Investment in Swedish manufacturing: Analysis and forecasts*

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Bengt Assarsson♦ Claes Berg♣ Per Jansson♠

♦Department of Economics, Uppsala University, SE-751 20 Uppsala, Sweden and Monetary Policy Department, Sveriges Riksbank, SE-103 37 Stockholm, Sweden

♣Monetary Policy Department, Sveriges Riksbank, SE-103 37 Stockholm, Sweden

♠Department of Macroeconomics and Forecasting, National Institute of Economic Research, P.O. Box 3116, SE-103 62 Stockholm, Sweden

Abstract

This paper uses a neoclassical investment model extended with installation costs for capital, agency costs for investment financing, and the possibility of the firm being output constrained as a framework for an empirical analysis of investment behaviour in the Swedish manufacturing industry. The theory is implemented within a multivariate error-correction approach on data covering the time period 1951 to 1995, and we gain the following main results: (1) Tobin's average Q is not the sole determinant of investment, neither in the short nor in the long run, and other variables like real output and capital gearing also affect investment activity; (2) the out-of-sample forecasts of the model track the evolution of actual investment growth quite impressively, especially at short- and medium-term horizons (1-2 years); (3) a relative equity-price variable is shown to constitute a good approximation of average Q, both for empirical modelling in general and forecasting in particular.

Key Words: Forecasting investment, multivariate error-correction model, neoclassical investment theory, Tobin's Q.

JEL codes: C32, E22, E27.

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1. Introduction

Empirical investment models have a mixed history. Often, these models perform poorly when evaluated econometrically and their forecasting properties are often disappointing. Partly, this may be due to the fact that investment activity is relatively volatile and therefore difficult to model empirically, but unsatisfying theoretical assumptions and inappropriate econometric methods may also be part of the answer.

In a neoclassical investment model real investment is determined solely by Tobin's *Q*. Other variables, like real output and interest rates, affect investment as well, but indirectly through their effects on marginal *Q*. Under linear homogeneity of the production and adjustment-cost functions, the standard price-taking model implies that Tobin's marginal *Q* equals average *Q* (or the valuation ratio of the firm). However, empirically, average *Q* does not appear to provide a satisfactory explanation of investment, and other variables like real output and different financial aggregates are often found to be important as well.[1] Unfortunately, the possibility to consider less restricted versions of the model is limited by the fact that marginal *Q*, in contrast to average *Q*, is unobservable.

In this paper we follow Cuthbertson and Gasparro (1995) and use a version of a neoclassical investment model extended with installation costs for capital, agency costs for investment financing, and the possibility of the firm being output constrained as a framework for an empirical analysis of investment behaviour in the Swedish manufacturing industry. Consistent with the above-discussed established "stylised facts", the model does not restrict investment to be solely determined by average *Q*, and allows for influences from both output and financial mechanisms (through a term that captures agency and transaction costs for financing investment). The empirical results are derived using a multivariate error-correction approach, which among other things permits us to impose long-run restrictions rooted in economic theory. The results suggest that both average *Q* and output are significant explanatory variables for investment in the long run. As concerns the short-run dynamics of investment, all variables of the system are found to be statistically important, either directly or indirectly.

Our empirical analysis extends that of Cuthbertson and Gasparro (1995) in that we consider an econometric system in which all the included macro variables are modelled

[1] See for example Anderson (1981), Bean (1981), Jenkinson (1981), Hayashi (1982), Poterba and Summers (1983), Bond and Devereux (1988), Henley and Carruth (1989), Sumner (1989), Lomax (1990), Schaller (1990), Bond and Meghir (1990), Cuthbertson and Gasparro (1995).

endogenously. Apart from eschewing the problem of having to rely on results that are conditioned on strong and untested exogeneity restrictions, such a system approach has the distinct advantage of offering the possibility to undertake dynamic (multi-step) forecasting of investment. A rather promising feature of our empirical results is that the out-of-sample forecasting performance of the model turns out to be quite impressive, especially at short- and medium-term horizons (1-2 years). In addition, this performance can be maintained for a simplified, less data-demanding, version of the model in which average Q is approximated by a relative equity-price variable.

The paper is organised as follows. The next section gives a brief review of the theoretical neoclassical investment model of Cuthbertson and Gasparro (1995). In Section 3 we specify our econometric system and present the empirical results. These are obtained using annual data for the Swedish manufacturing industry covering the time period 1951 to 1995. In Section 4 we study forecasting properties and suggest an approximation based on a relative equity-price variable. Section 5 provides concluding remarks.

2. A brief review of the model

In the standard neoclassical intertemporal model of investment with adjustment costs, the representative firm maximises the discounted present value of future profits subject to linearly homogeneous production and cost functions. The Cuthbertson-Gasparro model adds two (as we believe not unrealistic) assumptions to this standard framework. Firstly, following Chirinko (1987), it is assumed that the (representative) firm faces agency and transaction costs when issuing new debt and when managing the stock of outstanding debt. Secondly, following Precious (1987), the firm may move between states such that it sometimes is demand constrained. With these modifications, marginal Q is not equal to average Q but determined by average Q and components that depend on output and financial mechanisms. More specifically, under certain additional conditions:[2]

$$I = I(Q, G, Y), \qquad (1)$$

[2] See Cuthbertson and Gasparro (1995) for details. In a more general version of the model there may also be room for a real-wage effect in the solution for investment. However, empirically, when experimenting with a larger system that also allows for influences from the real (product) wage, the statistical behaviour of the model turns out to deteriorate markedly. Furthermore, apart from the autoregressive lags in the wage equation, the wage variable does not appear to have any further significant effects. Also, the forecasting performance of the model does not appear to improve. On these grounds we decided not to include data on real wages in our preferred final analysis (see Sections 3 and 4).

where I is investment, Q Tobin's average Q, G capital gearing (the stock of debt in relation to the value of the capital stock), and Y output.

In this paper we follow Cuthbertson and Gasparro (1995) and use the above-described theoretical framework mainly as a basis for analysing investment behaviour in the long run. Emanating from (1) we will thus test for the existence of a possible long-run equilibrium relationship (a so-called cointegrating relationship) which involves real investment being linearly related to output, capital gearing, and the valuation ratio. Our modelling strategy then entails conditioning a dynamic system analysis on the extracted long-run properties of the data (provided, of course, that the data are cointegrated). This modelling strategy allows us to acknowledge the complicated dynamic interactions present in the short-run information of the data, while at the same time gaining interpretability and efficiency by imposing long-run restrictions suggested by theory.

3. Empirical results[3]

The data is annual and run from 1951 to 1995. The (log levels of the) four time series (i.e., capital gearing G, the valuation ratio Q, output Y, and investment I) are graphed in Figure 1.[4] As can be seen, the series display the non-stationary behaviour that is typical for most macro aggregates: they are trending and deviations from trend are characterised by persistence. These properties imply that the series probably are integrated of order one (i.e., I(1)), a conclusion which is also supported by formal univariate unit-root tests (not shown).[5]

[**Figure 1.** about here]

If there among non-stationary I(1) variables exist linear combinations that cancel the stochastic trends and are stochastically stationary (i.e., I(0)), then the variables are said to be cointegrated and there exists an error-correction representation of the data. While Cuthbertson and Gasparro (1995) based their cointegration analysis on the Engle-Granger approach, this

[3] The empirical analysis has been undertaken using PcFIML version 9.0.
[4] Figure 1 also provides the graph of the relative equity-price variable used in Section 4.2. This variable is denoted by S. Details of definitions and sources of the data are given in an appendix.
[5] At this point, we emphasise that our empirical analysis does not require all the series to be individually I(1) (for more details on this, see section 3.2). The only property that has to be ruled out from the outset is that of I(2)-ness. Given the evidence presented above, this does not appear to be an overly restrictive pre-requisite in the present application.

paper applies the multivariate Johansen methodology, which in many simulation experiments has been found to outperform other methods for testing for cointegration.[6]

Our empirical analysis may be divided into the following basic steps: (1) lag-order determination within the unrestricted vector-autoregressive (VAR) representation; (2) cointegration analysis; (3) system reduction using the general-to-specific approach; and (4) evaluation of forecasting properties.

3.1 Lag-order determination

Table 1 displays results of applying information criteria and lag-reduction *F* tests to unrestricted VAR systems using a maximum lag length of four years. The information-criteria results are shown in Panel 1.1 while the outcomes for the *F* tests are shown in Panel 1.2. The information criteria suggest that one lag (SC) or two lags (HQ and AIC) may be appropriate. The significance tests strongly favour two lags. From this evidence it seems reasonable to conclude that a two-year lag is an appropriate choice for obtaining a statistically well-behaved model. This conclusion is given further support by the diagnostic-test results compiled in Table 2. In this table, both multivariate (Panel 2.1) and univariate (Panel 2.2) diagnostic tests are displayed. As can be seen, there is no evidence of mis-specification problems: the residuals of all equations easily pass the tests at the conventional significance levels.

[**Table 1.** about here]

[**Table 2.** about here]

3.2 Integration and cointegration analysis

Techniques for testing for integration and cointegration within an unrestricted VAR model have been developed by Johansen (1988, 1991). Johansen's so-called ML procedure starts from the following re-parameterisation of the unrestricted VAR:

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \varepsilon_t \, , \qquad (2)$$

[6] See for example Hargreaves (1994) and Gonzalo (1994). As an alternative we have also used the univariate technique suggested by Pesaran and Shin (1997) and Pesaran and Pesaran (1997). The results using this technique are very similar.

where deterministic variables have been omitted for expository convenience. In our case, the underlying VAR model has two level lags, and so the re-parameterised model (2) only has one lag of ΔX_t. Of course, $X_t = \left[G_t \quad Q_t \quad Y_t \quad I_t\right]'$.

The key to the analysis is the rank of the matrix Π. If this matrix has reduced rank, then $\Pi = \alpha\beta'$ where α and β both are $4 \times r$ matrices. The stochastic parameter r gives the number of cointegrating vectors that characterise the system. The cointegrating vectors, which are contained in the columns of β, are such that $\beta' X_t$ is I(0), although X_t is I(1).[7]

The results of Johansen's so-called trace tests are shown in Panel 3.1 of Table 3. Because X_t appears to be linearly trending (see Figure 1), an unrestricted vector of constants is added to the right-hand side of the system (2).[8] According to the results, the hypothesis of $r = 0$ cannot be rejected at the 5 percent test level. However, as shown in Jacobson and Nessén (1998) and Jacobson *et al.* (2000) these asymptotic tests do not always work very well in applications with small samples. Panel 3.2 of Table 3 therefore investigates the effects of determining r using information criteria rather than asymptotic inference. As can be seen, both the SC and HQ criteria favour $r = 1$ while the AIC favours a VAR in first differences ($r = 0$). Synthesising this evidence, we conclude that our system is characterised by at most one cointegrating vector (i.e., $r = 0$ or $r = 1$). With $r = 0$, however, the residuals of the investment equation show signs of being serially correlated: the *F* test for second-order serial correlation rejects with a *p* value of approximately three percent. Once we impose the restriction $r = 1$, there are no signs of serial correlation and the residuals of all equations appear approximately to be white noise.

[**Table 3.** about here]

In its unrestricted version, the unique (normalised) cointegrating vector has the following appearance:

$$I_t = \underset{(0.54)}{0.71} G_t + \underset{(0.15)}{0.37} Q_t + \underset{(0.13)}{0.62} Y_t, \qquad (3)$$

[7] Note that the statement that a vector of time-series variables is I(1) does not imply that *all* variables in that vector are I(1). For a vector of time-series variables to be called I(1) it is sufficient that *one* variable in the vector is I(1). Hence, some cointegrating vectors may be trivial in the sense that the variables themselves are the cointegrating vectors.

where the numbers within parentheses are standard errors. Somewhat surprisingly, the parameter estimate on the capital-gearing variable is positive. Its standard error, however, suggests that G_t may not be a significant determining factor of long-run investment. Indeed, using an *LR* test we can reject the hypothesis that G_t enters the long-run equilibrium relationship significantly: the *p* value of the test is slightly above 30 percent. As concerns Q_t and Y_t, the *LR* tests have *p* values well below the 10 percent level: slightly below five percent in the case of Q_t and slightly above two percent in the case of Y_t. Finally, for I_t the *p* value is 0.00, strengthening our view that the identified relationship determines long-run investment.

Imposing the data-acceptable exclusion restriction on G_t, we obtain the following long-run investment relationship:[9]

$$I_t = 0.29Q_t + 0.78Y_t.^{10} \tag{4}$$

Before further simplifying our model, we check that the residuals of the restricted VAR (i.e., the VAR subject to $r = 1$ and $\beta' = (0 \quad -0.29 \quad -0.78 \quad 1)$) fulfil the requirement of being approximately Gaussian white noise. The details of the diagnostic tests (not shown) suggest that the model is free of serial correlation, has homoscedastic and normally distributed error terms, is approximately constant, and does not exhibit any ARCH effects.

3.3 The parsimonious vector error-correction model

Having established that a VAR with a single restricted cointegrating vector may be used as a reasonable representation of the data, we now turn to the exercise of simplifying the dynamics of that model. Here, we employ the well-known general-to-specific approach popularised by, amongst others, David Hendry (see, for example, Hendry, 1995). The methodology starts from a general (possibly) over-parameterised but statistically well-behaved representation of

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[8] This also means that the cointegrating relationships are allowed to have non-zero means.

[9] We have also tested a version of the model in which $r = 3$ and Q_t, G_t, and $I_t - Y_t$ are I(0) (these hypotheses are all rejected given that $r = 1$). The results show that the imposition of these restrictions implies a significant deterioration in forecasting performance (cf. Section 4).

[10] It is interesting to compare (4) with a simple OLS regression of investment on the valuation ratio and output (and a constant). The OLS parameter estimates are 0.26 and 0.78 for the valuation ratio and output respectively. Using a critical value calculated via MacKinnon's (1991) response-surface results we can reject the null of no cointegration at the 5 percent test level (ADF(1) = -4.37 < -3.94 = critical value at the 5 percent test level).

the data; in our case a VAR with two lags and a cointegration restriction (i.e., an unrestricted (vector) error-correction model). It then undertakes a sequential parametric reduction procedure (usually through *F* tests) to derive the final parsimonious model. In order for a particular parametric reduction to be acceptable, the significance tests have to accept the null hypotheses against all larger models within which the smaller model is nested, and, at the same time, the residuals have to pass the diagnostic checks. If the error terms do not pass the diagnostic tests, then the reduction cannot be accepted even if the significance tests accept.

Panel 4.1 of Table 4 displays the results for the preferred parsimonious specification. While the unrestricted error-correction model has a total of 24 parameters, the restricted parsimonious model only has 15 parameters. In particular, the model's key equation – the investment equation – appears appropriately parameterised through only four parameters. As Panels 4.2 and 4.3 of the table make clear, the model's error terms all pass the diagnostic tests at the conventional significance levels.[11]

In the final specification of the investment equation, the growth rate of investment is a dynamic function of its own history, of the lagged growth rate of real output, and of deviations of investment from its long-run equilibrium level (see the third column in Panel 4.1 of Table 4). The standard error of the equation is 8.0 percent, which is 0.2 percentage points lower than that of the investment equation in the unrestricted error-correction model.

As expected, the growth rate of investment is *not* weakly exogenous with respect to the long-run parameters related to the cointegrating relationship: the *t* value of the parameter estimate on the long-run relationship is approximately –5.7.[12] This provides further informal support for our interpretation of relationship (4) as a long-run investment function. On the other hand, both the growth rates of output and the valuation ratio are statistically unaffected by the long-run relationship, and are thus treated as weakly exogenous with respect to the model's long-run parameters. Provided that one is only interested in inference on the model's parameters, this implies that it is sufficient to limit the analysis to the conditional models for ΔG_t and ΔI_t. However, if one, as we do here, wishes to derive dynamic forecasts of ΔG_t or ΔI_t, then weak exogeneity is not sufficient. In this case, the relevant concept is that of strong exogeneity which, in addition to weak exogeneity, requires the absence of Granger causality

[11] To check the stability properties of the model, we compute recursive 1-step residuals and a battery of Chow tests (for details see Doornik and Hendry, 1997, chapter 10). The analysis is undertaken for the period 1988-1995. From the tests it can be concluded that the stability properties of the model are satisfactory. According to the results, no test value is significant at the 1 percent test level and only one value is significant at the 5 percent level (1-step Chow test for 1994, *p* value = 0.02).

[12] The concept of weak exogeneity (and related issues) is discussed in, for example, Engle *et al.* (1983).

from the modelled variables (ΔG_t and ΔI_t) to the non-modelled conditioning variables (ΔY_t and ΔQ_t). As can be seen from the estimated equations in Panel 4.1 of Table 4, this condition is clearly not fulfilled in the present application.

According to the estimated investment equation, there is no Granger causality from ΔG_t to ΔI_t. Hence, investment is not directly related to capital gearing.[13] This means that, in direct terms, investment depends on average rather than marginal *Q*, and on output Y_t.[14] It should be noted, however, that investment *indirectly* still depends on the capital-gearing variable via output and the valuation ratio.

[**Table 4.** about here]

4. Forecasting investment

In this section we investigate the forecasting properties of our investment model. The first sub-section is devoted to the model developed in the previous section. The computation of Tobin's average *Q* is tedious and some of the data that are needed often arrive too late to be useful in practice, e.g. for macroeconomic forecasting purposes. Therefore, section 4.2 gives an analysis of a simplified, less data-demanding, version of the model in which average *Q* is approximated by a relative equity-price index.

4.1 Forecasting with average *Q*

In this section we look into the forecasting properties of our parsimonious error-correction model. Graphs 2.1, 2.2, and 2.3 of Figure 2 display recursive 1-step-ahead, recursive 2-step-ahead, and dynamic forecasts of the growth rate of investment over the period 1991-1995. The recursive forecasts are derived as follows. First, the model is re-estimated on the sub-

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[13] Recall that the capital-gearing variable is not part of the long-run equilibrium relationship, see equation (4).

[14] Note that although the estimated investment equation suggests that ΔI_t is not affected by the lags of ΔQ_t, investment still directly depends on the valuation ratio through the long-run relationship (4). The conditional process of ΔI_t provides further potential for a direct relationship between investment and average *Q* (cf. the discussion above). However, re-estimation conditional on ΔY_t and ΔQ_t reveals the contemporaneous values of ΔQ_t to be insignificantly related to ΔI_t (the *t* value of the parameter estimate on ΔQ_t in the unrestricted error-correction model is only 0.4).

sample 1951-1990.[15] Then, using this estimate of the model, forecasts of the growth rate of investment for 1991,…, 1990+h are derived (here, $h = 1$ in case of 1-step-ahead forecasts and $h = 2$ in case of 2-step-ahead forecasts). Next, the model is re-estimated on the sub-sample 1951-1990+h. Using this new estimate of the model, forecasts for 1990+h+1,…, 1990+2h are computed. The new sub-sample for re-estimation then is 1951-1990+2h, etc. The dynamic (or multi-step) forecasts just use the estimate of the model over the first sub-sample (i.e., 1951-1990) to compute all the forecasts. The dynamic forecasts are thus equivalent to (recursive) 5-step-ahead forecasts.

As is evidenced by the recursive analysis in Graphs 2.1 and 2.2, the model's short-run forecasting performance is quite impressive. Although our forecasting experiment happens to be undertaken in a time period when Swedish manufacturing-industry investment is very volatile, the recursive forecasts have no problems in tracking the evolution of the growth rate of investment. As expected, when we extend the forecast horizon, the reliability of the forecasts decreases (Graph 2.3). Thus, while our model may have some problems in accurately tracking the growth rate of investment at more distant forecast horizons, for the typical horizons that are of interest in practice, it appears quite accurate.[16]

[**Figure 2.** about here]

The graphical findings are summarised numerically in Table 5. This table reports the root mean square errors (RMSEs) for the three different forecasts, and also gives a comparison with seven different naive alternatives. The first three keep to the assumption that the growth rate of investment is I(0) but replace the parsimonious error-correction system by a simple ARIMA model. Alternatives four and five ("dynamic" random walk and "recursive" random walk) assume that the growth rate of investment is I(1). The "dynamic" random walk derives its forecasts conditional on the information available in the year 1990 while the "recursive" random walk simply uses the values at time $t-1$ as the forecasts of the values at time t. Alternatives six and seven ("dynamic" mean and "recursive" mean) again are based on the assumption that the growth rate of investment is I(0). The "recursive" mean, however, uses $(\Delta I_{1951} + ... + \Delta I_{t-1})/(t-1951)$ as its forecast for the year t, and thus (to some extent)

[15] The only parameters which are not re-estimated are those of the long-run equilibrium relationship (8). The parameter estimates that are used for this relationship are throughout those obtained using the full sample 1951-1995. However, because these estimates are fairly stable, the results do not change much in case one also re-estimates these parameters. A formal test of the hypothesis that the cointegration parameters are all constant does not reject at conventional significance levels.

allows for deterministic shifts in the mean. The "dynamic" mean just uses the sample mean over the period 1951-1990.[17]

As expected, the recursive 1-step-ahead forecasts have the lowest RMSE. The RMSE of these forecasts, at 8.7 percentage points, is 4.6 percentage points lower than the RMSE of the recursive 2-step-ahead forecasts and 10.7 percentage points lower than the RMSE of the dynamic forecasts. The parsimonious error-correction model's recursive forecasts are throughout more accurate than the corresponding forecasts generated by the naive alternatives (recursive ARIMA, "recursive" random walk, and "recursive" mean). Here, the RMSE of the recursive 1-step-ahead forecasts is 9 percentage points lower than that of the recursive ARIMA and "recursive" random walk, and 16 percentage points lower than that of the "recursive" mean. For the recursive 2-step-ahead forecasts, the differences are 6, 4, and 11 percentage points, respectively. In qualitative terms, the same picture emerges for the comparisons of the dynamic forecasts. In this case, the RMSE of the forecasts of the parsimonious error-correction model is 20 percentage points lower than that of the ARIMA forecasts. For the "dynamic" random walk and the "dynamic" mean, the differences are 7 and 5 percentage points, respectively.

While the theory used in this paper may give a motivation for the empirical modelling of investment, the VAR equations for ΔY_t, ΔG_t, and ΔQ_t basically have no theoretical support. Yet, they may nevertheless of course generate good forecasts of these variables. In order to investigate this issue Table 5 also computes dynamic forecasts assuming that the future values of ΔY_t, ΔG_t, and ΔQ_t are known. As can be seen, the RMSE only improves marginally (by roughly 2 percentage points), suggesting that the equations for the non-investment variables indeed work well for purposes of forecasting.

Finally, to ascertain the importance of the error-correction mechanism in (2), we compute forecasts restricting the Π matrix to zero. As shown in Table 5, the RMSE increases substantially (by almost 20 percentage points) compared to the unrestricted case. This suggests that the long-run investment relation in (4) contributes significantly to the good forecasting performance of the model.

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[16] Official forecast institutes (in Sweden and other countries) typically use a forecast horizon of two years.

[17] Note that the full sample length for our rawdata in levels is 1951-1995 in the case of G_t and Q_t but 1950-1995 in the case of I_t and Y_t. This explains why the mean computations ("recursive" and "dynamic") use level information from 1950 and onwards while the econometric system analysis only uses level information from 1951 and onwards. The ARIMA fit is also based on level information from 1950.

[**Table 5.** about here]

4.2 Forecasting with equity prices

As suggested by Barro (1989), changes in equity prices may approximate changes in Tobin's average *Q*. Here, we investigate this hypothesis and use a relative equity-price index (real stock-price index) defined as the ratio between the equity-price index for the manufacturing industry and the implicit price index for investment goods in the manufacturing industry (the log level of this variable is denoted by *S*).[18] The most important advantage of this measure compared to average *Q* is that it can be constructed much quicker from actual data. It thus appears more useful for forecasting purposes than average *Q*. The time-series plot of the variable is given in the bottom-left graph of Figure 1. The bottom-right graph of this figure also gives the plots of *Q* and *S* in a combined graph (in this graph, both *Q* and *S* have been normalised to have zero mean and unit variance). As can be seen, it may be conjectured that *S* is rather good proxy for *Q*. The correlation between the changes of the two series is 0.88.

To examine the implications for forecasting from approximating Tobin's average *Q* with real stock prices, we replace Q_t by S_t and re-estimate system (6).[19] The results are given in Table 6. (The final "specific" model is obtained using the steps described in Section 3.)

The results in Panels 4.1 and 6.1 are quite similar and hence indicate that S_t constitutes an acceptable approximation of average *Q*. Also, the standard error of the investment equation is roughly the same at 8.0 percent. Similar to the case with Q_t, the S_t variable affects investment significantly in the long run but not in the short run. The forecasts of the model are evaluated in Table 7. As can be seen, the RMSEs are very similar to those of the average-*Q*-based model for all three types of forecasts. The 1-step-ahead RMSE decreases by 0.3 percentage points, the 2-step-ahead RMSE by 1.6 percentage points, and the RMSE for the dynamic forecasts by 0.1 percentage points. Graphically, the forecasts are presented in Figure 3.

[**Table 6.** about here]

[**Table 7.** about here]

[18] As a test of robustness we have also undertaken estimations using the consumer price index (CPI) to construct *S*. The results, which are available from the authors upon request, are not affected by this change.
[19] For this specification, the capital-gearing variable G_t was left out. Including it does not improve the results.

[**Figure 3.** about here]

In view of the often-noted substantial volatility of investment, the forecasting performances of these *Q*-theory-based models seem quite promising. Also, since there is a considerable delay in the publication of the data needed to compute average *Q*, it is even more noteworthy that the model with the equity-price-index approximation performs as well as the original model in terms of general model properties and forecasting.

5. Concluding remarks

Investments are known to display substantial volatility and are therefore difficult to predict. The neoclassical investment theory based on Tobin's *Q* is one of the dominating theories in the literature, though its empirical success has been rather limited so far. In this paper we undertake an empirical analysis of investment in the Swedish manufacturing industry emanating from a traditional neoclassical investment model extended with capital installation costs, agency costs for investment financing, and the possibility of the firm being output constrained. An interesting feature of this model is that it, contrary to the traditional *Q* model, does not restrict investment to be solely determined by average *Q*, and allows for influences from both real output and financial mechanisms.

The empirical results are derived using a multivariate error-correction approach, which among other things permits us to impose long-run restrictions rooted in economic theory. The results suggest that both average *Q* and output are significant explanatory variables for investment in the long run. In the short run, other variables also matter, for example costs for financing investment. The model's forecasting performance turns out to be quite impressive, particularly in the short and medium run.

In practice, a measure of average *Q* is available only after a considerable time lag. This makes investment models based on data for average *Q* less useful for short- and medium-term forecasting. However, a relative equity-price index is shown to be a good approximation of average *Q*, both for empirical modelling in general and forecasting in particular.

Data appendix

Jan Södersten, Uppsala University, has kindly provided us with most of the data for this analysis. The data for Tobin's Q and the capital-gearing variable G have been computed by Södersten (see Södersten and Lindberg, 1983).

The data for investments and output for the manufacturing industry are from the Swedish national accounts, and the equity-price index is *Affärsvärldens Generalindex* for the manufacturing industry. In order to obtain a relative price measure, the equity-price index has been deflated by the implicit price index for investment goods.

The market value debt-equity ratios have been estimated in two stages. In the first stage the replacement-cost value attributable to equity is estimated. Then net capital stock calculations, valued at current replacement cost, and balance-sheet data on financial assets and liabilities together with calculations of the contingent tax liability resulting from accelerated depreciation and inventory write-down are used, and the replacement-cost value of equity is determined residually. Net trade credit is excluded in these calculations. In the second stage, the market value of equity is estimated by using a sample of 13 major engineering companies, accounting for 40 percent of the sales in manufacturing and 25 percent of the market value of the Stockholm Stock Exchange in 1980. The calculations indicate that equity in 1960 had a market value very close to its estimated replacement value. Average Q then fell to 0.6 in 1970 and further to 0.3 in 1980. These values for average Q are then treated as representative of the manufacturing industry as a whole and used to compute the market values of equity as average Q times the estimates of the replacement-cost value of equity, using the 1970-1980 average value of average Q (equal to 0.51).

The capital-gearing variable G is calculated as the debt-equity ratio, i.e. the ratio between the market value of debt and the market value of equity. The former is estimated as the book value of debt. The division of equity finance between retained earnings and new issues is estimated from sources of funds data, and a three-year average is used. Since new share issues to acquire an existing company do not constitute a source of net new finance, such issues are excluded.

References

Anderson, G. J. (1981), "A new approach to the empirical investigation of investment expenditures", *Journal of Monetary Economics*, Supplement 12, 39-91.

Barro, R. J. (1989), "The stock market and investment", NBER Working Paper No. 2925.

Bean, C. J. (1981), "An econometric model of manufacturing investment in the U.K.", *Economic Journal* 91, 106-121.

Bond, S., and Devereux, M. (1988), "Testing the sensitivity of Q investment equations to measurement of the capital stock", Discussion Paper No. 88/5, Institute for Fiscal Studies.

Bond, S., and Meghir, C. (1990), "Dynamic investment models and the firms financial policy", Mimeo, Institute of Economics and Statistics.

Chirinko, R. S. (1987), "Tobin's Q and financial policy", *Journal of Monetary Economics* 19, 69-87.

Cuthbertson, K., and Gasparro, D. (1995), "Fixed investment decisions in UK manufacturing: The importance of Tobin's Q, output and debt", *European Economic Review* 39, 919-941.

Doornik, J. A., and Hendry, D. F. (1997), *Modelling dynamic systems using PcFIML 9.0 for Windows*, International Thomson Business Press: London.

Engle, R. F., Hendry, D. F., and Richard, J-F. (1983), Exogeneity, *Econometrica* 51, 277-304.

Gonzalo, J. (1994), "Five alternative methods of estimating long-run equilibrium relationships", *Journal of Econometrics* 60, 203-233.

Hargreaves, C. (1994), "A review of methods of estimating cointegrating relationships", in C. Hargreaves (ed.), *Nonstationary Time Series Analysis and Cointegration*, Oxford University Press.

Hayashi, F. (1982), "Tobin's marginal-Q and average Q: A neoclassical interpretation", *Econometrica* 50, 213-224.

Hendry, D. F. (1995), *Dynamic econometrics*, Oxford University Press: Oxford.

Henley, A., and Carruth, A. (1989), "An econometric analysis of aggregate investment expenditure in the UK", Discussion Paper in Economics No. 89/6, University of Kent.

Jacobson, T., Jansson, P., Vredin, A., and Warne, A. (2000), "Monetary policy analysis and inflation targeting in a small open economy: A VAR approach", forthcoming in *Journal of Applied Econometrics*.

Jacobson, T., and Nessén, M. (1998), "Long-run perspectives on purchasing power parity", Sveriges Riksbank Working Paper Series No. 75.

Jenkinson, N. (1981), "Investment, profitability and the valuation ratio", Discussion Paper No. 17, Bank of England.

Johansen, S. (1988), "Statistical analysis of cointegrating vectors", *Journal of Economic Dynamics and Control* 12, 231-254.

Johansen, S. (1991), "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models", *Econometrica* 59, 1551-1580.

Lomax, J. (1990), "A model of manufacturing sector investment and employment decisions", Discussion Paper No. 48, Bank of England.

MacKinnon, J. G. (1991), "Critical values for cointegration tests", in R. F. Engle and C. W. J. Granger (eds.), *Long-Run Economic Relationships*, Oxford University Press.

Osterwald-Lenum, M. (1992), "A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics", *Oxford Bulletin of Economics and Statistics* 54, 461-472.

Pesaran, M. H., and Pesaran, B. (1997), *Working with Microfit 4.0. Interactive econometric analysis*, Oxford University Press: Oxford.

Pesaran, M. H., and Shin, Y. (1997), "Long-run structural modelling", Department of Applied Economics: University of Cambridge.

Poterba, J. M., and Summers, L. H. (1983), "Dividend taxes, corporate investment and 'Q'", *Journal of Public Economics* 22, 135-167.

Precious, M. (1987), "Rational expectations non-market clearing and investment theory", Oxford University Press: Oxford.

Schaller, H. (1990), "A re-examination of the Q theory of investment using US firm data", *Journal of Applied Econometrics* 5, 309-325.

Sumner, M. (1989), "Investment, Q and taxes", *Public Finance* 44, 285-294.

Södersten, J., and Lindberg, T. (1983), "Skatt på bolagskapital" ("The taxation of corporate capital"), Research Report 20, The Industrial Institute of Economic and Social Research.

Figure 1. The data in levels (logs)

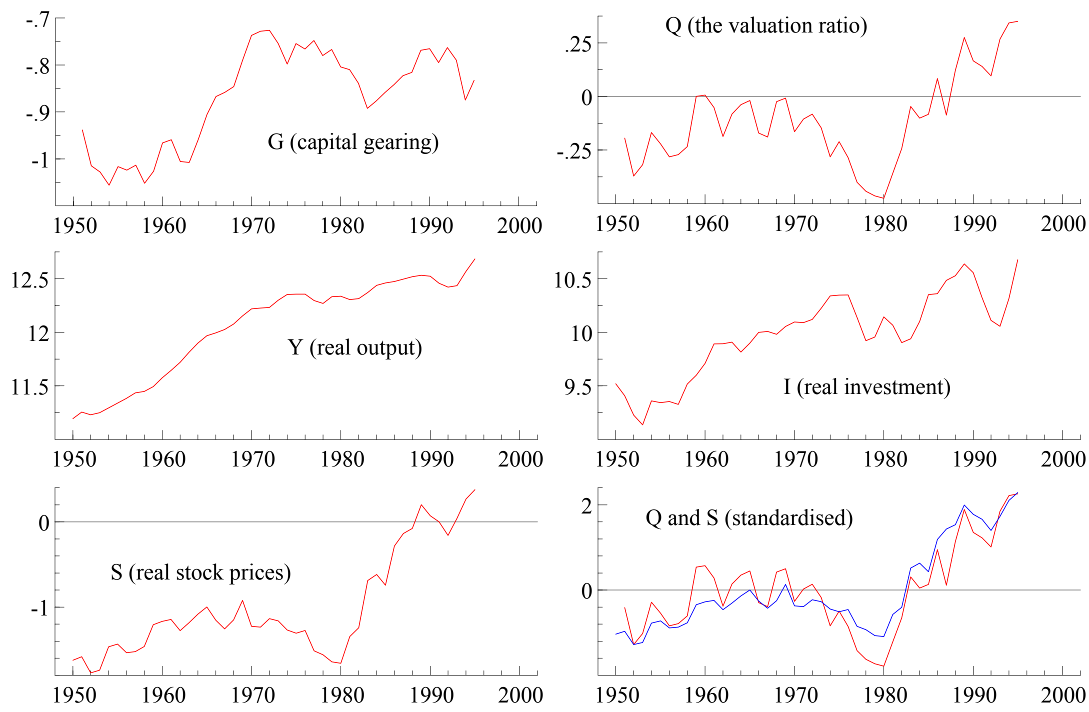
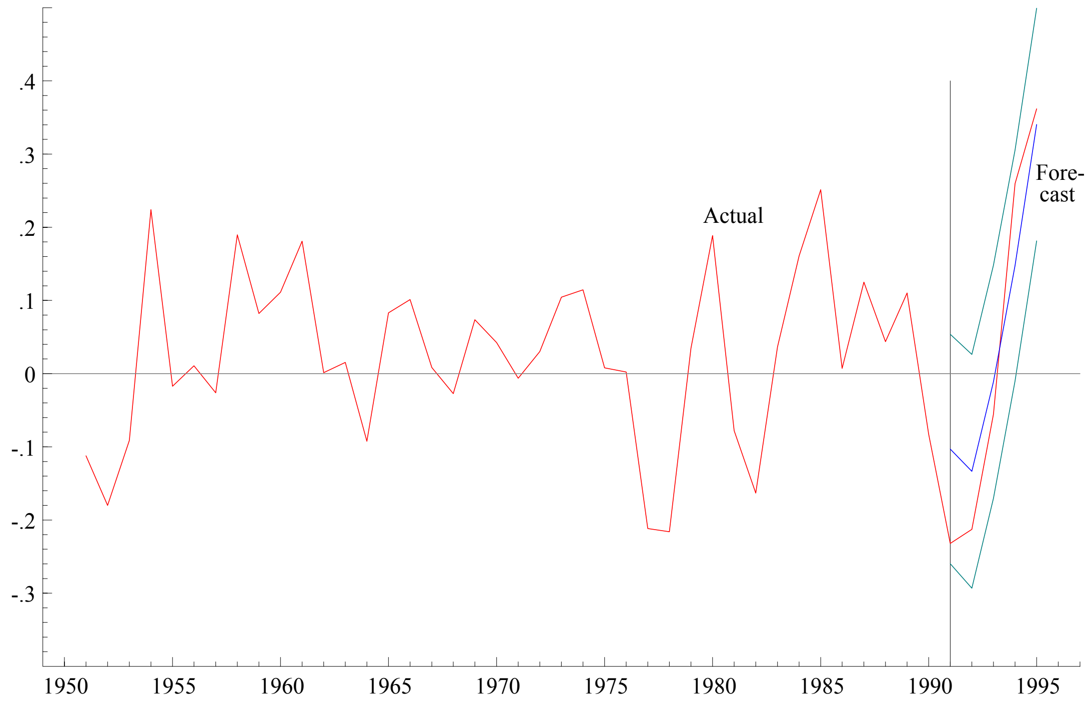
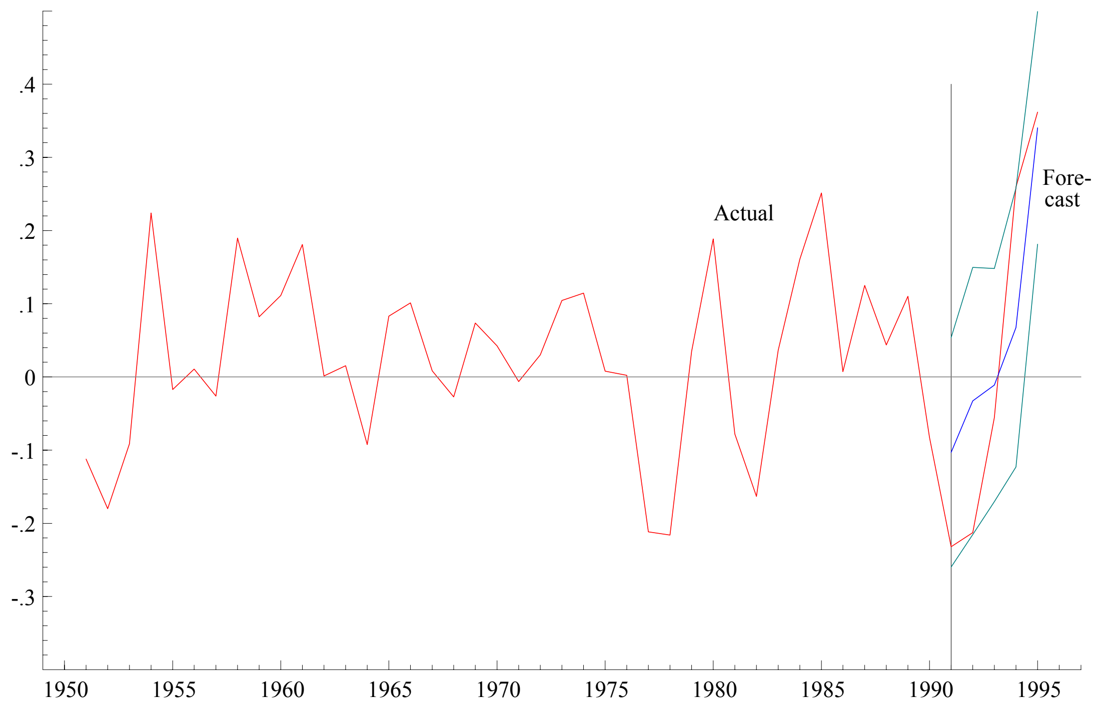


Figure 2. Forecasts of ΔI_t 1991-1995

Graph 2.1. Recursive 1-step-ahead forecasts

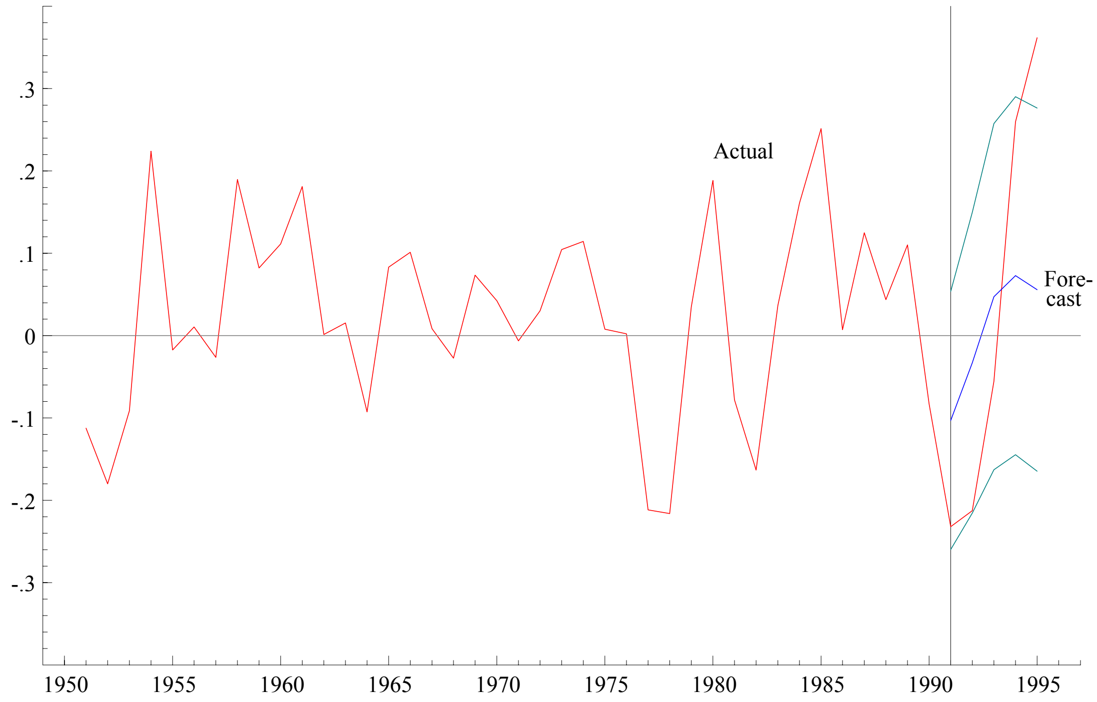


Graph 2.2. Recursive 2-step-ahead forecasts



(**Figure 2.** continued)

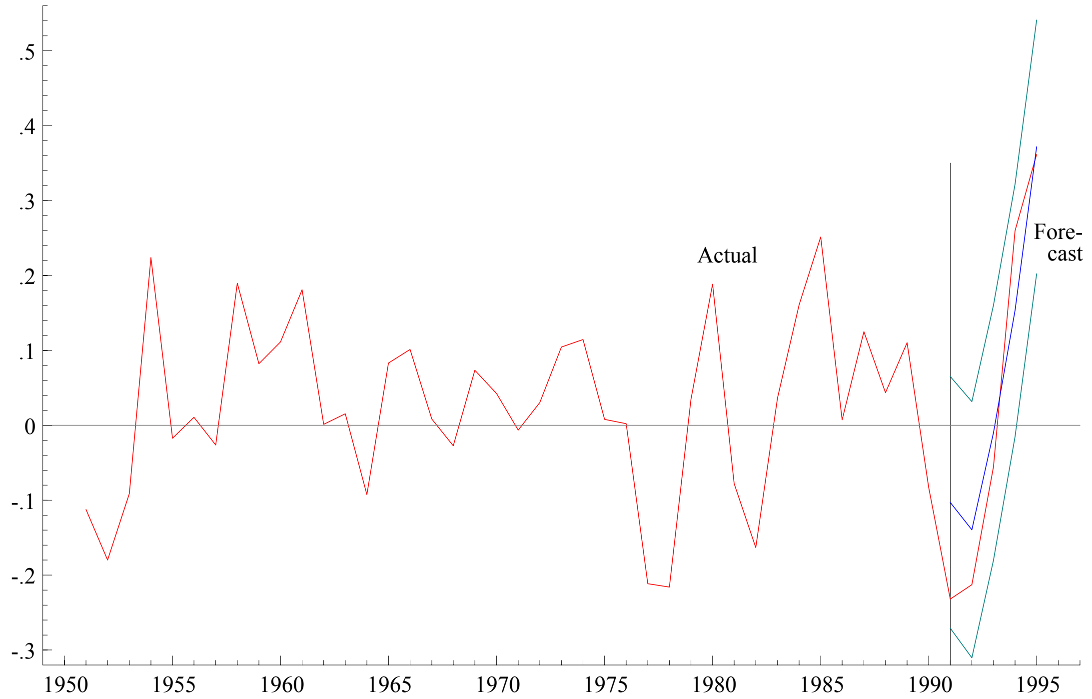
Graph 2.3. Dynamic forecasts



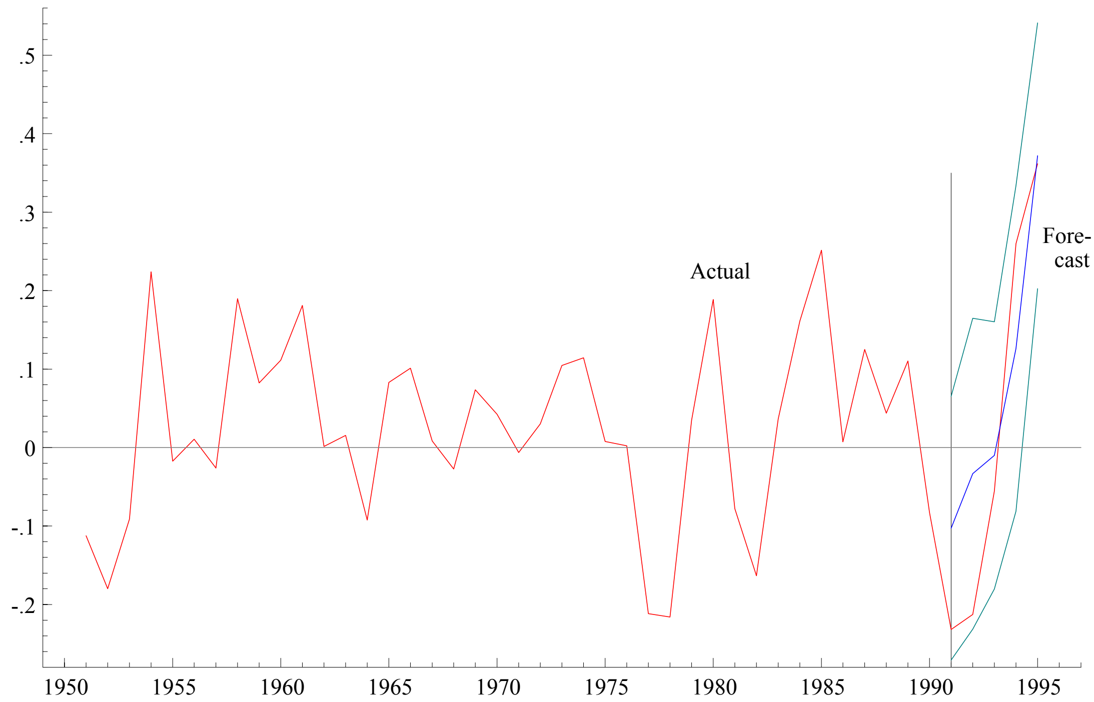
Notes: The 95 percent confidence intervals are based on error variances (see Doornik and Hendry, 1997, chapters 7 and 10).

Figure 3. Forecasts of ΔI_t 1991-1995 using the real stock-price-based model

Graph 3.1. Recursive 1-step-ahead forecasts

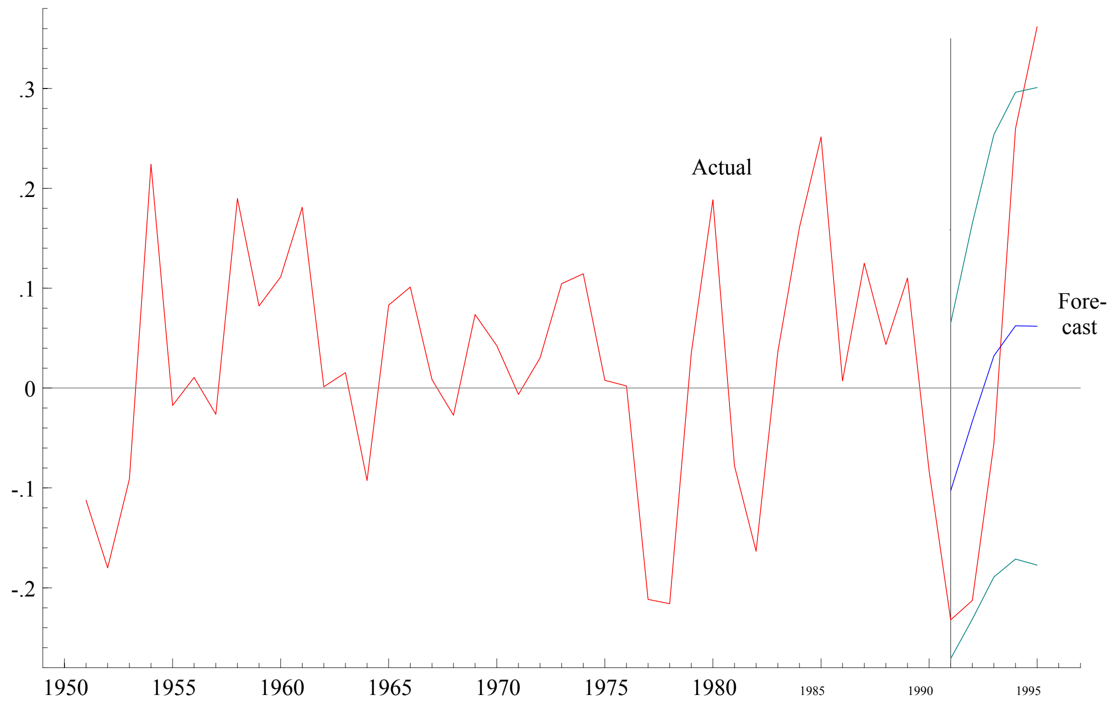


Graph 3.2. Recursive 2-step-ahead forecasts



(**Figure 3.** continued)

Graph 3.3. Dynamic forecasts



Notes: The 95 percent confidence intervals are based on error variances (see Doornik and Hendry, 1997, chapters 7 and 10).

Table 1. *F* tests and information criteria

Panel 1.1. System information and information criteria

k	*T*	*p*	Log likelihood	SC	HQ	AIC
1	41	20	477.38	-21.48*	-22.00	-23.29
2	41	36	503.45	-21.30	-22.25*	-23.56*
3	41	52	511.06	-20.22	-21.60	-22.93
4	41	68	517.21	-19.07	-20.88	-22.23

Notes: *k* refers to the number of lags in the VAR. *T* refers to the number of observations. *p* refers to the number of estimated parameters. SC is the Schwartz criterion. HQ is the Hannan-Quinn criterion. AIC is Akaike's criterion. * indicates a minimum.

Panel 1.2. *F* tests of system reduction

Reduction hypothesis	*F*-test value (*p* value)
2 lags vs. 1 lag	2.88** (0.00)
3 lags vs. 2 lags	0.62 (0.86)
4 lags vs. 3 lags	0.42 (0.97)

Notes: The *F* statistics are distributed as $F(16, 89)$ (2 vs. 1), $F(16, 77)$ (3 vs. 2), and $F(16, 64)$ (4 vs. 3) respectively. ** indicates significance at the 1 percent test level.

Table 2. Multivariate and univariate residual diagnostics

Panel 2.1. Multivariate tests

Test	Test value (p value)
Vector autocorrelation 2 $F(32, 86)$	0.68 (0.89)
Vector normality $\chi^2(8)$	2.68 (0.95)
Vector heteroscedasticity $F(160, 87)$	0.54 (1.00)

Notes: See Doornik and Hendry (1997), chapter 10, for details of the tests.

Panel 2.2. Univariate tests

Test/Eq. for	G_t	Q_t	Y_t	I_t
Autocorr. 2	0.23	2.07	1.47	0.80
$F(2, 32)$	(0.80)	(0.14)	(0.24)	(0.46)
Normality	1.67	0.97	0.21	1.24
$\chi^2(2)$	(0.43)	(0.62)	(0.90)	(0.54)
ARCH 1	0.24	0.21	0.79	0.14
$F(1, 32)$	(0.63)	(0.65)	(0.38)	(0.71)
Heterosced.	0.80	0.75	0.63	1.16
$F(16, 17)$	(0.67)	(0.72)	(0.82)	(0.38)

Notes: The numbers within parentheses are p values. See Doornik and Hendry (1997), chapter 10, for details of the tests.

Table 3. Cointegration analysis

Panel 3.1. Testing for cointegration using Johansen's likelihood-ratio (*LR*) trace tests

Null hypothesis	Alternative hypothesis	Test value	95 percent critical value
$r = 0$	$r > 0$	39.37	47.20
$r \leq 1$	$r > 1$	16.71	29.70
$r \leq 2$	$r > 2$	6.49	15.40
$r \leq 3$	$r > 3$	0.70	3.80

Notes: r refers to the number of cointegrating vectors. The critical values have been computed using a response surface fitted to the results of Osterwald-Lenum (1992). The analysis is based on a VAR(2) which includes an unrestricted vector of constants.

Panel 3.2. Testing for cointegration using information criteria

r	T	p	Log likelihood	SC	HQ	AIC
0	43	20	506.54	-21.81	-22.33	-23.56*
1	43	24	517.87	-21.99*	-22.61*	-23.09
2	43	28	522.98	-21.88	-22.60	-23.33
3	43	32	525.87	-21.66	-22.49	-23.46
4	43	36	526.22	-21.33	-22.26	-23.48

Notes: r refers to the number of cointegrating vectors. T refers to the number of observations. p refers to the number of estimated parameters. SC is the Schwartz criterion. HQ is the Hannan-Quinn criterion. AIC is Akaike's criterion. * indicates a minimum.

Table 4. General-to-specific modelling results

Panel 4.1. The parsimonious vector error-correction model

Explanatory var./ Eq. for	ΔG_t	ΔI_t	ΔY_t	ΔQ_t
Constant	-0.05**	0.28***	0.01*	0.02
	(0.02)	(0.06)	(0.01)	(0.02)
ΔG_{t-1}			-0.28**	-0.79*
			(0.13)	(0.45)
ΔI_{t-1}		0.28**	-0.10**	
		(0.13)	(0.05)	
ΔY_{t-1}	0.26**	1.44***	0.79***	
	(0.11)	(0.38)	(0.14)	
ΔQ_{t-1}	0.09**		0.11**	
	(0.04)		(0.04)	
EC_{t-1}	0.08**	-0.54***		
	(0.04)	(0.09)		
Stand. error	0.03	0.08	0.03	0.11

Notes: *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level. The numbers within parentheses are standard errors of parameter estimates. The last row gives the standard errors of the equations. *EC* is the error-correction mechanism, $EC = I - 0.29Q - 0.78Y$.

Panel 4.2. Multivariate residual diagnostics

Test	Test value (p value)
Vector autocorrelation 2 $F(32, 108)$	0.63 (0.93)
Vector normality $\chi^2(8)$	5.66 (0.69)
Vector heteroscedasticity $F(100, 155)$	0.78 (0.91)

Notes: See Doornik and Hendry (1997), chapter 10, for details of the tests.

(**Table 4.** continued)

Panel 4.3. Univariate residual diagnostics

Test/Eq. for	ΔG_t	ΔI_t	ΔY_t	ΔQ_t
Autocorr. 2	0.72	1.22	1.97	2.62
$F(2, 35)$	(0.49)	(0.31)	(0.15)	(0.09)
Normality	3.65	1.11	1.43	1.90
$\chi^2(2)$	(0.16)	(0.57)	(0.49)	(0.39)
ARCH 1	0.89	0.73	0.84	0.00
$F(1, 35)$	(0.35)	(0.40)	(0.36)	(0.97)
Heterosced.	1.03	0.85	1.65	0.60
$F(10, 26)$	(0.45)	(0.59)	(0.15)	(0.80)

Notes: Numbers within parentheses are p values. See Doornik and Hendry (1997), chapter 10, for details of the tests.

Table 5. Evaluation of forecast performance 1991-1995

Type of forecast	Root mean square error
Dynamic [with actual values of RHS variables]	0.194 [0.177]
Recursive 1-step-ahead	0.087
Recursive 2-step-ahead	0.133
Dynamic without error-correction mechanism	0.388
Dynamic, ARIMA(2, 1,1)	0.393
Recursive 1-step-ahead, ARIMA(2, 1,1)	0.180
Recursive 2-step-ahead, ARIMA(2, 1,1)	0.189
"Dynamic" random walk	0.266
"Recursive" random walk	0.177
"Dynamic" mean	0.244
"Recursive" mean	0.247

Notes: Rows 2-4 use the model in Panel 4.1 of Table 4 on sub-samples 1951-*t*, $t = 1990,\ldots,1994$. "Dynamic" random walk uses $\Delta\widetilde{I}_t = \Delta I_{1990}$, where $\Delta\widetilde{I}_t$ is the forecasted growth rate of investment and $t = 1991,\ldots,\ 1995$. "Recursive" random walk uses $\Delta\widetilde{I}_t = \Delta I_{t-1}$, where $t = 1991,\ldots,\ 1995$. "Dynamic" mean uses $\Delta\widetilde{I}_t = (\Delta I_{1951} + \ldots + \Delta I_{1990}) / \ (1990 - 1951 + 1)$. "Recursive" mean uses $\Delta\widetilde{I}_t = (\Delta I_{1951} + \ldots + \Delta I_{t-1}) / (t - 1951)$, where $t = 1991,\ldots,\ 1995$.

Table 6. General-to-specific modelling results using the real stock-price-based model

Panel 6.1. The parsimonious vector error-correction model

Explanatory var./ Eq. For	ΔI_t	ΔY_t	ΔS_t
Constant	0.49***	0.10***	0.38**
	(0.09)	(0.03)	(0.17)
ΔI_{t-1}	0.34***		
	(0.12)		
ΔY_{t-1}	1.42***	0.61***	
	(0.36)	(0.12)	
EC_{t-1}	-0.58***	-0.10**	-0.38**
	(0.10)	(0.04)	(0.19)
Stand. Error	0.08	0.03	0.17

Notes: *** indicates significance at the 1 percent level and ** significance at the 5 percent level. The numbers within parentheses are standard errors of parameter estimates. The last row gives the standard errors of the equations. *EC* is the error-correction mechanism, $EC = I - 0.11S - 0.76Y$. *S* is the real stock-price index. The full sample period is 1950-1995.

Panel 6.2. Multivariate residual diagnostics

Test	Test value (*p* value)
Vector autocorrelation 2 $F(18, 93)$	0.80 (0.70)
Vector normality $\chi^2(6)$	5.19 (0.52)
Vector heteroscedasticity $F(48, 136)$	0.82 (0.78)

Notes: See Doornik and Hendry (1997), chapter 10, for details of the tests.

Panel 6.3. Univariate residual diagnostics

Test/Eq. For	ΔI_t	ΔY_t	ΔS_t
Autocorr. 2	0.33	2.56	2.19
$F(2, 37)$	(0.72)	(0.09)	(0.13)
Normality	1.77	0.13	2.65
$\chi^2(2)$	(0.41)	(0.94)	(0.27)
ARCH 1	1.90	1.09	0.33
$F(1, 37)$	(0.18)	(0.30)	(0.57)
Heterosced.	0.70	1.38	1.37
$F(8, 30)$	(0.69)	(0.24)	(0.25)

Notes: Numbers within parentheses are *p* values. See Doornik and Hendry (1997), chapter 10, for details of the tests.

Table 7. Evaluation of forecasts 1991-1995 using the real stock-price-based model

Type of forecast	Root mean square error
Dynamic	0.193 [0.194]
Recursive 1-step-ahead	0.084 [0.087]
Recursive 2-step-ahead	0.117 [0.133]
Dynamic, ARIMA(2, 1,1)	0.393
Recursive 1-step-ahead, ARIMA(2, 1,1)	0.180
Recursive 2-step-ahead, ARIMA(2, 1,1)	0.189
"Dynamic" random walk	0.266
"Recursive" random walk	0.177
"Dynamic" mean	0.244
"Recursive" mean	0.247

Notes: Rows 2-4 use the model in Panel 6.1 of Table 6 on sub-samples 1950-t, $t = 1990,\ldots,1994$. The numbers within square brackets are the results for the model in Panel 4.1 of Table 4 (see Table 5). For details of the various naive models see the notes in Table 5.