Stock Prices, News, and Business Conditions

Grant McQueen
Brigham Young University

V. Vance Roley
University of Washington

Previous research finds that fundamental macroeconomic news has little effect on stock prices. We show that after allowing for different stages of the business cycle, a stronger relationship between stock prices and news is evident. In addition to stock prices, we examine the effect of real activity news on proxies for expected cash cows and equity discount rates. We find that when the economy is strong the stock market responds negatively to news about higher real economic activity. This negative relation is caused by the larger increase in discount rates relative to expected cash flows.

Apart from some types of monetary information, there is little empirical evidence to support the hypothesis that stock prices respond to macroeconomic news. Schwert (1981) finds that the daily response of stock prices to news about inflation from **1953** to 1978 is weak and slow. Pearce and Roley (1985) use survey data to measure expectations and find that daily stock prices respond to monetary information between September 1977 and October 1982, but news about the consumer price index, unemployment, and industrial

production have no significant effect on prices. Hardouvelis (1987) considers a somewhat broader set of variables through August 1984 and concludes that stock prices respond primarily to monetary news. Finally, Cutler, Poterba, and Summers (1989) use vector autoregressions to measure news about macroeconomic time series from 1871 to 1986. They conclude that less than one-third of the monthly return variance can be explained from these sources.'

Each of these studies assumes that investors' response to news is the same over different stages of the business cycle. For instance, Cutler, Poterba, and Summers (1989) implicitly assume that a positive surprise in industrial production at the end of the Great Depression evokes the same response as a surprise in late 1969, after nearly a decade of expansion. A positive surprise in industrial production during the depression could indicate the end of the depression and higher forecasts of firms' cash flows. Such an announcement would likely be "good news" for the stock market. In late 1969, with low unemployment and factories running near full capacity, a positive surprise in industrial production may result in fears of an overheating economy, inflation, and possible efforts by policymakers to increase real interest rates. Such an announcement could then be "bad news" for the stock market. If the same type of news is considered good in some states of the economy and bad in others, the response coefficient on the surprise in previous studies will be biased toward zero.[2]

The popular press uses this good news/bad news story to interpret daily stock price movements. For example, on February 4, 1983, after 16 months of recession, the Labor Department reported that the unemployment rate fell to 10.4 percent. This represented a rate of 0.2 or 0.3 percentage points below what was expected. This news was used by the media to explain the 13.25-point jump in the Dow Jones Industrial Average, and prompted the Chairman of the Council of Economic Advisers, Martin Feldstein, to comment that "a recovery is either beginning or already here" (*Wall Street Journal,* February 7, 1983). In contrast, on November 4, 1988, after six years of expansion, the Labor Department reported that the unemployment rate fell to 5.3 percent, matching a 14-year low. This represented a rate of 0.1 or 0.2 percentage points below what was expected. The media's interpreta-

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[1] Chen, Roll, and Ross (1986) also investigate whether monthly stock returns covary with various macroeconomic variables. They again find that the explanatory power is low. The main focus of their study, however, is whether the covariance of economic variables with stock returns can explain ex ante returns.

[2] Several recent studies find significant effects from business conditions on stock returns. Ferson and Merrick (1987). for example, find shifts in consumption-based asset pricing parameters across stages of the business cycle measured by recession versus nonrecession. Fama and French (1989) and Fama (1990) consider term-premium and default-risk-premium variables as determinants of equity discount rates. They suggest that the term premium is related to NBER business cycles, while the risk premium is related to business conditions over longer periods.

tion in this instance was "bond market investors reacted with gloom, sending interest rates higher on fears of tighter Fed policy. The stock market also fell" (*Wall Street Journal,* November 7, 1988). The problem with this type of evidence, however, is that it is anecdotal and largely after the fact.

In this article we examine whether the response of stock prices to macroeconomic news varies over different stages of the business cycle. By allowing the response to vary over different states of the economy, we can test the good news/bad news story and provide unbiased estimates of the effects of fundamental information about the economy. We study daily percentage changes in closing values of the Standard & Poors 500 Index and several variables related to equity discount rates and cash flows. By considering these other variables, we can investigate the sources of any business-condition effect on the response of stock prices.

Following this introductory section, we present in Section 1 a simple theoretical framework to consider how news affects stock prices and how this effect can vary over different stages of the business cycle. We describe the data in Section 2. In Section 3 we present the empirical results. We consider the robustness of the results in Section 4, and we summarize the main conclusions in Section 5.

1. Theoretical Framework

A common model that links stock prices to information posits that stock prices equal the present discounted value of rationally forecasted future dividends. This model can be represented as

$$P_t = E\left[\sum_{\tau=1}^{\infty} \frac{D_{t+\tau}}{1 + {}_t r_{t+\tau}} \,\middle|\, \Omega_t\right], \tag{1}$$

where P, is the price of the stock at time t, $E[\cdot|\Omega_t]$ denotes the mathematical expectation conditional on information available at time t (Ω_t), $D_{t+\tau}$ is the dividend paid at time $t + \tau$, and ${}_t r_{t+\tau}$ is the stochastic discount factor for cash flows that occur at time $t + \tau$.

Economic announcements affect daily share price movements if the new information revealed by announcements affects either expectations of future dividends or discount rates or both. The new information is represented by the difference in the announced value on day $t + 1$ and the expected value as of day t. Consequently, the unanticipated component of an announcement on day $t + 1$ is uncorrelated with information available on day t. The information set, Ω_t includes past announcements of other economic variables, so announcement surprises are uncorrelated under rational expectations if they are made on different days. Combining daily stock-price changes

with announcement surprises on different days allows us to isolate the effects of individual economic variables.

1.1 Impact of real economic activity surprises
We need not expect that real economic activity surprises will affect cash flows and discount rates in the same way across different states of the economy. As a result, stock prices may well react differently to surprises of this nature, depending on whether the economy is operating below capacity. When the economy is booming, for example, a real economic activity surprise could result in a larger increase in discount rates than cash flows, causing stock prices to fall. In this case, high capacity utilization and employment may constrain further increases in output and, consequently, cash flow in the absence of new investment in plant and equipment.

The announcement effect we examine corresponds to the disclosure in month t of production growth that already occurred in month $t - 1$. Information about the previous month is relevant in that it may change expectations about the future. That is, consistent with Fama (1990) and Schwert (1990), the information provided by an industrial production announcement causes stock prices to respond if this information causes revisions in expected future industrial production.

1.2 Impact of other economic announcement surprises
We also consider possible asymmetric effects of announcement surprises other than those related to real economic activity. This other economic information is, however, less closely related to the possible business-conditions effects discussed above. The announcements we consider are for foreign trade, inflation, and money. We briefly discuss each in turn.

First, foreign trade deficit announcements have at times received considerable attention in the popular press. For the 1979-1984 period, however, Hardouvelis (1987) does not find any significant effects on stock prices. We update his sample and test for varying effects over different economic states.

Second, following the empirical studies of Nelson (1976) and Fama and Schwert (1977), a number of studies estimate a significant negative relationship between inflation and stock returns. Among these, Feldstein (1980) argues that the tax treatment of depreciation and inventories results in lower real after-tax corporate profits and, hence, lower stock prices during times of inflation. Fama (1981), Geske and Roll (1983), and Kaul (1987) explain the negative relationship by appealing to real output effects. In terms of inflation announcement surprises, the significance of the stock-price response is mixed [e.g., Pearce and Roley (1985) and Hardouvelis (1987)]. We again extend

these announcement studies by lengthening the sample and by allowing business-condition-dependent responses.

Third, Pearce and Roley (1983, 1985), Cornell (1983), and Hardouvelis (1987) find that stock prices respond significantly to money announcement surprises. Varying responses over different monetary policy regimes are tested in these studies, but possible business-conditions effects are not considered.[3] We estimate the stock-price response not only to money announcements but also to Federal Reserve discount rate changes, over different economic states.

2. Data

Our sample period begins in September 1977 and ends in May 1988. The start of the sample period coincides with the initial availability of survey data from Money Market Services International (MMS). We discuss the robustness of the results using alternative sample periods and expectation measures in Section 4.3.

2.1 Asset prices and yields

We use daily percentage changes in the closing value of the S&P 500 Index to estimate the response of stock prices to new macroeconomic information. For economic announcements occurring either before or while the stock market is open, we use the percentage change in the index from the previous business day's closing price to the closing price on that day. For announcements made after the stock market is closed, we use the percentage change in the index from that day's closing quote to the next business day's closing quote. Throughout the sample, the stock market closed at 4:00 P.M. EST. (We use EST for all closing and announcement times.)

To measure the response of equity discount rates to new information, we consider several proxies. These include daily changes in the three-month Treasury-bill and lo-year Treasury-bond yields. Following Fama and French (1989) and Fama (1990), we also include variables denoted as the term spread and the default spread as equity discount rate proxies. We represent the term spread by Moody's Aaa corporate bond yield minus the three-month bill yield, and the default

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[3]Given the evidence that both short- and long-term interest rates respond differently to money announcement surprises over different Federal Reserve policy regimes [e.g., Roley (1983, 1986). Cornell (1983), and Roley and Walsh (1985)], another potentially interesting hypothesis is that stock prices respond differently to economic news over these regimes. For the October 1979 and October 1982 regimes, however, Pearce and Roley (1983, 1985) and Hardouvelis (1987) find no significant difference in the stock market's response to money surprises. We nevertheless investigate the effects of the monetary policy regimes in October 1979, October 1982, and February 1984. and the hypothesis that the stock market's response is the same across regimes for our set of economic announcements can be rejected only at the 25 percent significance level. Consequently, we do not examine the effects of monetary policy regimes further.

spread by Moody's Baa corporate bond yield minus the Aaa yield. These yield data are from the Federal Reserve's H.15 release, and they correspond to yields based on bid prices prevailing at 3:30 P.M.[4]

2.2 Economic announcements

Virtually all of the economic announcements are well-publicized events with regular schedules. Data on industrial production (IP) are initially released, seasonally adjusted monthly percentage changes in the Federal Reserve Industrial Production Index, all items. Between January 1979 and October 1985, the announcements were made at 9:30 A.M.; since October 1985, at 9:15 A.M. Before 1979, the industrial production press releases give no specific announcement time, stating only "for immediate release." However, the announcements were made before the market opened for our sample.

Data on the unemployment rate (UNEM) and the percentage change in nonfarm payroll employment (NFP) are based on the initial announcements by the Bureau of Labor Statistics, and both are seasonally adjusted. We convert the announced nonfarm payroll employment data into percentage changes from the previous month's announced level. During our sample period, both the unemployment rate and payroll employment announcements were made at the same time, typically the first Friday in the month. Each announcement may, however, contain unique information, since they are based on two different surveys. The unemployment data are collected from a survey of households, conducted and tabulated by the Bureau of the Census for the Bureau of Labor Statistics. The payroll employment data are collected by state agencies from payroll records of employers and are tabulated by the Bureau of Labor Statistics. These employment data were announced at 9:00 A.M. through March 1982 and at 8:30 A.M. from April 1982 to the present.

The merchandise trade deficit (MTD) is announced by the Foreign Trade Division of the Department of Commerce, and it represents the seasonally adjusted monthly trade deficit in billions of dollars (trade surpluses are negative). For most of the sample period, these announcements give information on the preceding month's deficit. Starting in March 1987, the announcements were delayed several weeks. So, an announcement in March, for example, would give information on January's trade deficit. Between February 1979 and November 1983, the announcements were made at 2:30 P.M., and in December 1983 it was made at 9:30 A.M. Since January 1984, the announcements have been made at 8:30 A.M.

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[4] We also use the 10-year Treasury-bond yield in the term and default spreads, replacing the Aaa yield. The test results reported in the next section ate qualitatively the same using these alternative definitions.

The data on inflation are seasonally adjusted monthly percentage changes in the Consumer Price Index (CPI) and Producer Price Index (PPI) as announced by the Bureau of Labor Statistics. Beginning in February 1978, we use the CPI-U (all urban consumers), consistent with the MMS expectations data. The PPI series corresponds to all finished goods, again consistent with the MMS expectations data. The PPI and CPI announcements were made on various days near the middle of each month. The PPI announcement is, however, made earlier in the month than the CPI announcement. With three exceptions, the inflation announcements were made before the stock market opened, specifically at 9:00 A.M. before March 1982 and at 8:30 A.M. from April 1982 to the present.[5]

The money stock data consist of seasonally adjusted weekly percentage changes in M1, as announced in the Federal Reserve's H.6 release. We convert the M1 data into percentage changes from the previous week's announced level. Before January 31, 1980, the announcements were made on Thursdays at 4:10 P.M., and they corresponded to changes in "old M1." Then, the announcements were made at 4:10 P.M. on Fridays, and they corresponded first to Ml-B and then to MI, where this latter M1 is equivalent to M1-B.[6] Beginning on November 29, 1982, money announcements were made at 4:15 P.M. Starting on February 16, 1984, money announcements were switched back to Thursdays, and since March 22, 1984, they have been made at 4:30 P.M. Changes in the Federal Reserve's discount rate and surcharge were announced intermittently with no typical announcement day or time.

2.3 Expected values of announcements

We use the survey data compiled by MMS International to form measures of the market's expectation of economic announcements. For Ml, the survey data start on September 27, 1977. The survey data for the CPI, PPI, and the unemployment rate begin in November 1977. For industrial production, the data begin in December 1977. For the merchandise trade deficit and nonfarm payroll employment, the survey data begin in February 1980 and February 1985, respectively. No survey data are available for discount rate and surcharge announcements. As a consequence, all such changes are treated as unantici-

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[5]The PPI announcements in October 1981 and August 1985 were made at 2:00 P.M., and the February 1979 CPI announcement was made at 2:30 P.M.

[6]Old M1 differs from the current definition mainly in that it excludes "other checkable deposits" at depository institutions. Following the introduction of nationwide NOW accounts in 1981, this category became substantial,

pated.[7] Finally, we convert the survey data for M1 and nonfarm payroll employment into expected percentage changes from the previously announced level.

Although not reported here, we subject the survey data to unbiasedness and efficiency tests for the entire sample period and over various subsamples [e.g., Pearce and Roley (1985)]. The overall results of these tests are mixed. While the survey data are not always unbiased and efficient, they generally have smaller root-mean-square errors than autoregressive models. To correct for any systematic biases, as well as to update the survey data with new information, we form revised expectations [e.g., Roley (1983, 1985) and Shiller, Campbell, and Schoenholtz (1983)]. Since the survey can be taken as long as five business days before an announcement, we use the change in the three-month Treasury-bill rate over the four business days before an announcement as the new information proxy. We estimate regression equations for each calendar year to form revised expectations.[8]

2.4 Classification of economic states
To test the hypothesis that the stock market's response to news varies over business conditions, some classification of different levels of economic activity is required. NBER business cycle turning points are one possibility, but they classify the direction of economic activity (i.e., expansion or recession) rather than the level. Unfortunately, widely accepted definitions analogous to NBER reference cycles are not available for relative levels of economic activity.

In this article, we define economic states using several alternative economic variables. For most of the reported results, we use the seasonally adjusted monthly industrial production index, all items (1977 = 100), to define economic states. First, we estimate a trend in the log of industrial production by regressing the actual log of industrial production on a constant and a time trend from September 1977. Then we add and subtract a constant from the trend, creating

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[7] Roley and Troll (1984) also make this assumption. Other researchers. however, attempt to forecast discount rate changes. See, for example, Smirlock and Yawitz (1985). Batten and Thornton (1984). and Hakkio and Pearce (1988). We do not use these approaches because they cannot isolate the specific day in which the change is expected to occur. In contrast to these approaches, Cook and Hahn (1988) simply classify changes into unexpected and expected categories based on Federal Reserve statements.

[8] When an economic announcement x_t^* i is made before the market opens, the revised expectation is the within-sample fitted value of the equation

$$x_t^* = a + b \cdot x_t^s + c \cdot (r_{t-1} - r_{t-5}) + e_t,$$

where x_t^s is the survey measure, r_{t-1} is the 3-month Treasury-bill yield at the close of day $t - 1$. e_i is a random error term. and $a, b,$ and c are coefficients. We perform the regressions over calendar years instead of economic states to avoid possible biases in later tests that examine the effects of business conditions. We include the last few months of 1977 and the first live months of 1988 in the 1978 and 1987 calendar years, respectively.
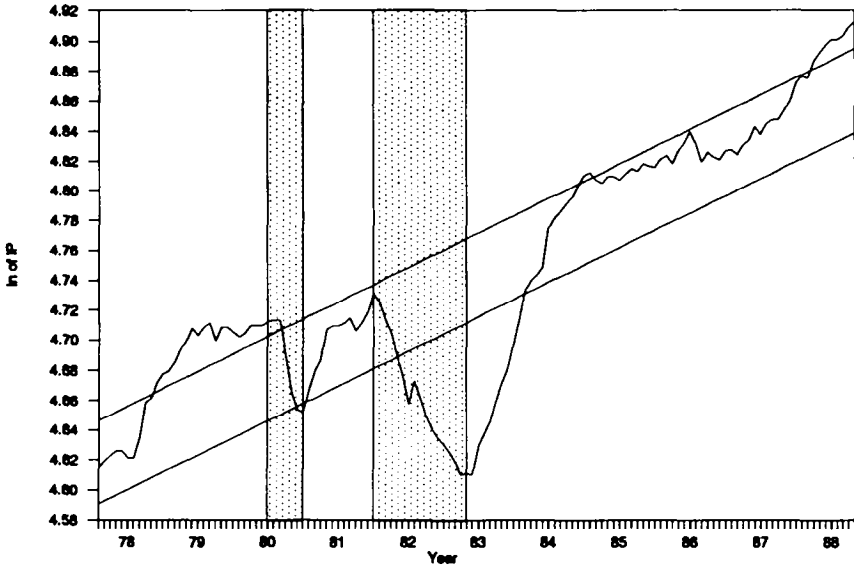
Figure 1
Natural log of industrial production, actual and bounds (trend ± .028)

the upper and lower bounds illustrated in Figure 1. We choose the constant 0.028 so that the log of industrial production is above the upper bound, denoted as "high" economic activity, 25 percent of the time. The log of industrial production is below the lower bound, indicating "low" economic activity, about 25 percent of the time as well. "Medium" economic activity is represented by the remaining observations between the bounds. As we discuss in Section 4.1, the empirical results are not very sensitive to moderate changes in the bounds or different series used to classify the states.

3. Empirical Results

3.1 Response to economic announcements
We first examine the impact of new economic information on stock prices, interest rates, and other discount rate proxies without conditioning on the state of the economy. The results for interest rates, the term spread, and the default spread are useful because they provide evidence that economic announcements contain relevant information for financial markets. Although there are over 3800 days in our sample period, we estimate how the markets respond to news only for the 932 days on which one or more announcements is made. Our initial estimation uses the following specification:

$$\Delta P_t = a + \mathbf{x}_t^u \mathbf{b} + \mathbf{d} + e_t, \qquad (2)$$

where

$\Delta P_t =$ percentage change in stock prices or change in interest rates (measured in basis points) from business day $t - 1$ to business day t

$\mathbf{x}_t^u =$ 1×9 vector of unanticipated components of economic announcements, calculated as $\mathbf{x}_t^a - \mathbf{x}_t^e$

$\mathbf{x}_t^a =$ 1×9 vector of economic announcements

$\mathbf{x}_t^e =$ 1×9 vector of expected economic announcements

$\mathbf{d} =$ 1×4 vector of day-of-the-week dummy variables for Monday through Thursday

$e_t =$ error term

$a, \mathbf{b} =$ scalar and 9×1 vector of coefficients, respectively

Following Pagan (1984), ordinary least-squares (OLS) estimation of Equation (2) results in consistent estimates of coefficients and standard errors in the absence of heteroskedasticity. In all tables, however, White's (1980) procedure is used to calculate standard errors to take possible heteroskedasticity into account [e.g., French, Schwert, and Stambaugh (1987) and Schwert (1989))

We report the results for Equation (2) in Table 1 for the September 1977-May 1988 sample.[9] The first row in the table shows, for example, that the S&P 500 Index falls by 0.1 percent in response to an unanticipated increase in industrial production of 1 percentage point. The lo-year bond yield and the three-month Treasury-bill yield increase by 5.5 and 9.5 basis points, respectively, in response to this same announcement. While interest rates exhibit statistically significant responses to most of the new economic information, stock prices do not. The S&P 500 Index response coefficient is significant at the 5 percent level only for unanticipated components of Ml announcements. These unconditional results are similar to those of other studies using much shorter sample periods [e.g., Pearce and Roley (1985)].[10]

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[9] In addition to specification (2). we also obtain results for a specification including the expected values of economic announcements $\mathbf{x}_t^e$. The inclusion of these variables has no effect on the estimated response coefficients, 6, since the measures of unanticipated announced changes, $\mathbf{x}_t^u$, are uncorrelated with $\mathbf{x}_t^e$ by construction. Test results are also unaffected. Correlations among the unanticipated components of economic announcements, with the exception of the correlations between the discount rate and Ml with nonfarm payroll employment, are not significantly different from zero. Even these two significant correlations are only -.089 and -.071, respectively. This lack of correlation is not surprising since the announcements usually occur on different days, and the expectations variables include information up to the time of an announcement.

[10] Similar to other studies, R^2 is very low for the S&P 500 regression. While Roll (1988) reports higher R^2's for daily data, his regressions relate individual stock returns to market returns. In contrast, the regression we report in Table 1 considers daily movements in a proxy for the market return. Because we consider only selected economic announcements, and all other news is ignored, it is not surprising that R^2 is low.

Table 1
Response of stock prices and interest rates to economic news (932 announcement day observations), September 1977-May 1988

Announce-ment	S&P 500	10-year Treasury-bond	Three-month Treasury-bill	Term spread	Default spread
IP"	−0.104	5.50*	9.52**	−7.97*	−0.51
	(0.171)	(3.11)	(4.53)	(4.20)	(1.47)
UNEM"	0.695	−20.31**	−18.88**	11.64*	3.48
	(0.500)	(6.61)	(8.13)	(7.07)	(2.85)
NFP"	−1.088	54.92**	56.97**	−37.35**	−18.07**
	(1.508)	(12.83)	(11.87)	(7.13)	(7.60)
MTD"	−0.070	−0.48	−0.39	0.58	−0.33
	(0.066)	(0.50)	(0.74)	(0.69)	(0.26)
PPI"	−0.455*	11.59**	7.61	−6.92*	2.13
	(0.252)	(4.07)	(4.63)	(4.10)	(2.01)
CPI"	−0.490	10.18*	12.32*	−8.40	1.58
	(0.410)	(5.21)	(6.86)	(6.34)	(2.74)
M1"	−0.363**	8.18**	17.63**	12.97**	−1.90**
	(0.097)	(1.40)	(2.64)	(2.46)	(0.57)
DISC"	−0.308	8.71**	35.74**	−29.53**	−2.51*
	(0.364)	(3.82)	(8.63)	(8.15)	(1.42)
Summary statistics					
$\bar{R}^2$	.020	.089	.144	.113	.016
SE	0.996	12.06	19.70	17.85	5.62
DW	2.10	2.03	1.89	1.97	2.01

* and ** indicate significance at the 10 and 5 percent levels, respectively. Term spread = Moody's Aaa corporate bond yield minus the three-month Treasury-bill yield. Default spread - Moody's Baa corporate bond yield minus the Aaa yield. _P" = _unanticipated percentage change in industrial production (12/77-5/88. 126 observations). **UNEM"** = unanticipated change in the unemployment rate (11/77-5/88, 127 observations). **NFP"** = unanticipated percentage change in nonfarm payroll employment (2/85-5/88, 40 observations). **MTD"** = unanticipated percentage change in the merchandise trade deficit (2/80-5/88, 100 observations). **PPI"** = unanticipated percentage change in the Producer Price Index (1 1/77-5/88, 127 observations). **CPI"** = unanticipated percentage change in the Consumer Price Index (11/77-5/88, 127 observations). **M1"** = unanticipated percentage change in the narrowly defined money stock (9/77-5/88, 557 observations). **DISC"** = unanticipated change in the Federal Reserve's discount rate (9/77-5/88, 38 observations). $\bar{R}^2$ = multiple correlation coefficient corrected for degrees of freedom. SE = standard error. DW = Durbin-Watson statistic. Estimation results are for specification (2). Standard errors of estimated coefficients are in parentheses, and they are corrected for heteroskedasticity by using White's (1980) procedure. Changes in yields are from 3:30 P.M. to 3:30 P.M. on adjacent business days. Changes in stock prices are from close to close on adjacent business days.

3.2 Response conditional on the state of the economy

We estimate the conditional responses to economic news, using the following specification:

$$\Delta P_t = a + H_t \cdot \mathbf{x}_t^u \mathbf{b}^H + M_t \cdot \mathbf{x}_t^u \mathbf{b}^M + L_t \cdot \mathbf{x}_t^u \mathbf{b}^L + \mathbf{d} + e_t, \qquad (3)$$

where $H_t = 1$ if economic activity is in the high state at time t, and zero otherwise; $M_t = 1$ if economic activity is in the medium state, and zero otherwise; and $L_t = 1$ if economic activity is in the low state, and zero otherwise. The other variables and coefficients are as defined in Equation (2), and the regression again includes only announcement days.

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Table 2
Response of stock prices to economic news in different states of the economy, September 1977-May 1988

Announce- ment	Estimation results			H_0: $\mathbf{b}^{\prime\prime} = \mathbf{b}^l$ for each variable	
	High	Medium	Low	$F(1, 903)$	p value
IP"	−0.844**	0.227	0.119	4.803**	.029
	(0.368)	(0.316)	(0.241)		[.054]
UNEM"	2.166*	0.558	−0.640	3.683*	.055
	(1.111)	(0.531)	(0.953)		
NFP"	−5.020	0.786	N.A.	N.A.	N.A.
	(3.352)	(1.540)			
MTD"	−0.631**	0.029	−0.073	2.577	.108
	(0.299)	(0.052)	(0.178)		
PPI"	−1.561**	−0.144	−0.333	3.371*	.067
	(0.560)	(0.403)	(0.375)		
CPI"	0.140	−0.775**	−0.242	0.071	.789
	(0.991)	(0.419)	(1.037)		
M1"	−0.424**	−0.279**	−0.412	0.001	.970
	(0.172)	(0.121)	(0.273)		
DISC"	0.549	−0.490	−0.486	0.890	.346
	(0.973)	(0.458)	(0.458)		

	Summary statistics		
	$\bar{R}^2$	SE	DW
	.039	0.986	2.07

	Joint tests		
Null hypothesis	$F(m, n)$	m, n	p value
$H1$: $\mathbf{b}^{\prime\prime} = \mathbf{b}^l$ for all announcements	2.002*	7, 903	.052
$H2$: $\mathbf{b}^{\prime\prime} = \mathbf{b}^l$ for IP" and UNEM"	4.332**	2, 903	.013
$H3$: $\mathbf{b}^{\prime\prime} = \mathbf{b}^l$ for PPI" and CPI"	1.717	2, 903	.180
$H4$: $\mathbf{b}^{\prime\prime} = \mathbf{b}^l$ for M1" and DISC"	0.446	2, 903	.640

$\mathbf{b}^{\prime\prime}$, $\mathbf{b}^l$ = estimated responses in Equation (3) in high and low states, respectively. $F(m, n)$ = F-statistic with (m, n) degrees of freedom. p value = probability of obtaining that value of the F-statistic or higher under the null hypothesis. Estimation results are for specification (3). "High," "medium," and "low" states of economic activity are calculated relative to trend industrial production, as described in Section 2.4. Standard errors of estimated coefficients are in parentheses. The number in brackets below the p value for H_0 for IP" is an estimated p value from 1000 bootstrap simulations. Standard errors and test statistics use White's (1980) heteroskedasticity consistent covariance matrix.

We report the results of Equation (3) in Table 2. In contrast to the previous tables, the S&P 500 Index now responds significantly to a variety of economic information when the response is made conditional on the state of the economy. In particular, the results suggest that good news about economic activity in the high state is bad news for the stock market. For a 1-percentage-point unanticipated increase in industrial production, stock prices decline by about 0.8 percent in the high state. Similarly, we estimate that an unanticipated decline in the unemployment rate of 1 percentage point causes stock prices to decline by about 2.2 percent in the high state. The point estimates

of the responses to these two announcements change signs in the low state, although these estimates are now not statistically significant. The response coefficients are nevertheless significantly different from the coefficients in the high state, as shown on the right-hand side of Table 2 *(H₀)*. These results imply that previous estimates obtained without any allowances for business cycle effects are biased toward zero, contributing to the insignificant responses estimated in earlier studies.

We estimate that unanticipated increases in both the merchandise trade deficit and the PPI have significant negative effects on stock prices in the high output state. Money announcement surprises affect stock prices in both high and medium states, but the sign of the response is the same across all three states. Finally, CPI announcements produce mixed results, with a positive coefficient in the high state. However, a test of the hypothesis that the coefficients on CPI and PPI surprises in the high state are the same has a *p* value of .138.

We test asymmetric stock-price responses for groups of economic announcements on the bottom of Table 2. In the first row, we test the hypothesis that all coefficients in the high and low economic states are the same $(\mathbf{b^H} = \mathbf{b^L})$. This hypothesis can be rejected at less than the 10 percent significance level. In the next three rows (H2-H4), we examine the effects of different types of economic information. The hypothesis that the stock market's responses to industrial production and unemployment rate surprises are the same across high and low states (H2) can be rejected at low significance levels. However, hypotheses that the stock market's response to other types of information-inflation (H3) and monetary (H4)-differs over high and low states cannot be rejected at the 10 percent significance level.

We also disaggregate the industrial production and unemployment rate surprises in Table 2 into positive and negative surprises in each of three states. In the high state, positive and negative industrial production surprises have estimated coefficients of -0.934 and -0.815, respectively. In the low state, the estimates are 0.131 and 0.125 for positive and negative surprises, respectively. We obtain similar results for unemployment rate surprises, except that positive unemployment rate surprises in the low state have a small positive coefficient insignificantly different from zero. The null hypothesis that positive and negative industrial production surprises have the same coefficients within high and low states (i.e., the specification estimated in Table 2) has a p value of .989. The same hypothesis for unemployment rate surprises has a *p* value of .263. These results suggest that the response to news within high and low states is symmetric. Stock prices fall in response to positive surprises about the economy in the high state.

When news about economic activity is weaker than expected, stock prices increase.

An alternative explanation of the results for the real activity variables, especially for industrial production, is that they are an artifact of selection bias. That is, since we form the economic states using ex post industrial production, future industrial production and, therefore, current stock prices are likely to fall in response to any news in the high state. If ex ante state definitions are available, selection bias would not be a cause for concern. In particular, under rational expectations, the announcement surprises have zero means and are orthogonal to all information available up to the day of the announcement, including the state of the economy. If the economy is in the high state, for example, the expected value of an announcement already includes information that industrial production growth is likely to fall in the future. The stock price immediately before the announcement also contains this information. So, stock-price movements are orthogonal to the state of the economy.

We examine selection bias several ways. First, as discussed in Section 4.1, we use both capacity utilization and the unemployment rate as alternatives to industrial production in defining economic states. To anticipate these results, the tests we report in Table 2 appear to be robust with respect to state definitions constructed from variables other than industrial production.

Second, we examine the relationship between industrial production surprises and the economic states. With ex ante state definitions, the expected values of the surprises in each state equal zero and the surprises are uncorrelated with the states under rational expectations. With the ex post state definitions used in Table 2, the means of the industrial production surprises in the high, medium, and low states are -0.037, -0.020, and 0.014 percent, respectively. All of the means are insignificantly different from zero at the 10 percent level. The correlation of the surprises with the variable used to define states in Figure 1 (i.e., the difference in the log of industrial production from its trend) is -.159, which is insignificantly different from zero at the 5 percent level but not at the 10 percent level. As a whole, these results do not suggest large specification biases.

Finally, we examine the effects of specification bias on the results for industrial production surprises in a simulation experiment. First, we estimate an equation, using the actual industrial production announcement days:

$$\Delta \mathrm{SP}_t = a + b \cdot \mathrm{IP}_t^u + e_t, \qquad (4)$$

where ASP, = percentage change in stock prices from business day t - 1 to business day *t*, and the other variables are as defined previously.

In this specification, the stock-price response to industrial production surprises is not state dependent. Next, we regress the difference between the log of actual industrial production in month t from its trend ($DIFF_t$) on the announcement surprise in month t:

$$DIFF_t = \begin{matrix} 0.000 \\ (0.004) \end{matrix} - \begin{matrix} 0.021^* \cdot IP_t^u + \epsilon_t, \\ (0.012) \end{matrix} \quad \bar{R}^2 = .018, \quad (5)$$

where standard errors are in parentheses. The size of DIFF, in Figure 1 determines whether we classify a month as being in the high, medium, or low state. Consequently, Equation (5) is intended to capture the correlation between industrial production surprises and the state definitions present in the ex post classification scheme. We then bootstrap the variables IP_t^u and ϵ_t and calculate new values for $DIFF_t$ using (5). We use the highest and lowest 25 percent of these values to classify high and low states, respectively. We calculate new values for the daily change in stock prices from (4), using bootstrapped values of e, and the previously bootstrapped values of IP_t^u. Our last step is to estimate Equation (4), using these bootstrapped data and allowing separate coefficients in the high, medium, and low states, analogous to (3), and then to test the null hypothesis that coefficients in the high and low states are the same $(\mathbf{b^H = b^L})$. Repeating the above experiment 1000 times yields 54 cases in which the F- statistic is higher than that using historical data, implying a simulated p value of .054. While this is higher than the p value of .029 we report in Table 2, it does not suggest that the reported test results are a consequence of specification bias.

3.3 Discount rates or expected cash flows?

We examine several variables related to equity discount rates and expected cash flows to determine the source of the varying stock-price response reported above. Our proxies for discount rates are the lo-year Treasury-bond yield, the three-month Treasury-bill yield, the term spread, and the default spread. We use the growth rate of industrial production as a proxy for expected cash flows [e.g., Fama and French (1989) and Fama (1990)]. We discuss results using alternative cash flow proxies in Section 4.2.

We report test results for the discount rate proxies in Table 3. To perform these tests, we estimate Equation (3) for announcement days for each of the four proxies. We then conduct the same tests as those reported in Table 2 for each of the four dependent variables. In contrast to the results for stock prices, the hypothesis that the response is the same across high and low economic states cannot be rejected for any of the proxies except for the term spread's response to trade deficit announcements. Consequently, the variation in the response

Table 3
Tests for asymmetric responses of discount rate proxies to news different states of the economy, September 1977-May 1988

H_a: $\mathbf{b}'' = \mathbf{b}^t$ for each variable

Announcement	10-year Treasury-bond		Three-month Treasury-bill		Term spread		Default spread	
	$F(1, 903)$	p value	$F(1, 903)$	p value	$F(1, 903)$	p value	$F(1, 903)$	p value
IP"	1.735	.188	0.911	.340	0.967	.381	0.937	.333
UNEM"	0.261	.610	0.045	.833	0.426	.514	1.655	.199
MTD"	0.360	.549	2.509	.114	4.339**	.037	1.260	.262
PPI"	2.365	.124	1.299	.255	0.484	.487	0.033	.855
CPI"	0.064	.799	0.002	.965	0.160	.689	0.592	.442
M1"	0.866	.352	1.882	.170	0.502	.479	0.445	.505
DISC"	0.886	.347	0.027	.870	0.451	.502	2.229	.136

			Summary statistics					
$\bar{R}^2$	SE	DW	$\bar{R}^2$	SE	DW	$\bar{R}^2$	SE	DW	$\bar{R}^2$	SE	DW
.085	12.088	2.02	.137	19.791	1.89	.105	17.930	1.96	.008	5.640	2.00

Joint tests

Hypothesis	10-year Treasury-bond			Three-month Treasury-bill			Term spread			Default spread		
	$F(m, n)$	m, n	p value	$F(m, n)$	m, n	p value	$F(m, n)$	m, n	p value	$F(m, n)$	m, n	p value
H1	0.735	7, 903	.642	0.995	7, 903	.433	1.161	7, 903	.322	1.060	7, 903	.387
H2	1.001	2, 903	.365	0.482	2, 903	.617	0.598	2, 903	.550	1.294	2, 903	.275
H3	1.218	2, 903	.296	0.651	2, 903	.522	0.323	2, 903	.724	0.314	2, 903	.731
H4	0.888	2, 903	.412	0.952	2, 903	.386	0.481	2, 903	.618	1.403	2, 903	.246

H1 is $\mathbf{b}'' = \mathbf{b}^t$ for all announcements. *H2* is $\mathbf{b}'' = \mathbf{b}^t$ for IP" and UNEM". *H3* is $\mathbf{b}'' = \mathbf{b}^t$ for PPI" and CPI". *H4* is $\mathbf{b}'' = \mathbf{b}'$ for M1" and DISC". Test results are for specification (3). "High," "medium," and "low" states of economic activity are calculated relative to trend industrial production, as described in Section 2.4. Test statistics use White's (1980) heteroskedasticiry-consistent covariance matrix. Nonfarm payroll employment is excluded in the tests, but not in the estimation, because it lacks observations in the low state.

of stock prices to economic news does not appear to be due to the asymmetric response of the equity discount rate proxies.

To consider the role expected cash flows play in the stock market's response, we estimate autoregressive models of announced and expected industrial production growth." We use autoregressive models to account for the autocorrelation of industrial production growth. We include twice-lagged industrial production, IP^a_{t-2}, because we examine announcement effects for month $t - 1$, including IP^u_{t-1} which is correlated with IP^a_{t-1}. Finally, we allow the effect of lagged industrial production to vary over different economic states because of the observed asymmetric behavior of real activity over the business cycle [e.g., Hamilton (1989)]. The specific model is

$$\text{IP}_t^i = a^H \cdot H_t + a^M \cdot M_t + a^L \cdot L_t + c^H \cdot H_t \cdot \text{IP}_{t-2}^a + c^M \cdot M_t \cdot \text{IP}_{t-2}^a$$
$$+ c^L \cdot L_t \cdot \text{IP}_{t-2}^a + H_t \cdot \mathbf{x}_{t-1}^u \mathbf{b}^H + M_t \cdot \mathbf{x}_{t-1}^u \mathbf{b}^M$$
$$+ L_t \cdot \mathbf{x}_{t-1}^u \mathbf{b}^L + \epsilon_t, \quad (i = a, e), \tag{6}$$

where

$$\text{IP}_t^i = \text{announced growth rate in industrial}$$
$$\text{production } (\text{IP}_t^a) \text{ or expected industrial}$$
$$\text{production } (\text{IP}_t^e) \text{ in month } t$$
$$a^j, \mathbf{b}^j, c^j (j = H, M, L) = \text{estimated coefficients}$$
$$\epsilon_t = \text{random error term}$$

The other variables are as previously defined. The vector $\mathbf{x}_{t-1}^u$ includes the previous month's industrial production surprise(IP_{t-1}^u) as well as the unanticipated components of the other variables closest to the date of this surprise. Because money announcements are weekly, money surprises four and five weeks prior to IP_t^a($\text{M1}_{t-1,4}^u$ and $\text{M1}_{t-1,5}^u$) are included in $\mathbf{x}_{t-1}^u$.

We summarize test results of Equation (6) for announced and expected industrial production in Table 4. We test hypotheses analogous to those in Tables 2 and 3. The hypothesis that the information content of economic announcements in month t - 1 in predicting industrial production in month t is the same across high and low economic states (H1) can be rejected at extremely low significance levels. The tests indicate that the real economic activity variables are responsible for this rejection. This pattern is the same as that exhibited by the response of stock prices in Table 2. Although not reported in the table, the estimated coefficients also are consistent with the stock-price response. For unanticipated industrial production in month t - 1 in the IP: specification, for example, the estimated coefficients in the high and low states are -0.444 and 0.712, respectively, with t-statistics greater than 2 in absolute value. Consequently, the evidence suggests that stock prices respond differently to economic activity news across economic states because expected cash flows respond differently.

We also disaggregate industrial production and unemployment rate surprises into positive and negative surprises in Equation (6). For announced industrial production (IP_t^a), for example, positive and negative industrial production surprises have estimated coefficients of -0.541 and -0.398 in the high state. In the low state, the estimated coefficients are 1.286 and 1.198 for positive and negative surprises, respectively. The null hypothesis that these coefficients are the same within states has a p value of .98. Consequently, the results suggest that forecasts of future industrial production do not fall (rise) in response to all industrial production news in the high (low) state.

Table 4
Tests of the asymmetric relation of future industrial production to economic news across different states of the economy, January 1978-May 1988, 125 observation.

H_o: $\mathbf{b}'' = \mathbf{b}^t$ for each variable

Announcement	IP^a		IP^c	
	$F(1, 95)$	p value	$F(1, 95)$	p value
IP$''_{t-1}$	11.097**	.001	5.915**	.017
		[.098]		
UNEM$''_{t-1}$	12.375**	.001	6.139**	.015
MTD$''_{t-1}$	0.033	.856	0.019	.891
PPI$''_{t-1}$	2.235	.138	0.609	.437
CPI$''_{t-1}$	0.146	.703	0.547	.461
M1$''_{t-1}$	0.012	.914	0.055	.815
M1$''_{t-15}$	1.628	.205	0.537	.466

			Summary statistics			
$\bar{R}^2$	SE	DW	$\bar{R}^2$	SE	DW
.390	0.669	1.69	.468	0.476	1.32

	Joint tests					
	IP^a_t			IP^c_t		
Null hypothesis	$F(m, n)$	m, n	p value	$F(m, n)$	m, n	p value
H1: $\mathbf{b}'' = \mathbf{b}^t$ for all announcements	7.244**	7, 95	.000	3.233**	7, 95	.004
H2: $\mathbf{b}'' = \mathbf{b}^t$ for IP$''_{t-1}$ and UNEM$''_{t-1}$	15.012**	2, 95	.000	7.025**	2, 95	.001
H3: $\mathbf{b}'' = \mathbf{b}^t$ for PPI$''_{t-1}$ and CPI$''_{t-1}$	1.428	2, 95	.245	0.504	2, 95	.606
H4: $\mathbf{b}'' = \mathbf{b}^t$ for M1$''_{t-1}$ and M1$''_{t-15}$	1.151	2, 95	.321	0.305	2, 95	.737

IP$''_t$ = announced change in industrial production in month t. IP^c_t = expected change in industrial production in month t from MMS survey data. Test results are for specification (6). "High," "medium," and "low" states of economic activity are calculated relative to trend industrial production. The number in brackets below the p value for IP$''_{t-1}$ is an estimated p value from 1000 bootstrap simulations. Test statistics use White's (1980) heteroskedasticity consistent covariance matrix. Nonfarm payroll employment is excluded in the tests, but not in the estimation, because it lacks observations in the low state.

The specification bias issue again arises with the Table 4 results, especially since the dependent variable is industrial production growth. To examine this issue, we follow procedures similar to those discussed in Section 3.2. First, we use both capacity utilization and the unemployment rate as alternatives to industrial production in defining economic states. As discussed further in Section 4.1, hypothesis *H2* in Table 4 can again be rejected at less than the 1 percent level in each case for both announced (IP^a_t) and expected (IP^c_t) industrial production.

Second, we examine the effects of specification bias in another simulation experiment. We bootstrap industrial production surprises IP$''_t$ along with ϵ_t to form values of DIFF, in Equation (5). Again, this equation is intended to capture the empirical relationship between industrial production surprises and the state definitions. Next, we use values of DIFF, to classify economic states, as before. Then we esti-

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mate a version of Equation (6) including industrial production surprises and lagged industrial production, analogous to Equation (4). We form both the dependent and lagged dependent variables in this specification from the simulated values of $DIFF_t$. That is, the first difference of $DIFF_t$ plus the trend in the log of industrial production equals industrial production growth during period t. Our final step is to test the hypothesis that coefficients on industrial production surprises are the same in high and low states $(\mathbf{b}^H = \mathbf{b}^L)$. Repeating the above experiment 1000 times yields 98 times in which the F-statistic is higher than that using historical data, implying a simulated p value of .098. As before, the simulated p value is about twice as large as that using historical data (.047). In this case, however, the p value of .047 is substantially above the p value of .001 that we report in the first row of Table 4. If instead we double the p values in Table 4, we would still reject the hypothesis of equal coefficients on real activity variables at low significance levels. In any event, specification bias does not appear to have a significant influence on the reported results.

4. Sensitivity Analysis

4.1 Economic states
We examine alternative approaches to defining economic states to determine the robustness of the significant state-dependent stock price and expected cash flow responses to real activity news. The test results prove to be insensitive to the width of the bounds around trend industrial production used to define the states. When we form the bounds by adding and subtracting 0.040 (12 percent high states) or 0.024 (30 percent high states), the p values for hypothesis H2 in Table 2 are .06 and .11, respectively. Other bounds formed by adding and subtracting 0.026, 0.030, 0.032, and 0.036 all lead to *p* values less than .05.

We also use two alternative series to classify economic states: capacity utilization and the unemployment rate. As with industrial production, we form the bounds such that no more than 50 percent of the observations are in the high and low states.[12] For capacity utilization, all observations from 1977 to early 1980 are placed in the high state. As a whole, 15 of the 129 months have different classifications, including 10 differences for the high state. For the unemployment rate, the low state in the early 1980s both starts and ends somewhat

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[12] We do not construct the bounds for the unemployment rate symmetrically. Instead, the deviations from the trend unemployment rate (defined as the sample mean of the unemployment rate) are +0.3 and - 1.3 percentage points. This classification puts 23.3 percent of the observations in the high state and 26.4 percent in the low state. Symmetric bounds of $\pm$ 0.3 imply that 45.7 percent of the observations are in the high state with 26.4 percent in the low state.

Table 5
Tests of the asymmetric relation of alternative cash-flow proxies to industrial production and unemployment rate news across different states of the economy

	$H2$: $\mathbf{b}'' = \mathbf{b}'$ for industrial production and unemployment rate surprises							
	IP$_r''$		IP$_r'$		Cash flow		Corporate profits	
State variable	$F(2, 95)$	p value	$F(2, 95)$	p value	$F(4, 24)$	p value	$F(4, 24)$	p value
Industrial production	15.012**	.000	7.025**	.001	25.306**	.000	438.53**	.000
Capacity utilization	13.354**	.000	6.608**	.002	10.413**	.000	12.624**	.000
Unemployment rate	19.624**	.000	10.141**	.000	8.034**	.000	7.382**	.001

Cash Row - real net cash flow from the National Income and Product Accounts (NIPA) plus real dividends, 11978:Q1 -1988:Q2. Corporate profits = real corporate profits (NIPA). 1978:Q1-1988:Q2. Test results for IP$_r''$ and IP$_r'$ are from the specification (6). Test results for cash flow and corporate profits are from specification (7). Industrial production states are defined using trend industrial production plus and minus 0.28, as before. Capacity utilization states are defined using mean capacity utilization plus and minus 1.5. Unemployment rate states are defined using the mean unemployment rate plus 0.3 and minus 1.3. Test statistics use White's (1980) heteroskedasticity-consistent covariance matrix.

later in comparison to the base case using industrial production. In this case, 19 months have different classifications, including six differences for the high state. When we use average capacity utilization and unemployment to form economic states, somewhat weaker rejections of the real activity hypothesis (H2) for stock prices result (*p* values of .070 and .117, respectively, in Table 2).[13] As shown in the first two columns of Table 5, hypothesis *H2* for the industrial production cash flow proxy is rejected at very low significance levels when we use capacity utilization and the unemployment rate to classify economic states.

Finally, following Garbade (1977), we use variable parameter regression (VPR) as an alternative way to estimate the pattern of temporal variation in the response coefficients. We use this technique for industrial production and the unemployment rate separately in stock market regressions. In both cases, we estimate that the parameter allowing temporal variation *(P)* is equal to zero to four decimal points using an iterative grid search. For $P = 0$, the VPR model collapses to OLS. The VPR model, however, smoothes coefficient estimates and is not capable of estimating discrete shifts.

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[13] Trend industrial production and average capacity utilization might be expected to perform better than the average unemployment rate in creating the states since the natural rate of unemployment may have changed over the sample period and the unemployment rate changes from a leading to a lagging economic indicator over the business cycle according to the Bureau of Economic Analysis. In addition to the economic state sensitivity, we consider NBER business cycle turning points (illustrated in Figure 1), but the level of economic activity appears to be more importantempirically than the direction (i.e.. expansion or recession).

4.2 Cash flow proxies

We examine alternative cash flow proxies by using two quarterly data series. The first is real net cash flow (which excludes dividends) from the National Income and Product Accounts (NIPA) plus real dividends. The second is real corporate profits, also from NIPA. We use quarterly percentage changes for both variables.

Because these alternative cash flow proxies are measured quarterly, we are required to make some modifications to the procedures used in Table 4. First, we place a calendar quarter in the high or low state if two or more months in the quarter are in these states. Second, to preserve degrees of freedom in the quarterly regressions, we only consider industrial production and unemployment rate surprises. We also only include surprises during the first two months of the quarter ($\mathbf{x}_{t,1}^u$ and $\mathbf{x}_{t,2}^u$), because when we include the third month $\mathbf{x}_{t,3}^u$) the independent variable matrix is nearly singular. In any event, by the third month of the quarter, most of the quarter's cash flow has already been determined. The specific equation can be represented as

$$
\begin{aligned}
\mathrm{CF}_t = {} & a^H \cdot H_t + a^M \cdot M_t + a^L \cdot L_t + c^H \cdot H_t \cdot \mathrm{CF}_{t-1} + c^M \cdot M_t \cdot \mathrm{CF}_{t-1} \\
& + c^L \cdot L_t \cdot \mathrm{CF}_{t-1} + H_t \cdot \mathbf{x}_{t,1}^u \cdot \mathbf{b}_1^H + M_t \cdot \mathbf{x}_{t,1}^u \cdot \mathbf{b}_1^M + L_t \cdot \mathbf{x}_{t,1}^u \cdot \mathbf{b}_1^L \\
& + H_t \cdot \mathbf{x}_{t,2}^u \cdot \mathbf{b}_2^H + M_t \cdot \mathbf{x}_{t,2}^u \cdot \mathbf{b}_2^M + L_t \cdot \mathbf{x}_{t,2}^u \cdot \mathbf{b}_2^L + \epsilon_t,
\end{aligned}
\tag{7}
$$

where

$\mathrm{CF}_t =$ quarterly cash flow or corporate profits

$\mathbf{x}_{t,i}^u = (\mathrm{IP}_{t,i}^u,\ \mathrm{UNEM}_{t,i}^u),\ i = 1,\ 2$

$\mathbf{b}_1, \mathbf{b}_2 =$ estimated coefficients on announcement surprises in the first and second months in the quarter, respectively

and the other variables are as defined in Equation (6). We report test results for the hypothesis analogous to *H2* in Table 4 for the quarterly cash flow proxies $(H2:\ \mathbf{b}_1^H = \mathbf{b}_1^L$ and $\mathbf{b}_2^H = \mathbf{b}_2^L)$, with economic states defined for either industrial production, capacity utilization, or the unemployment rate, in the last two columns of Table 5. The results indicate that the hypothesis that news about real economic activity has the same effect on expected cash flows in high and low states can be rejected at extremely low significance levels. The coefficient patterns are also consistent with the stock-price response across economic states with one exception. In particular, for unemployment rate surprises in the first month of the quarter, we estimate significant positive responses in four of the six regressions.

4.3 Expectations proxies and sample period

When we use time-series models, instead of survey data, to measure the expected change in the economic announcements, hypothesis

H2 in Table 2 can be rejected at only the 36 percent significance level. The survey data, however, are more efficient than time-series models.[14] The survey data incorporate all information that the respondents deem important in forecasting the announcement, not just prior months' information about the series. For example, the root-mean-square error from an ARIMA model of industrial production is more than 80 percent greater than the root-mean-square error from the survey data.

We perform several additional tests to examine the robustness of results with respect to the sample period. First, results for a shorter sample period excluding the most recent high state from October 1987 through May 1988 are very similar to those in Table 2. The main difference is that the *t*- statistic on the stock market's response to unemployment rate surprises in the high state drops to 1.50. The hypothesis that the stock market's response to unemployment rate surprises in high and low states is the same can still be rejected at the 5 percent level.

Second, we consider an extension of the sample back to January 1970. Because of the lack of survey data, we use ARIMA models to generate expectations. The longer sample gives inconclusive test results. Although the high and low coefficients for industrial production and unemployment surprises are consistent with the good news/bad news story, the coefficients for nonfarm payroll are not. Moreover, hypothesis *H2* cannot be rejected at conventional significance levels. The failure of the extended sample to reject constant real activity coefficients may, however, be due to the ARIMA models used to estimate expectations.

Finally, following Cutler, Poterba, and Summers (1989), we measure economic news as the residuals from a vector autoregression (VAR), using monthly data from traditional sources. That is, to extend the sample back to 1947, we use nonannouncement data for six of the variables.[15] We then regress monthly stock returns on residuals from 3-, 6-, and 12-lag VARs across economic states formed by using trend industrial production.[16] The results indicate that hypothesis *H2* can be rejected at the 10 percent level by using residuals lagged one

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[14] In specifying the rime-series models, we add recent announced values of the other economic variables to the ARIMA models if they improve an equation's predictive ability. Tests using the unadjusted survey data are similar to those repotted in the tables.

[15] Similar to Table 4, we exclude changes in the Federal Reserve's discount rate in the VAR specification. Also, we exclude the merchandise trade deficit because a consistent monthly series from 1947 is not available.

[16] For this longer sample period. a linear time trend does not seem to adequately capture trend industrial production. Consequently, we include t, t^2, and t^3. To form high and low economic states, we add ± 0.041 to the trend. which results in 50 percent of the observations being classified in the medium state.

month from 3- and 12-lag VAR models, but that it cannot be rejected by using a 6-lag VAR.[17] In all cases, however, the estimated coefficients on industrial production and unemployment rate surprises are consistent with the good news/bad news hypothesis. When we regress monthly stock returns on both current and one-month lagged residuals, hypothesis *H2* can be rejected at less than the 7 percent level for all VAR lag lengths. In these regressions, however, the pattern of the response coefficients across economic states for the current month's unemployment rate surprise is inconsistent with the good news/bad news story. When we change the band around trend industrial production to allow less than half of the observations to fall in the medium state, hypothesis *H2* is rejected at lower significance levels. In contrast, when we widen the band, *p* values for this test increase. As a whole, the monthly stock-return evidence using VARs offers some support for the Table 2 results despite the use of empirical expectations proxies and one-month event windows.

5. Summary and Conclusions

Previous research finds that fundamental macroeconomic news has little effect on stock prices. In this study, we provide evidence that the stock market's response to macroeconomic news depends on the state of the economy. In particular, news of higher-than-expected real activity when the economy is already strong results in lower stock prices, whereas the same surprise in a weak economy is associated with higher stock prices. This result helps to explain the insignificance of macroeconomic news, apart from monetary information, in previous announcement studies.

The source of the varying response of stock prices across economic states appears to be expected cash flows. The responses of equity discount rate proxies to new economic information are not significantly different across economic states. In contrast, unanticipated increases in economic activity in a weak economy raise expectations about future economic activity and cash flows. This same information in a strong economy does not lead to higher expected cash flows.

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[17]We lag residuals one month 10 make them comparable to the announcement surprises considered in previous sections. Orphanides (1990) follows a similar procedure in his reexamination of the Cutler, Poterba, and Summers (1989) results. Moreover, he also rejects the *constant-response* hypothesis in a specification. allowing responses to economic news to depend on known values of economic variables.

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