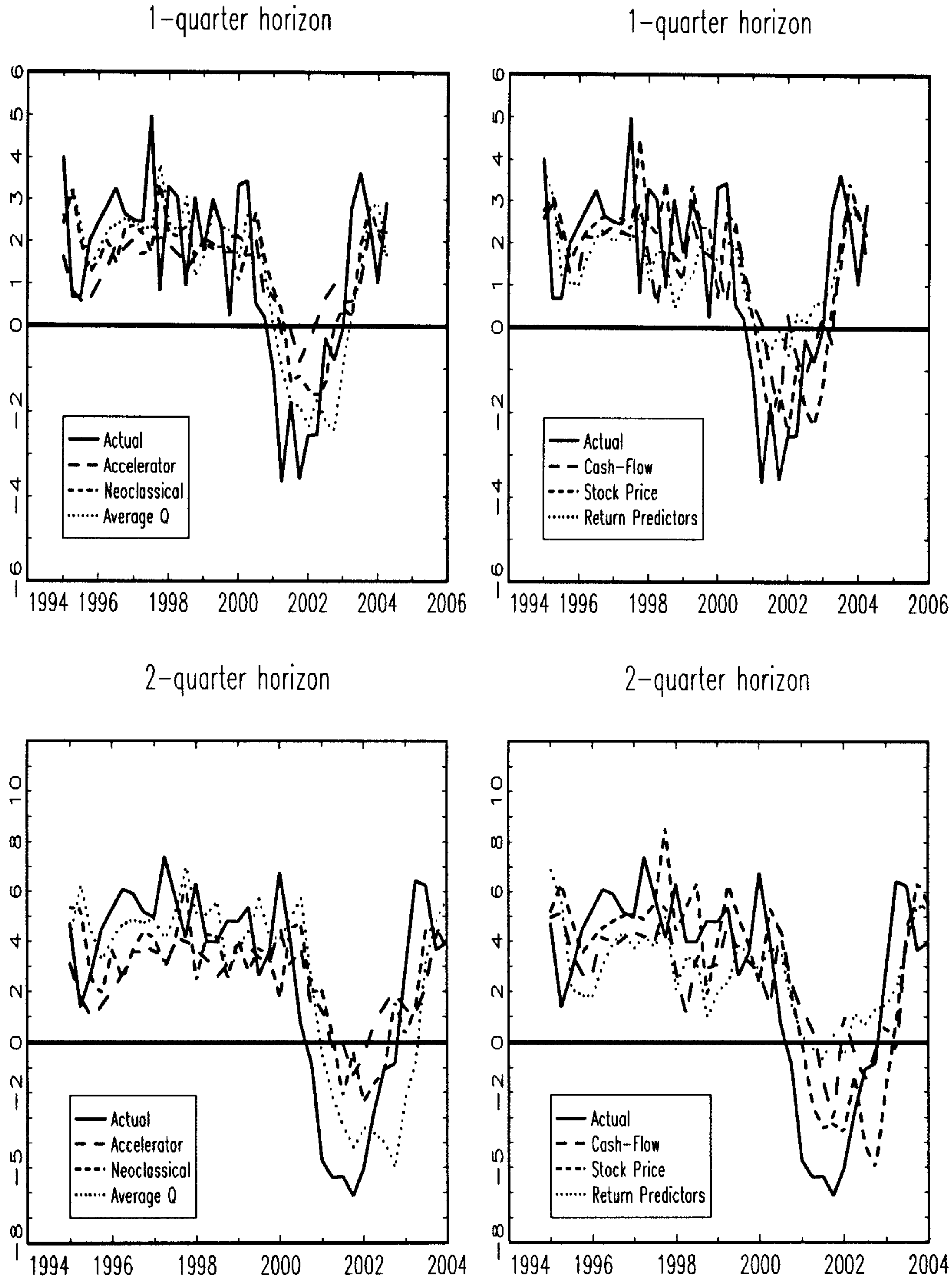

Figure 1a: Out-of-sample forecasts at horizons of 1 and 2 quarters—real fixed private nonresidential spending growth, 1995:1-2004:2 out-of-sample period

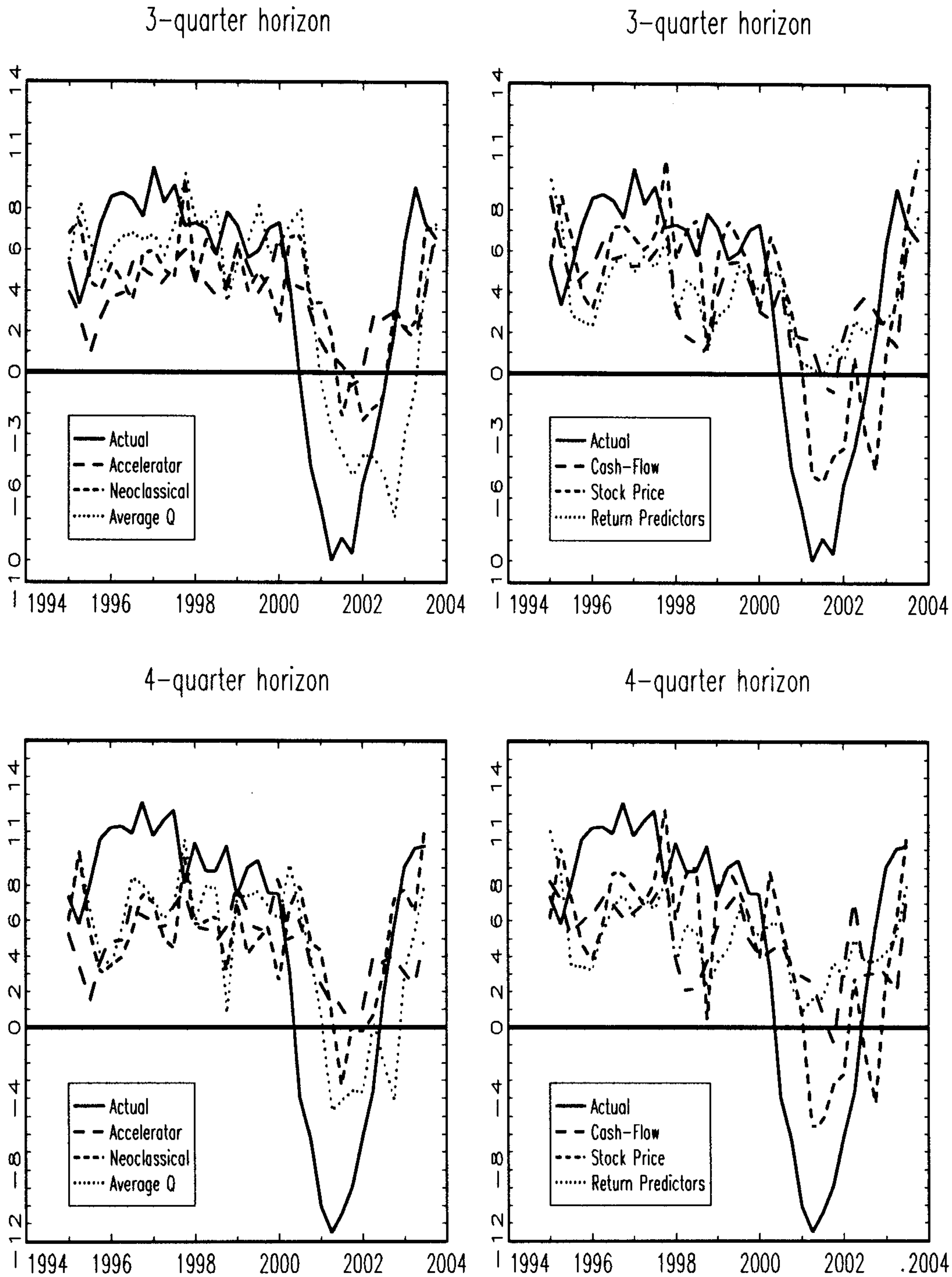

Figure 1b: Out-of-sample forecasts at horizons of 3 and 4 quarters—real fixed private nonresidential spending growth, 1995:1-2004:2 out-of-sample period

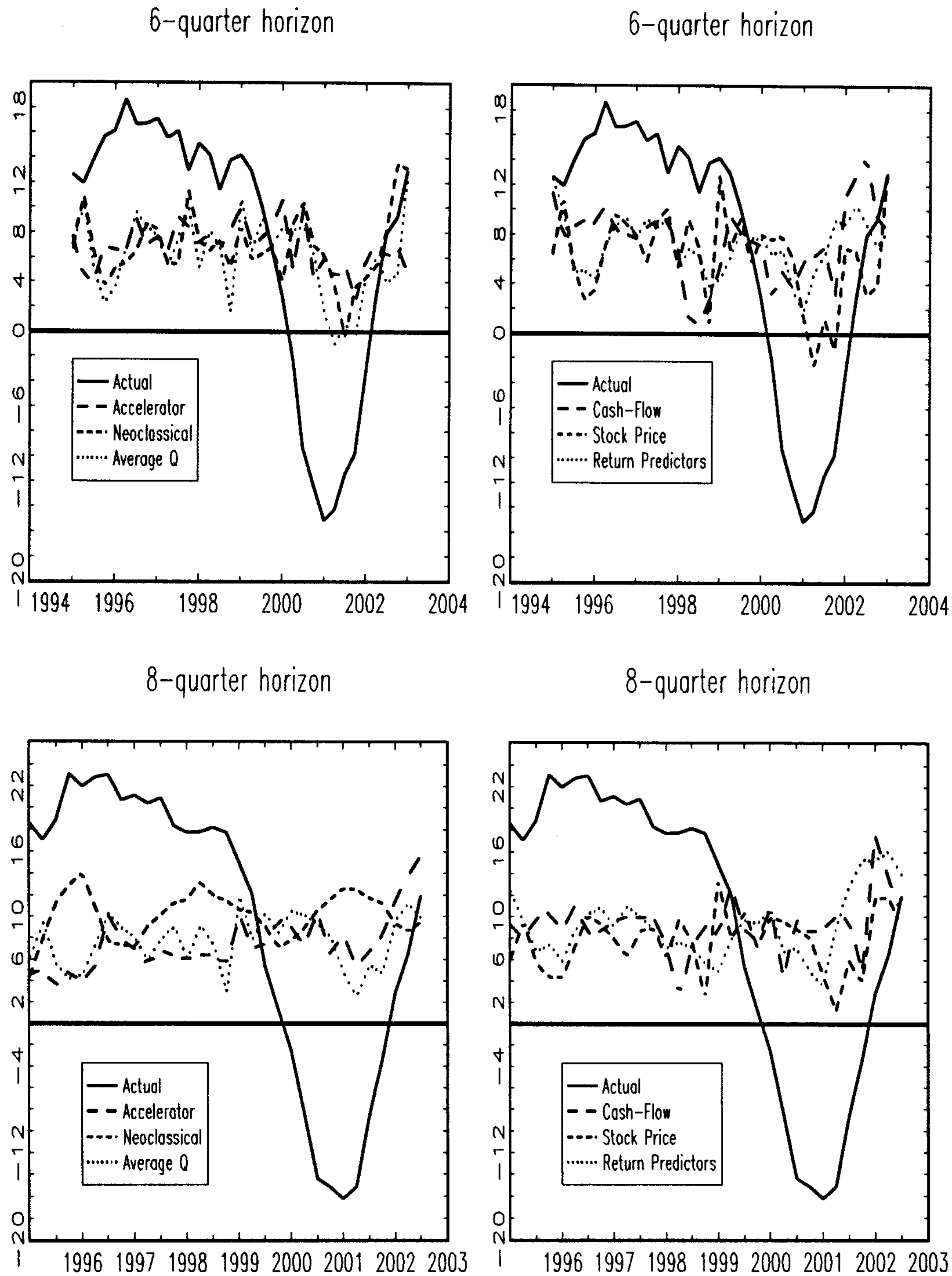

Figure 1c: Out-of-sample forecasts at horizons of 6 and 8 quarters—real fixed private nonresidential spending growth, 1995:1-2004:2 out-of-sample period