Macroeconometrics of Stock Price Fluctuations

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Abstract

This paper employs Granger causality tests and Sims' innovation accounting to explain fluctuations in monthly stock returns within a vector autoregressive framework. The results show that past money growth, budget deficits, inflation, and both short-and long-term interest rates are Granger causal prior to stock returns. These variables also explain a substantial proportion of the forecast error variance of stock returns. It is found that stock returns are related positively to inflation and money growth and negatively to budget deficits, trade deficits, and both short- and long-term interest rates, as economic theory would predict.

Introduction

The objective of this paper is to apply Sims' innovation accounting and Granger causality tests to explain monthly stock price fluctuations within a vector autoregressive (VAR) model following Sims (1980b). Specific issues to be examined within the VAR framework include:

- Identify a set of macroeconomic variables that are Granger causal prior to stock prices;
- Examine the relative contributions of the model variables in explaining fluctuations in stock prices;
- Determine the direction of movement of stock prices in response to changes in the model variables; and
- Examine the sensitivity of the results to the choice of a long-term or a short-term interest rate.

A vast literature exists on stock price determination. This study, however, is motivated by concern that many previous studies are based on daily and weekly models and are misspecified due to the unavailability of data for such important variables as output, inflation, and budget deficits on a daily or weekly basis. The primary contention is that the results from these studies may be modified when

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the analysis incorporates monthly data for other variables that theory predicts may influence stock price movements. For example, Schwert (1981) reports a slow adjustment of share prices to new information on inflation measured by the monthly Consumer Price Index. Fama and French (1988a and 1988b), among others, find that stock returns are somewhat predictable when analyzed over longer terms than the daily or weekly models often used to test the propositions of the efficient market hypothesis (EMH).

A related problem is the sensitivity of results to the choice of variables included in the empirical model. For example, Davidson and Froyen (1982) report that their result supporting EMH based on the monthly New York Stock Exchange stock price index and M1 is overturned when their estimating equation includes the federal funds rate. Unfortunately, similar misspecification problems are found in many past studies.

One pertinent issue examined in many previous studies is whether all available information is incorporated into current stock prices. In other words, do lags of economic variables have an important influence on current and future stock price movements? The proponents of EMH argue that stock prices respond only to unanticipated changes in macroeconomic variables (Sorensen, 1982; Davidson and Froyen, 1982; Pearce and Roley, 1983).[1] Fama (1981) finds a significant expected inflation–stock return relationship, however, when the previous year's growth rate in the monetary base is included in the regression.

There are also controversies with regard to the effects of inflation on stock prices. Contrary to traditional belief, Fama and Schwert (1977) and Gultekin (1983) find that unexpected inflation and stock prices are negatively related. Geske and Roll (1983) claim that such a relationship is spurious (also see Fama, 1981; Coate and Vanderhoff, 1986) and provide evidence in favor of an expected inflation and stock price relationship.

This brief discussion suggests that many important issues concerning stock price fluctuations are still open to empirical investigation. The VAR approach employed in this paper offers a special appeal—the specification procedure minimizes the intrusion of many potentially spurious *a priori* assumptions concerning choice of variables, lags, and the pattern of interrelationships among the variables included in the model.

[1] Analysis of Livingstone's survey data by various researchers also provides evidence contradicting the predictions of EMH. For example, Brown and Maital (1981) find that forecasts of stock prices lack full rationality. Pearce (1984, p. 326) also examines the survey data for rationality and finds that the "forecasts were biased and the forecast errors were correlated with information likely to have been known at the time of the surveys."

Selection of Variables

The selection of model variables is based on consideration of four interrelated markets consisting of money, goods, securities, and labor. Walras Law allows any one of these markets to be dropped. Following the trend in the stock market literature, the labor market is dropped from explicit consideration.

The authors' perception of the securities markets suggests that interest rates are vital to stock price movements. The standard economic argument revolves around the discount rate used in computing the present value of expected future dividends. Other arguments, however, also appear in the literature and seem compelling (Smirlock and Yawitz, 1985). For example, long-term bonds compete with stocks for investors' dollars. Thus, increases in long–term interest rates have a negative impact on stock prices from the perspective of asset portfolio allocation. Also, increases in interest rates may reduce future corporate profitability either by causing a recession or by raising financing costs. Finally, another argument that has gained prominence in recent years is the discouraging effect that higher interest rates have on mergers, acquisitions, and leveraged buyouts. Whichever argument appears more plausible, interest rates must be included in the model. The current research uses the Moody's AAA corporate bond yield (AAA) for the long-term interest rate.

To reflect the possible effects on stock prices of actions by the Fed and the banking system, the narrowly defined money supply M1 is included in the analysis. Changes in the money supply may affect stock prices through changes in inflationary expectations or through portfolio substitution. Homa and Jaffee (1971) and Hamburger and Kochin (1972) show that past increases in money lead to increases in equity prices. There is evidence to the contrary as well (Rozeff, 1974; Davidson and Froyen, 1982).

The level of aggregate economic activity may influence stock prices through its impact on corporate profitability. An increase in output may increase cash flows and hence raise stock prices, while a recession would have the opposite effect. GNP would be the most appropriate choice for this purpose, but it is not available on a monthly basis. The index of industrial production (IP) is used instead.

Past studies provide conflicting views of the relation between stock prices and inflation (Geske and Roll, 1983; Modigliani and Cohn, 1979). One argument is that stock prices react positively to inflation because equities serve as a hedge against inflation as they represent claims on real assets. The Consumer Price Index is used as the measure of inflation, following Coate and Vanderhoff

(1986), because market participants are believed to be responsive to consumer goods prices when assessing real returns on equities.[2]

The budget deficit (BDS) may influence the stock market in several ways (Roley and Schall, 1988). A growing budget deficit will tend to depress stock prices by raising both market interest rates and the discount rate used by investors to capitalize future profit flows. If the economy is operating below capacity, however, this effect may be offset by the higher output level that may result from the fiscal stimulus.

The trade deficit (TDS) may affect stock prices by its impact on investors' confidence. It also may signal potential future exchange rate adjustments and thereby influence foreign capital flows into U.S. securities. Thus, a growing trade deficit may lead to expectations of a policy or market-induced weakening of the dollar, which would impose foreign exchange losses on foreign investments in U.S. equities.

The Standard & Poor's 500 stock price index (CSP) is used to represent stock prices. Thus, seven variables (AAA, M1, IP, CPI, BDS, TDS, and CSP) are used to specify a VAR model.[3] To estimate the model, M1, IP, CPI, and CSP are transformed into growth rate form and designated as MG, IPG, INF, and CSR, respectively, for money growth, industrial production growth, inflation, and stock returns. AAA is used in level form as it is in the same dimension as are the growth rates. The trade deficit and the budget deficit are used in difference form to reflect the notion that it is changes in the level of these variables rather than growth rates that influence stock price movements. The budget deficit is measured as the year-over-year monthly change in the budget deficit (BDC) to eliminate the problems of seasonality caused by the uneven flow of tax revenues and government expenditures throughout the year. The change in the trade deficit (TDC) is measured as the first difference of TDS. These transformations of the variables are motivated by both economic theory and statistical considerations of stationarity discussed in Abdullah and Rangazas (1988).

[2]Money supply and price levels have not been decomposed into their anticipated and unanticipated components. The traditional approach of using the forecast values of a series as a proxy for the anticipated component, while using the residuals as the unanticipated component, is questionable. McCallum (1976) argues that the approach presupposes rationality of expectations. Hasbrouck (1984) also casts doubt on the economic validity of this data-generating process. One obvious weakness of this procedure is that the created series can be sensitive to the inclusion and exclusion of variables in the forecasting model. Consequently, the results of hypotheses tests may yield conflicting implications from one study to another.

[3]Experiments were run with the weighted average exchange rate of the U.S. dollar against the currencies of the other G-7 countries to reflect the impact of exchange rate fluctuations on foreign investment flows into U.S. equities. The joint F–test on the lag coefficients of the variable was insignificant, and the variable explained a small proportion of the forecast error variance of stock returns. Because its inclusion in the model only depleted the degrees of freedom without altering any of the implications of the seven variable system, it was dropped from the final analysis.

Methodological Considerations

The empirical analysis of this paper employs a constant coefficient unconstrained linear VAR model. The VAR analysis is motivated primarily by the fact that the technique forgoes many *a priori* spurious structural restrictions and works with unrestricted dynamic representations of the data. The model assumes that the contemporaneous correlations of errors across equations are nonzero. Because there are no contemporaneous explanatory variables in the model, these error terms (in the moving average representation of the model) may be exploited as a potential source of information about the movements of a variable in the current period. The VAR technique, as observed by Fischer (1981), allows one to capture the regularities in the stochastic process and thereby gain insights into the channels through which the model variables interact with each other.

Interpreting VAR Results

The most widely used procedures for interpreting and assessing the economic implications of the results from a VAR model are Sims' (1980a) innovation accounting and Granger (1969) causality tests. Innovation accounting involves the decomposition of the forecast error variance (FEV) for a variable at a given forecast horizon into components attributable to its own innovations and to innovations in each of the other variables in the model. This process is repeated for different forecast horizons to examine how the dynamics of the system affect the decompositions. (See Eun and Shim, 1989, for more details.)

The concept of Granger causality states that a variable X Granger causes another variable Y if, within the information set $\{X_{t-i}, Y_{t-i}\}$ with $i > 0$, Y can be forecast better using the entire set, rather than just Y. In plain words, the test indicates if lags of other variables can be used to reduce the one step ahead forecast error of a variable of interest.

Consider the autoregressive representation

(1) $X_t = b(L)X_t + e_t$

where:

X_t = Stationary stochastic process;
L = Lag operator such that $LX_t = X_{t-1}$;
b(L) = Autoregression parameters; and
e_t = Innovations.

To compute the FEVs, one estimates a moving representation of equation (1) of the following form:

(2) $X_t = C_t + a(L)\, e_t$

$E(e_t) = 0$ and $E(e_t\, e'_{t-k}) = W$ for $|k| = 0$

$\neq 0$ for $|k| \neq 0$

where:

C_t	=	Perfectly predictable component of X_t; and
Identify matrix	=	Moving average coefficients a(L) at lag 0.

According to the Wold decomposition theorem, the vector of errors e_t is the forecast error of the autoregression based on information available at time t-1.

Although, by construction, the errors in any series are serially uncorrelated, they may be correlated contemporaneously. To quantify the cumulative response of an element of X_t to an innovation, however, it is imperative that the components of e_t be orthogonal. The effect of the orthogonalization is to allocate the contemporaneous correlation of the innovations among them. The standard practice is to choose some particular ordering of the variables, motivated by economic theory, prior to orthogonalization. The most widely used orthogonalization procedure is the Choleski factorization. The procedure eliminates any contemporaneous correlation between any given innovation series and all those series that precede it in the chosen ordering.

One consequence of the Choleski factorization is that a variable that is placed later in the ordering will be assigned a reduced importance in the decomposition. Thus, the ordering of variables is crucial in interpreting the results of the decomposed FEVs (Cooley and Leroy, 1985). Following the standard practice in the VAR literature, *a priori* theoretical considerations guide the ordering of variables (Sims, 1980b; Gordon and Veitch, 1986).

Ordering of Variables in Choleski Decomposition

The order in which the variables enter the orthogonalization may influence the interpretation of the results. Generally, variables viewed as more exogenous should be placed higher in the ordering. Given the complex, interrelated nature of financial markets and the existence of many competing theories, however, it is not always apparent how to implement this principle. In selecting an ordering, it is sometimes useful to examine the contemporaneous correlations among the innovations, with variables whose innovations show high correlations placed lower in the ordering. The results presented in Table 1 do not strongly suggest any preferred ordering, however. Consequently, this paper examines the sensitivity of the variance decompositions by reporting the results from two theoretically motivated orderings.

Ordering 1: BDC, TDC, IPG, INF, MG, AAA, CSR

Ordering 2: MG, IPG, INF, BDC, TDC, AAA, CSR

Both orderings place CSR in the last position and AAA in the next to last position based on the efficient market hypothesis that securities prices reflect movements in all other variables in the system (Gordon and Veitch, 1986). In the first ordering, BDC and TDC are placed in the first and second positions because they are relatively more exogenous than the other variables in the system. This relative exogeneity follows from their policy and foreign components, i.e., the structural component of the budget deficit and the export component of the trade deficit. BDC precedes TDC because of the commonly expressed view that by raising interest rates and hence the value of the dollar, the budget deficit is responsible for a deterioration in the trade deficit. IPG is affected by both fiscal policy and by the trade balance and is placed in the third position. IPG affects INF through aggregate demand pressures on the capacity of the economy, so INF is placed in the fourth position. Money growth will respond to budget deficits if monetary policy is at all accommodating. Furthermore, money growth will respond to TDC, IPG, and INF via the reaction function of the monetary authorities. Hence, MG is placed fifth in the sequence.

In the second ordering, MG is moved to the first position in recognition of the exogenous component of monetary policy and the possibility that lending to finance an expansion of real economic activity precedes money growth. BDC and TDC are moved to the fourth and fifth positions, respectively, to reflect the effects of the cyclical component of the former and the import component of the latter. These components make BDC and TDC responsive to changes in real economic activity. INF precedes BDC because of the differential impact of inflation on government revenues and expenditures. INF precedes TDC because of the impact domestic prices have on exports and imports.

Model Specification

Based on the theoretical considerations discussed above, a seven variable model is specified. The order of autoregression ρ (lag length) is determined by employing a likelihood ratio test based on the chi-square statistic. As discussed in Abdullah and Rangazas (1988), the procedure involves sequentially testing a lower order VAR(ρ - 1) as a restricted model against a higher order VAR(ρ). The sequence of tests is continued until the unrestricted model cannot be rejected at the 10 percent marginal significance level. With the starting ρ arbitrarily set at six months, the optimal lag length is four (subsequently VAR(4))[4] over the 1979:10 to 1988:09 period. The model can be represented as:

$$(3) X_t = C + \sum_{i=1}^{4} b(L)X_{t-i} + e_t$$

where:

C	=	$(C_1, C_2, \dots, C_4)'$: 4 x 1 vector of constants;
X_t	=	$(X_{1t}, X_{2t}, \dots, X_{4t})'$: 4 x 1 vector of variables;
$b(L)$	=	Time invariant matrix of autoregressive coefficients;
e_t	=	$(a_{1t}, a_{2t}, \dots, a_{4t})'$: 4 x 1 vector of white noise error terms that are independently and identically distributed as multivariate normal with mean = 0 and covariance = $\sum$.

The estimation of the model uses monthly data for the sample period 1980:04 through 1988:09. The data prior to 1980:04 are reserved for differencing and lag length specification.

Results and Interpretation

Table 2 presents the estimated F-statistics indicating the joint significance of all lags of a variable for each variable in the stock price equation. Budget deficits, interest rates, and money growth are found to be Granger causal prior to stock prices (at a marginal significance level of 10 percent or less). One implication is that stock prices cannot be considered strictly exogenous with respect to these variables (Cooley and Leroy, 1985; Abdullah and Rangazas, 1988).[5] Three of the variables, IPG, TDC, and INF, fail to Granger cause stock prices at the 10

[4]The choice of sample period is based on prior examination of the data for possible structural breaks in October 1979 and October 1982 using the familiar Chow test. The first date corresponds to the Fed's policy regime change from interest rate to nonborrowed reserve targeting, while the second refers to a shift from nonborrowed to borrowed reserve targeting. Two VAR models are estimated for each policy shift. The tests based on estimations of the model from 1975:01 to 1979:08 and 1975:01 to 1982:08 indicate structural breaks (F-statistics significant at less than 1 percent) at 1979:09 in the interest rate and inflation equations of the VAR(4) system. Similar tests reject any structural break at 1982:09.

[5]A variable may fail to Granger cause another variable for many different reasons. Past empirical studies shown that Granger noncausality may arise due to omission of some key variables, choice of lag lengths, and estimation period (Abdullah and Rangazas, 1988). This is why Sims places more emphasis on variance decompositions than on Granger causality tests in his recent works.

percent marginal significance level. This does not necessarily mean, however, that they are unimportant.[6] Given the arguments in footnote six, further analysis of the model is pursued by estimating the variance decompositions.

Table 3 presents variance decompositions of stock prices for several time horizons. The FEVs for the first few periods are presented primarily to show the dynamics of the estimated system. The usual practice is to quote the decomposed variances for time horizons at which the system approaches a stable equilibrium path. The FEVs at 12 and 18 month horizons are not substantially different. Consequently, the FEVs at the 18 month horizon are used to assess the economic implications of the model.

Innovations in IPG, BDC, AAA, INF, and MG account for substantial proportions of the FEVs of CSR and are statistically significant judged by a two standard error criterion. The results indicate that own innovations account for less than one third of the FEV of CSR. The effects of TDC are somewhat smaller in magnitude, but are also significant. These findings conform to this research's theoretical arguments linking these variables to stock prices.

The variance decompositions in Table 4 are based on the second ordering discussed earlier. The results of Table 3 generally continue to hold. To examine the exogeneity of CSR, the FEVs also are computed replacing CSR in the first position, following Abdullah and Tank (1989). The results show that own innovations account for only 44.60 percent at the 18 month horizon. This proportion attributable to own innovations is not sufficiently large to regard stock prices as exogenous, because the FEVs of an exogenous variable will be accounted for primarily by its own innovations when it is placed in the first position of the ordering.[7] This reinforces the earlier finding in Table 1 that stock prices are not exogenous.[8]

Finally, the sums of the lag coefficients for each variable in the stock price equation are computed. The estimated results are presented in Table 5. With the exception of IPG, the signs of all summed coefficients are consistent with this

[6]Cooley and Leroy (1985) argue that even if variable Y does not Granger cause variable X, one may not conclude that X is strictly exogenous with respect to Y (meaning neither contemporaneous nor lagged Y appear in the structural equation for X). They point out, however, that strict exogeneity does imply Granger noncausality.

[7]As discussed earlier, a variable placed first in the ordering in the Choleski factorization scheme is assigned the benefit of contemporaneous correlations of all other variables in the system. As a consequence, the proportion of its variance explained by own innovations and those of other variables provides an upper bound.

[8]The October 1987 stock market crash had virtually no effects on the relationships of model variables with CSR. This is examined by comparing the FEVs of Tables 1 and 2 with those obtained by truncating the estimation period at September 1987. The sums of lagged coefficients also indicate that the crash had no discernible effects on the relationships. As indicated in Table 4, the same variables (AAA and BDC) show significant t-ratios on their individual sums of lagged coefficient (which are -0.007 [0.018] and -0.002 [0.085], respectively) prior to the crash.

research's theoretical predictions concerning the linkages of stock prices with the system variables. The positive relationship of stock price with inflation contradicts Fama and Schwert (1977) and Geske and Roll (1983), but is consistent with economic theory that suggests that investment in equities is a hedge against inflation. The sum of lagged coefficients on IPG is negative, but not significant statistically, even at the 25 percent level. One plausible explanation for the negative sign (indicating an inverse relationship of IPG with CSR) is that higher output growth may worsen fears of inflation, leading to expectations of higher interest rates due to a tightening of monetary policy. The estimated sum of coefficients further suggests that only budget deficits and interest rates have long-run implications (using a 10 percent marginal significance level) for stock prices. The insignificance of the summed coefficients of the other variables does not necessarily imply that they do not have short-run influences on stock prices.[9]

Forecast errors are obtained from a VAR model based on a more parsimonious specification consisting of the variables (MG, INF, AAA, BDC, and CSR) that account for a substantial proportion of the forecast error variance of stock prices. These forecast errors are compared with those obtained from a naive model (a univariate autoregressive model of CSR). The model augmented by the four macroeconomic variables generated forecast errors at both one month and three month forecast horizons that are smaller than those of the univariate model. For example, the one step ahead mean absolute percent error is 0.0209 versus 0.0226, while the Thiel U-statistic is 0.844 versus 0.861.

Sensitivity of Results to Choice of Interest Rates

To examine if the above results are sensitive to the choice of an interest rate, the model is respecified and analyzed using the federal funds rate (RFF). The choice of RFF is motivated by the notion that both policy and nonpolicy factors are reflected quickly in RFF. The analysis using RFF will reflect not only how efficiently the stock market absorbs information from the Fed's reaction function, but also the effects of nonpolicy-induced changes embodied in RFF. Davidson and Froyen (1982) show that while the market efficiently absorbs relevant information contained in the monetary aggregates, the information contained in RFF is reflected significantly in stock prices with lags.

Substitution of RFF for AAA in the model produces one additional causal implication, that is, INF is now Granger causal prior to stock returns (Table 2). Like AAA, RFF also Granger causes CSR. These results are plausible, given the fact that monetary policy first affects short-term interest rates which, in turn,

[9]In this paper short- and medium-term effects are assessed by Granger causality tests and variance decompositions. These techniques essentially reflect the dynamics in the time series.

transmit to inflation and long-term interest rates. The variance decompositions in Table 5 (based on ordering 1, except that RFF is substituted for AAA), which are similar to those in Table 3, show that none of the earlier implications of the model are altered. One important conclusion from a comparison of the FEVs of CSR explained by AAA (15.13 percent in Table 3) and RFF (9.92 percent in Table 6) at the 18 month horizon is that AAA is related more closely to CSR than to RFF. The implications of these results, particularly the findings that RFF Granger causes CSR and accounts for a statistically significant proportion of the FEV of CSR, are broadly consistent with Davison and Froyen (1982).

The sum of lag coefficients in the CSR equation and the related summary statistics are virtually identical with RFF as the rate of interest in the model. (Complete results are available from the authors upon request.) Consistent with the findings in Table 5, only the sum of lag coefficients on interest rates and budget deficits are statistically significant.

Summary and Conclusion

This paper analyzes stock price fluctuations within a VAR model. The results of Granger causality tests and innovation accounting provide compelling evidence rejecting the view that stock prices are strictly exogenous. A number of variables such as budget deficits, long-term interest rates, and money growth appear Granger causal prior to stock prices. These variables, along with output growth and inflation, also account for substantial proportions of the forecast error variance of stock prices. One important implication of these findings is that lagged information contributes substantially to the determination of stock price movements. The sums of lagged coefficients in the stock return equation show linkages between the model variables and stock returns that are consistent with economic theory. Contrary to the findings of Geske (1983), a positive stock return and inflation relationship is found. Long-term interest rates and budget deficits appear to have significant negative effects on stock returns.

These results are found to be virtually insensitive to the choice of short-term or long-term interest rates in the model. The long-term interest rate is found to be related more closely to stock returns than is the short-term rate, as economic theory predicts.

One of the primary motivations of this study is to broaden the selection of variables used in empirical models of stock returns. The contention is that the use of daily or weekly data in stock price studies restricts the variable set by eliminating relevant macroeconomic variables. As a consequence, many of the previous empirical studies report test results based primarily on bivariate and trivariate regression models. Evidence is provided that indicates that variables such as output, budget deficits, and inflation (which are not available on a daily or weekly basis) cannot be ignored in an empirical analysis of stock price determination. It is imperative that empirical models describing stock price behavior are based on relevant information rather than on available information.

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Table 1
Contemporaneous Correlation of Innovations

	CSR	MG	IPG	BDC	TDC	RFF/AAA	INF
CSR	****	0.2952	0.0580	-0.1498	0.0042	0.1716	0.0724
MG	———	****	0.2278	-0.1082	-0.0411	0.7148	0.5122
IPG	———	———	****	-0.1073	-0.0131	0.2800	0.3278
BDC	———	———	———	****	-0.0912	-0.1519	-0.0693
TDC	———	———	———	———	****	-0.0415	-0.0844
RFF/AAA	0.1415	0.6458	0.2479	-0.1450	-0.0436	****	0.8175
INF	———	———	———	———	———	0.8652	****

Note: The upper triangular matrix presents the contemporaneous correlation of innovations with AAA included in the model, while the lower triangular matrix displays the same model with AAA replaced by RFF. The blanks (———) in the lower triangular matrix indicate that the correlation coefficient is unchanged when RFF is substituted for AAA

Table 2
Granger Causality Tests Based on F-Statistics
Estimation Period: 1980:04 to 1988:09
CSR = Dependent Variable

AAA Model		RFF Model	
Lag Variables	F-Statistics (Significance Level)	Lag Variables	F-Statistics (Significance Level)
CSR	2.32 (0.065)	CSR	3.61 (0.009)
MG	2.56 (0.046)	MG	3.95 (0.006)
IPG	0.92 (0.454)	IPG	1.82 (0.134)
BDC	2.59 (0.043)	BDC	2.71 (0.036)
TDC	0.33 (0.856)	TDC	0.44 (0.774)
AAA	2.30 (0.067)	RFF	3.18 (0.018)
INF	0.95 (0.442)	INF	2.08 (0.092)

The variables are:
CSR = Common stock returns measured by first differences of the logs of the S&P 500;
BDC = Year over year monthly changes in the budget deficit;
MG = Money growth (first differences of the logs of the M1 money stock);
IPG = Industrial production growth (first differences of the logs of the Index of Industrial Production);
INF = Inflation rate (first differences of the logs of the Consumer Price Index);
TDC = Changes in trade deficits (first differences of trade deficits);
AAA = Interest rates on Moody's AAA corporate bonds;
RFF = Federal funds rate.

The AAA model is the VAR(4) model with the long-term interest rate. The RFF model is the same model with the federal funds rate substituted for AAA

Table 3
Variance Decomposition of Stock Prices With Standard Errors in Parentheses
Estimation Period: 1980:04 to 1988:09

	Proportion of Mean Forecast Error Variance at Time Horizons of			
	One Month	Six Months	12 Months	18 Months
BDC	2.36 (2.42)	8.33 (3.30)	11.85 (4.32)	12.25 (4.28)
TDC	0.99 (1.33)	5.31 (3.73)	6.83 (3.46)	7.95 (3.81)
IPG	1.49 (2.16)	6.27 (3.58)	9.68 (3.68)	11.176 (4.03)
INF	5.14 (4.16)	10.97 (5.05)	10.27 (4.38)	10.29 (4.31)
MG	3.23 (2.84)	9.37 (4.38)	11.55 (4.14)	11.94 (4.06)
AAA	13.61 (5.23)	14.25 (4.29)	15.03 (4.48)	15.13 (4.84)
CSR	73.18 (6.94)	45.51 (5.73)	34.80 (4.99)	31.27 (5.26)

In the orthogonalization scheme, variables are ordered as in column 1 following the arguments presented in the text

The standard errors of variance decompositions are estimated using the Monte Carlo simulations procedure described in the RATS manual. The estimates are based on 100 random draws that are made directly from the posterior distribution of the VAR coefficients. (See Runkle, 1987; Sims, 1987 for more details.) The statistical significance of the decomposed FEVs are judged based on the usual standard error criterion

To assess economic implications from innovations accounting, the usual practice is to refer to the results of forecast horizons at which the dynamics of the system appear to have worked themselves out to approach a stable equilibrium path. Based on this criterion, the FEVs explained at the 18 month horizon are used. The FEVs for the first 12 months are presented to show how evolutions of the shocks affect the decompositions.

Table 4
Variance Decomposition of Stock Prices With Standard Errors in Parentheses
Estimation Period: 1980:04 to 1988:09

	Proportion of Mean Forecast Error Variance at Time Horizons of			
	One Month	Six Months	12 Months	18 Months
MG	3.64	9.75	12.29	12.62
	(3.05)	(4.66)	(4.83)	(4.68)
IPG	1.23	5.55	8.33	10.43
	(1.83)	(3.14)	(3.37)	(3.71)
INF	5.12	9.45	9.20	9.25
	(3.98)	(4.71)	(4.04)	(3.94)
BDC	1.68	8.57	12.23	12.31
	(1.82)	(3.59)	(4.17)	(4.19)
TDC	2.49	6.47	8.13	8.92
	(2.70)	(4.02)	(4.02)	(4.50)
AAA	13.28	14.31	14.80	14.85
	(5.51)	(4.81)	(4.60)	(4.49)
CSR	72.56	45.91	35.02	31.64
	(6.48)	(6.48)	(6.07)	(6.04)

See notes to Table 3

Table 5
Single Equation Estimates of the Stock Price Equation

The estimated stock return equation with the sum of (four) lag coefficients of each variable is:

$$\underset{\substack{(1.636)\\ [0.085]}}{CSR_t = 0.052} + \underset{\substack{(0.128)\\ [0.899]}}{0.025\ CSR} + \underset{\substack{(0.894)\\ [0.375]}}{0.947\ MG} + \underset{\substack{(0.439)\\ [0.662]}}{0.716\ INF} - \underset{\substack{(-1.130)\\ [0.262]}}{0.805\ IPG} - \underset{\substack{(-0.661)\\ [0.511]}}{0.00001\ TDC} - \underset{\substack{(-1.907)\\ [0.060]}}{0.005\ AAA}$$

$$- \underset{\substack{(-1.974)\\ [0.052]}}{0.002\ BDC}$$

where t-statistics and the corresponding marginal significance levels are given in parentheses and brackets, respectively.

Summary statistics

$\bar{R}^2 = 0.2335$, Q (df = 30) = 22.21 [0.807], Durbin h = 0.0742 [0.9409]

The estimated $\bar{R}^2$ in the absence of the lagged dependent variable is found to be 0.1801

The Box-Pierce Q-statistic (df = degrees of freedom) is not an appropriate indicator of white noise residuals when the regression equation contains variables other than lagged dependent variables. One may use, however, the Q-statistic in a diagnostic rather than in a strict statistical sense. In the absence of a lagged dependent variable Q (30) = 33.65 [0.2948] indicates that the estimated residuals are not significantly different from white noise residuals

The Durbin h-statistic clearly rejects the presence of serial correlation in the estimated equation

Table 6
Variance Decomposition of Stock Prices With Standard Errors in Parentheses
Estimation Period: 1980:04 to 1988:09

	Proportion of Mean Forecast Error Variance at Time Horizons of			
	One Month	Six Months	12 Months	18 Months
BDC	3.487	10.443	15.574	16.404
	(3.22)	(3.67)	(4.98)	(5.09)
TDC	1.240	5.054	6.498	7.720
	(1.55)	(3.01)	(3.05)	(3.27)
IPG	1.967	7.865	10.313	11.280
	(2.38)	(4.17)	(4.35)	(4.69)
INF	1.210	9.307	9.515	9.442
	(1.54)	(4.19)	(3.64)	(3.41)
MG	4.977	13.598	13.240	13.404
	(3.60)	(5.01)	(4.62)	(4.51)
RFF	2.649	8.661	9.766	9.921
	(2.61)	(3.57)	(3.44)	(3.33)
CSR	84.470	45.072	35.094	31.830
	(5.51)	(6.49)	(5.89)	(5.94)

See notes to Table 3