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Delayed Reaction to Good News and the Cross-Autocorrelation of Portfolio Returns

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ABSTRACT

We document a directional asymmetry in the small stock concurrent and lagged response to large stock movements. When returns on large stocks are negative, the concurrent beta for small stocks is high, but the lagged beta is insignificant. When returns on large stocks are positive, small stocks have small concurrent betas and very significant lagged betas. That is, the cross-autocorrelation puzzle documented by Lo and MacKinlay (1990a) is associated with a slow response by some small stocks to good, but not to bad, common news. Time series portfolio tests and cross-sectional tests of the delay for individual securities suggest that existing explanations of the cross-autocorrelation puzzle based on data mismeasurement, minor market imperfections, or time-varying risk premiums fail to capture the directional asymmetry in the data.

IN AN ARTICLE ANALYZING the source of contrarian profits, Lo and MacKinlay (1990a) point out that the return on a portfolio of small stocks is correlated with the lagged return on a portfolio of large stocks. Lo and MacKinlay also point out a size asymmetry, noting that the return on a portfolio of large stocks is not correlated with the lagged return on small stocks.[1] Boudoukh, Richardson, and Whitelaw (1994, hereafter BRW), among others, show that this cross-autocorrelation between large and small stock portfolio returns can also be characterized by the autocorrelation of the small stock portfolio. However, Lo and MacKinlay (1990a and 1990b) argue that such autocorrelation cannot be explained by appeals to traditional nontrading arguments. Thus, a search for new, more viable, explanations of why small stock returns can be predicted by past larger stock returns has begun.

BRW categorize extant explanations into three camps: "Loyalists," "Revisionists," and "Heretics." Loyalists defend the efficiency of stock markets by pointing to data mismeasurement or to market imperfections as the sources of the predictability. Revisionists attribute the predictability of small stock returns to time-varying risk premiums. Finally, Heretics attribute the predictability to market fads, bubbles, or overreaction. Each explanation is typically

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[1] Conrad, Gultekin, and Kaul (1991) report a size asymmetry in conditional variances. Volatility surprises to large market value firms impact the behavior of the mean and variance of small firms, but shocks to smaller firms do not impact the return behavior of large firms.

supported by some, but not all, empirical characteristics of the data. For example, Mech's (1993) transaction cost explanation (Loyalist) is consistent with his finding that, cross-sectionally, stocks with higher bid-ask spreads exhibit more predictability than stocks with lower bid-ask spreads; however, Mech's time series findings are not consistent with this explanation.

This article extends prior work in two directions. First, it poses a new challenge to those seeking to explain the cross-autocorrelation between large and small stock returns by documenting a new empirical characteristic of the data: *directional asymmetry*. Specifically, we show that the cross-autocorrelation is asymmetric in up and down markets. When we condition on months when the stock market falls, we find a high concurrent beta for the small stock portfolio and no significant lagged beta. When we condition on months when the stock market rises, we find a smaller concurrent beta and a significantly positive lagged beta. Thus, the small stock betas on both the current and lagged market proxy return exhibit directional asymmetry. This evidence, combined with additional tests, suggests that all stocks, large and small, react quickly to negative macroeconomic news, but that some small stocks adjust to positive news about the economy with a delay. The lagged response to good news, but not bad, is evident in *monthly* as well as *weekly* return tests.

Our finding of cross-autocorrelation directional asymmetry is inconsistent with the Revisionist and Loyalist explanations that assume symmetric responses to good and bad news. Our finding is more consistent with the Heretic views such as Sias and Starks (1994), who find that herding behavior by institutional investors is related to the delay. Our finding sheds further light on such explanations by showing that institutional behavior, for example, leads to long delays in small stock returns only when the macroeconomic news is good. The current and lagged asymmetries we document from monthly and weekly returns is consistent with the Lamoureux and Panikkath (1994) finding using *daily* returns that "the cross-sectional dispersion of daily returns is . . . asymmetric between large up and down moves in the market," and with Chang, Pinegar, and Ravichandran's (1994) finding that an asymmetric response to macroeconomic news helps explain day-of-the-week effects. Our findings are also consistent with those of Grinblatt, Titman, and Wermers (1995, hereafter GTW) and Keim and Madhavan (1995) who find asymmetric trading patterns by institutional investors. These findings, together with ours, suggest a need for asset pricing models and models of trading that allow for different behavior and parameters in up and down markets.

Our second extension is to provide tests on the various hypothesized explanations of the cross-autocorrelation puzzle. These tests use both the time series of portfolio returns and cross-sectional returns on individual stocks. Mech (1993) develops a measure of delay and finds cross-sectional evidence inconsistent with the Revisionist explanations of time-varying risk premiums and the Loyalist explanations of nontrading, stale limit orders, and market-maker inventory policy. His cross-sectional tests, however, support a new transaction costs (Loyalist) explanation. This paper extends Mech's cross-sectional work by 1) improving his measure of delay; 2) providing additional evidence against time-varying risk premiums; 3) providing further evidence that nontrading explains, at best, only a small portion of the puzzle; and 4) showing that the cross-sectional evidence is not consistent with the predictions of the transaction cost explanation. Moreover, in contrast to Badrinath, Kale, and Noe, (1995, hereafter BKN), our cross-sectional tests suggest that the delay in small stock responses to large stock movements does not decrease with the fraction of outstanding shares held by institutions. If anything, the "informationally favored" stocks are actually more susceptible to delay than the "informationally unfavored" stocks. This finding is consistent with those reported by Sias and Starks (1994) for one-day cross-autocorrelations and suggests momentum trading akin to that documented by GTW (1995). Again, however, our finding of directional asymmetry implies a tendency to buy "past winners" but not to sell "past losers."

The remainder of the article is organized as follows. In Section I, the data are described, the previously reported cross-autocorrelation size asymmetry between portfolios of large and small stocks is confirmed, our new directional asymmetry is documented, and a sensitivity analysis is performed. In Section II, the existing explanations for the cross-autocorrelation between the size portfolios are reexamined in light of our new empirical finding. In Section III, a new measure of delay is developed and used in cross-sectional regressions to assess the stock characteristics associated with the delay. In Section IV, concluding remarks are given.

I. Cross-Autocorrelation Asymmetry

A. Data

We illustrate directional asymmetry using a base case consisting of monthly nominal returns from January 1963 to December 1994 for five portfolios, sorted by size, of common stocks traded on the New York Stock Exchange (NYSE). Portfolio 1 contains the quintile of smallest common stocks and Portfolio 5 the largest, with the portfolio assignments based on the prior year-end market capitalization. Within each portfolio, the stocks are equally weighted. The sensitivity analysis shows that the results of this base case are generally robust to changes, such as using Nasdaq stocks, alternative time periods, or weekly returns. Table I reports summary statistics for the size-based quintile portfolios.

The characteristics for the quintile portfolios reported in Table I are well known. The smaller stock portfolios exhibit progressively higher mean returns, standard deviations, and first-order autocorrelation. This autocorrelation is another manifestation of the cross-autocorrelation reported by Lo and MacKinlay (1990a). Unlike the three smallest portfolios, the autocorrelations and the Ljung-Box portmanteau test, Q(3), are not significantly different from zero for Portfolio 5. Thus, the large stock portfolio can be used as a proxy for macroeconomic news, since all of the stocks in the portfolio respond to news in the same month.

Table I

Quintile Portfolio Monthly Return Summary Statistics (January 1963 to December 1994)

Statistics are for monthly continuously compounded equally-weighted returns on firm size quintile portfolios (1 = smallest size portfolio) of all New York Stock Exchange (NYSE) common shares. Portfolio assignments are based on prior year-end market capitalization. ρ_t is the sample autocorrelation coefficient at lag t and $S(\rho)$ is the asymptotic standard error of the autocorrelations. Q(3) is the Ljung-Box portmanteau test statistic for 3 autocorrelations, distributed χ^2 with 3 degrees of freedom, and p-value is the marginal significance level of the Ljung-Box test. ρ_1^{UP} is the first-order autocorrelation coefficient conditional on a positive return in the prior month and ρ_1^{DN} is the first-order autocorrelation coefficient conditional on a negative return in the prior month.

	Portfolio Quintile				
Statistic	1	2	3	4	5
Mean	0.013	0.011	0.010	0.010	0.008
Standard deviation	0.067	0.057	0.053	0.050	0.045
ρ_1	0.189	0.160	0.155	0.107	0.043
ρ_2	−0.018	−0.041	−0.047	−0.048	−0.050
ρ_3	−0.070	−0.042	−0.042	−0.028	−0.023
$S(\rho)$	0.053	0.052	0.052	0.052	0.051
Q(3)	15.9	11.2	10.8	5.6	1.9
p-value	0.001	0.010	0.013	0.131	0.595
ρ_1^{UP}	0.203	0.171	0.158	0.109	0.024
ρ_1^{DN}	0.091	0.091	0.099	0.068	0.050

Table I also reports the first-order autocorrelation after including a binary variable to allow the coefficient to take on different values when the prior month's return is positive, ρ_1^{UP}, or negative, ρ_1^{DN}. For quintile 1, the autocorrelation conditional on an up market, 0.203, is over twice the size of the coefficient conditional on a down market, 0.091. The conditional and unconditional first-order autocorrelation coefficients yield two insights into the previously documented tendency of small stocks to react slowly to news. First, the slowness is more severe than previously thought as it is evident in *monthly* as well as weekly returns. Second, the slowness is directionally asymmetric—driven primarily by a slow response to good news.

B. Asymmetric Betas

Panel A of Table II documents the cross-autocorrelation discovered by Lo and MacKinlay (1990a) using the following specification:

$$r_{1,t} = \alpha + \beta_0 r_{5,t} + \beta_1 r_{5,t-1} + \epsilon_t$$

$$\epsilon_t \sim N(0, h_t),\ h_t = \gamma_0 + \gamma_1 \epsilon_{t-1}^2. \qquad (1)$$

The small stock portfolio monthly return, $r_{1,t}$, is regressed on the concurrent, $r_{5,t}$, and lagged, $r_{5,t-1}$, large stock portfolio returns. The regression allows for autoregressive conditional heteroskedasticity (ARCH). The cross-autocorrela-

Table II

Symmetric and Asymmetric ARCH Regression of Small Stock Portfolio Monthly Returns on Contemporaneous and Lagged Large Stock Portfolio Returns (January 1963 to December 1994)

t-statistics are in parentheses. $r_{1,t}$ and $r_{5,t}$ are the continuously compounded monthly small-cap and large-cap New York Stock Exchange (NYSE) quintile portfolio returns at time t, respectively. The Panel B regression adds binary variables to allow for differing behavior in up (positive) and down (negative) large-cap portfolio returns in months t and $t-1$, and the corresponding coefficients are labeled with superscripts UP and DN. χ_1^2 is the chi-squared test statistic with one degree of freedom, and p-value is the probability of obtaining that value of the χ^2 statistic or higher under the null hypothesis.

Specification:
$$r_{1,t} = \alpha + \beta_0\, r_{5,t} + \beta_1\, r_{5,t-1} + \epsilon_t$$
$$\epsilon_t \sim N(0, h_t),\; h_t = \gamma_0 + \gamma_1 \epsilon_{t-1}^2$$

Panel A: Symmetric Betas

α	β_0	β_1	$\gamma_0 \times 100$	γ_1
−0.001	1.160	0.291	0.111	0.381
(0.3)	(28.7)	(6.5)	(9.9)	(3.8)

Panel B: Asymmetric Betas

α	β_0^{UP}	β_0^{DN}	β_1^{UP}	β_1^{DN}	$\gamma_0 \times 100$	γ_1
0.000	0.954	1.413	0.418	−0.079	0.086	0.593
(0.1)	(14.2)	(20.4)	(6.1)	(1.1)	(9.0)	(4.9)

Panel C: Test Statistics

H_0:	$\beta_0^{UP} = \beta_0^{DN}$ $\chi_1^2 = 15.9$ p-value = 0.000
H_1:	$\beta_1^{UP} = \beta_1^{DN}$ $\chi_1^2 = 18.1$ p-value = 0.000

tion puzzle is evidenced by the Panel A β_1 coefficient of 0.291, which is significantly different from zero (t-statistic of 6.5).

Panel B of Table II reexamines the regression in Panel A after including binary variables to allow the parameters to differ when the market is up ($r_5 > 0$) or down ($r_5 < 0$). The directional asymmetry manifests itself in differences in β_1 across up and down markets. When the market is up, $\beta_1^{UP} = 0.418$; when the market is down, $\beta_1^{DN} = -0.079$. Hypothesis 1 (H_1) states that $\beta_1^{UP} = \beta_1^{DN}$. However, H_1 is rejected with a p-value less than 0.0005. Thus, the monthly cross-autocorrelation is completely driven by a delayed response in some small stocks to *good*, but not to bad, macroeconomic news. In fact, in down markets the monthly delayed beta, β_1^{DN}, is negative, although the point estimate is not significantly different from zero.[2]

The focus of our article is primarily on the lagged betas; however, the asymmetry in concurrent betas also deserves notice. Conditional on good macroeconomic news, the small stock portfolio has a concurrent calculated beta of only 0.954. However, the down-market beta is 1.413. The comparatively low up-market beta is contrary to the conventional wisdom that small stocks typically have greater than average exposure to systematic risk.[3] Hypothesis 0, H_0, states that $\beta_0^{\mathrm{UP}} = \beta_0^{\mathrm{DN}}$, and is rejected at the 0.001 level. Thus, the *concurrent*, as well as the *lagged*, beta is directionally asymmetric. However, the asymmetry is offsetting. The concurrent small stock up-market beta is "too low," whereas the lagged small stock up-market beta is "too high." When we allow for a concurrent and a one-month delayed response to good news by summing β_0^{UP} and β_1^{UP}, the up-market small stock beta increases to a traditionally more reasonable estimate of 1.372 (0.954 + 0.418). Interestingly, this estimate is very close to the sum of the concurrent and lagged betas in down markets of 1.334 (1.413–0.079). This finding indicates that monthly betas calculated using only the current month's market return may result in betas that are "too low" for the typical small stock in the 1st quintile and suggests that the apparent small stock excess return anomaly may be partially caused by a mismeasurement of small stock betas. Thus, an adjustment, in the spirit of Scholes and Williams' (1977), may be needed for betas calculated with monthly returns. Examples of such adjustments include Dimson (1979), Fama and French (1992), Peterson and Sanger (1994), and Vijh (1994). Our results, however, suggest that even these beta adjustments could be improved by conditioning on up or down markets.

One interesting consequence of allowing for separate up- and down-market concurrent and lagged betas can be illustrated by considering the well-known turn-of-the-year effect (See Rozeff and Kinney (1976) and Keim (1983)). To allow for January and December differences due to this effect, we estimate the following extended version of equation (1) with binary variables JAN and DEC:

$$r_{1,t} = \alpha + \beta_0 r_{5,t} + \beta_1 r_{5,t-1} + \mathrm{JAN}(\alpha^J + \beta_0^J r_{5,t} + \beta_1^J r_{5,t-1}) + \mathrm{DEC}\ (\alpha^D + \beta_0^D r_{5,t} + \beta_1^D r_{5,t-1}) + \epsilon_t$$
$$\epsilon_t \sim N(0, h_t), \qquad h_t = \gamma_0 + \mathrm{JAN}\ \gamma_0^J + \mathrm{DEC}\ \gamma_0^D + \gamma_1 \epsilon_{t-1}^2. \quad (2)$$

[2] The sensitivity analysis shows that although β_1^{DN} point estimates are typically negative, they are rarely significant. Significant negative estimates of β_1^{DN} would suggest a small stock *overreaction* to bad macroeconomic news (corrected in the following month) in contrast to the partially *delayed reaction* to good news.

[3] Wiggins (1992) also documents asymmetries in concurrent betas. However, Wiggins uses an equally-weighted market index that emphasizes small stocks and is itself asymmetric and also uses pre-War returns whose variance is high. With the heavy OLS weighting on the pre-World War II returns, Wiggins concludes that concurrent betas are more positive in up than in down markets.

Table III

Symmetric and Asymmetric ARCH Regressions of Small Stock Portfolio Monthly Returns on Contemporaneous and Lagged Large Stock Portfolio Returns with Turn-of-the-Year Binary Variables (January 1963 to December 1994)

t-statistics are in parentheses. $r_{1,t}$ and $r_{5,t}$ are the monthly small-cap and large-cap New York Stock Exchange (NYSE) quintile portfolio returns at time t, respectively. JAN and DEC are January and December binary variables that capture the difference in the coefficients in these two months from all months. Superscripts UP and DN differentiate coefficients conditional on up (positive) and down (negative) large-cap portfolio returns. H_j: p-value is the rejection marginal significance level of the null hypothesis that the up and down betas at lag j are equal.

$$\text{Specification:}\quad \begin{aligned} r_{1,t} &= \alpha + \beta_0\, r_{5,t} + \beta_1\, r_{5,t-1} \\ &+ \text{JAN}\,(\alpha^J + \beta_0^J\, r_{5,t} + \beta_1^J\, r_{5,t-1}) \\ &+ \text{DEC}\,(\alpha^D + \beta_0^D\, r_{5,t} + \beta_1^D\, r_{5,t-1}) + \epsilon_t \end{aligned}$$

$$\epsilon_t \sim N(0, h_t), \qquad h_t = \gamma_0 + \text{JAN}\ \gamma_0^J + \text{DEC}\ \gamma_0^D + \gamma_1 \epsilon_{t-1}^2$$

Panel A: Symmetric Betas $\gamma_1 = 0.261$ (3.3)

	α	β_0	β_1	$\gamma_0 \times 100$
All months	−0.006	1.149	0.262	0.076
	(3.5)	(30.9)	(6.6)	(9.6)
JAN	0.058	−0.356	0.346	0.273
	(5.0)	(2.0)	(1.1)	(2.8)
DEC	0.001	−0.153	−0.048	0.013
	(0.2)	(0.8)	(0.3)	(0.4)

Panel B: Asymmetric Betas $\gamma_1 = 0.317$ (3.7)

	α	β_0^{UP}	β_0^{DN}	β_1^{UP}	β_1^{DN}	$\gamma_0 \times 100$
All months	−0.004	0.870	1.437	0.434	−0.102	0.065
	(1.4)	(13.0)	(22.1)	(6.6)	(1.5)	(9.2)
		H_0: p-value = 0.000		H_1 p-value = 0.000		
JAN	0.033	0.353	−1.179	0.253	1.271	0.185
	(1.6)	(1.2)	(2.8)	(0.7)	(1.4)	(2.6)
		H_0: p-value = 0.015		H_1: p-value = 0.350		
DEC	0.006	0.350	−1.231	−0.659	0.746	0.008
	(0.6)	(1.4)	(2.0)	(2.8)	(3.6)	(0.3)
		H_0: p-value = 0.032		H_1: p-value = 0.000		

Table III reports the results of equation (2) using symmetric (Panel A) and asymmetric (Panel B) concurrent and lagged betas. Consistent with Reinganum (1981) and Keim (1983), the symmetric regressions show that the mean January return is approximately 5.8 percent higher than the mean return for all months combined and that the difference is significant at the 0.01 level (t-statistic = 5.0). The incremental January variance is also significant ($\gamma_0^J =$

0.273, t-statistic = 2.8). However, concurrent and lagged symmetric betas in December and January are not incrementally different from betas for all months combined. In contrast, directionally asymmetric concurrent and lagged betas in Panel B are frequently significant, and allowing for these asymmetries causes the differences between the mean returns in January and the rest of the year to become much less significant (t-statistic = 1.6). Thus, part of the turn-of-the-year effect in mean returns may be attributable to directional asymmetries in concurrent and lagged betas. The opposite is not true, however, since the directional asymmetries in Panel B of Table III are, if anything, more pronounced than the directional asymmetries in Panel B of Table II.[4]

C. Sensitivity Analysis

Table IV repeats the key coefficients and test results for specification (2) using the base case from Table III. Table IV also reports results for alternative portfolios, specifications, and time periods. The results labeled 2, 3, and 4 are for the second, third, and fourth quintile portfolios, respectively. The directional asymmetry in both the contemporaneous and lagged betas found in the smallest quintile is also significant in the three middle quintiles. β_1^{UP} decreases monotonically from 0.434 for quintile 1 to 0.161 for quintile 4, indicating that the larger the stock, the more timely the response to good news. Result 5 repeats specification (2) using quintiles 1 and 5 of the Nasdaq exchange in place of quintiles 1 and 5 of the NYSE. Because data are unavailable earlier, the Nasdaq results are for the 1973 to 1994 period. The Nasdaq results generally confirm the NYSE results, although the lagged "down beta" is significantly positive at the 10 percent level. One interpretation of this difference is that the Nasdaq small stocks are so small that they respond to good and bad news with a delay, although the delay for good news is still more pronounced. The directional asymmetry in Nasdaq returns rules out Loyalist explanations of this new anomaly that are based on market micro-structure characteristics (i.e., specialists) specific to the NYSE.

Result 6 uses the S&P 500, instead of the 5th quintile of NYSE stocks, as the independent variable to proxy for good and bad macroeconomic news. Result 7 uses real returns for both the small stock and large stock portfolios. Continuously compounded real returns are calculated based on nominal returns and the continuously compounded monthly inflation rate measured by the Consumer Price Index. These perturbations to the base case do not affect any of the key results.

Results 8 and 9 explore alternative specifications for heteroskedasticity in the returns. Result 8 shows that replacing the ARCH(1) specification with a GARCH(1,1) does not influence the test results (the additional parameter associated with GARCH is insignificant); Result 9 does the same for White's

[4] Peterson and Sanger (1994) show that the delay evident in monthly returns is related to the IPO performance puzzle, and Chang, Pinegar, and Ravichandran (1994) show that the asymmetric response to good and bad news helps explain the day-of-the-week effect. We suggest that the asymmetric delayed response to news may also be related to the size and turn-of-the-year puzzles.

Table IV

Robustness Tests of Asymmetric ARCH Regression

Case 1 is the base case reported in Table III, Panel B. Cases 2 to 4 replace the base case dependent variable (i.e., the smallest size New York Stock Exchange (NYSE) quintile portfolio) with the three mid-size NYSE quintile portfolios. Case 5 replaces the base case variables with the largest and smallest size Nasdaq quintile portfolios. Case 6 replaces the information proxy in the base case (i.e., the largest sized NYSE quintile portfolio) with the S&P 500 portfolio. Case 7 uses real, rather than nominal, returns. Case 8 is a GARCH(1,1) regression, and Case 9 is an ordinary least squares (OLS) regression using White's (1980) heteroskedastic-consistent covariance matrix, both using the base case data set. Cases 10 to 12 are sub-period results for the base case. Case 13 is the base case where the dependent variable $r_{5,t-1}$ is replaced by $r_{1,t-1}$; that is, β_1 represents autocorrelation rather than cross-autocorrelation. Case 14 defines good and bad news in relation to the in-sample mean return, rather than zero. Constant parameter (α), turn-of-the-year parameters, and variance parameters (γ_0 and γ_1) estimates are not reported.

	Key Results from Specification 2					
Alternative Specifications	β_0^{UP}	β_0^{DN}	H_0: p-value	β_1^{UP}	β_1^{DN}	H_1: p-value
1) Base case	0.870	1.437	0.000	0.434	−0.102	0.000
2) Quintile 2	0.936	1.353	0.000	0.314	−0.072	0.000
3) Quintile 3	0.939	1.260	0.000	0.255	−0.072	0.000
4) Quintile 4	1.012	1.160	0.001	0.161	−0.062	0.000
5) Nasdaq (73–94)	0.470	0.864	0.000	0.382	0.119	0.004
6) S&P500	0.904	1.411	0.000	0.472	−0.130	0.000
7) Real	0.847	1.414	0.000	0.440	−0.079	0.000
8) Garch (1,1)	0.862	1.438	0.000	0.428	−0.113	0.000
9) White's het-cov	0.795	1.435	0.000	0.342	−0.051	0.011
10) Subperiod A (63–72)	1.006	1.434	0.031	0.347	0.081	0.165
11) Subperiod B (73–82)	0.729	1.863	0.000	0.408	−0.240	0.002
12) Subperiod C (83–94)	0.629	1.306	0.000	0.391	−0.023	0.010
13) Lagged small stock	0.836	1.423	0.000	0.332	−0.050	0.000
14) Good news	0.883	1.426	0.000	0.431	−0.094	0.000

(1980) correction for heteroskedasticity. Results 10 through 12 explore three subperiods between 1963 and 1994. All three of these subperiods are characterized by positive and significant lagged "up betas."[5] In result 13, $r_{5,t-1}$ is replaced with $r_{1,t-1}$, the lagged value of the dependent variable. Result 13 shows that the small-stock directional asymmetry is evident in terms of *autocorrelation* as well as cross-autocorrelation. Finally, result 14 defines "good" and "bad" news in relation to the in-sample mean rather than zero. Results conditional on returns that are above or below the mean are similar to the results conditional on returns that are positive or negative. Overall, the sen-

[5] A deviation from the base case merits comment. Subperiod A (1963–1972) fails to reject Hypothesis 1 (p-value of 0.165). However, this is not due to a lack of cross-autocorrelation in up markets; rather, it is driven by a small, insignificant tendency of the small stocks to react to bad, as well as good, news with a delay. Due to the limited number of observations, the three sub-period regressions do not allow for turn-of-the-year binary variable coefficients, γ_0^J and γ_0^D, in equation (2).

Table V

Weekly Symmetric and Asymmetric Regressions of Small Stock Portfolio Returns on Contemporaneous and Lagged Large Stock Portfolio Returns with Overlapping Observations (January 1963 to December 1994)

t-statistics are in parentheses and have been corrected for overlapping observations following Richardson and Smith (1991) and for heteroskedasticity following White (1980). $r_{1,t}$ and $r_{5,t}$ are the weekly continuous returns on the equally-weighted small-cap and large-cap quintile portfolios at time t, respectively. Superscripts UP and DN differentiate coefficients conditional on up (positive) and down (negative) large-cap portfolio returns in week t. The sample period is from January 1963 to December 1994, excluding turn-of-the-year weeks. A double (single) asterisk ** (*) indicates significance at the 0.01 (0.05) level. Total β is the sum of β_j from $j = 0$ to $j = 7$.

$$\text{Specification:} \quad r_{1,t} = \alpha + \sum_{j=0}^{7} \beta_j \, r_{5,t-j} + \epsilon_t$$

	Symmetric	Asymmetric	
j	β_j	β_j^{UP}	β_j^{DN}
0	0.898**	0.803**	0.993**
	(38.7)	(18.4)	(18.2)
1	0.224**	0.176**	0.253**
	(9.7)	(5.0)	(4.5)
2	0.071**	0.061*	0.057
	(4.3)	(2.0)	(1.7)
3	0.071**	0.084**	0.043
	(4.5)	(2.6)	(1.5)
4	0.077**	0.131**	0.018
	(4.8)	(4.2)	(0.7)
5	0.048**	0.059*	0.040
	(3.3)	(2.3)	(1.4)
6	0.011	0.039	−0.012
	(0.7)	(1.4)	(0.5)
7	0.030	−0.001	0.060
	(1.9)	(0.0)	(1.9)
Total β	1.430	1.352	1.452

sitivity analysis in Table IV suggests that the asymmetry of the cross-autocorrelation documented in Table III is robust to changes in the portfolios, specifications, and subperiods.

D. Weekly Returns

The results reported in Tables I to IV suggest that small stocks respond to good news with a delay, but respond to bad news in a timely fashion. These results, however, are based on monthly returns. Thus, they cannot detect daily or weekly delays potentially present after bad, as well as good, macroeconomic events. Table V reports the results of the following ordinary least squares

(OLS) specification using overlapping weekly returns:

$$r_{1,t} = \alpha + \sum_{j=0}^{7} \beta_j r_{5,t-j} + \epsilon_t. \tag{3}$$

In specification (3), the weekly returns on the small stock portfolio, $r_{1,t}$, are regressed on concurrent, $r_{5,t}$, and 7 lagged weekly returns, $r_{5,\,t-j}$, on the large stock portfolio. The weekly return regressions use overlapping observations, since Richardson and Smith (1991) note that relying on Wednesday to Wednesday results limits power and may lead to incorrect results. We correct for the autocorrelation induced by overlapping observations by procedures suggested by Richardson and Smith. Additionally, we correct for heteroskedasticity with White's (1980) heteroskedasticity-consistent covariance matrix.[6] Lo and MacKinlay's (1990a) finding can be reconfirmed by examining the value of β_1 in the first column of Table V for a symmetric regression (before conditioning on up and down markets). The β_1 of 0.224 is significantly different from zero at conventional levels (t-statistic = 9.7).

A new finding in Table V is that the cross-autocorrelation is not limited to a one-week lag since longer lags are also significant. The significance of lags 2 to 5 in weekly regressions should not be surprising given the monthly results. The significant cross-autocorrelation for such long horizons implies that explanations based on minor frictions in the market microstructure (i.e., transaction cost or nontrading) may not be complete. Column one also reports a contemporaneous beta of only 0.898, which is small relative to traditional beliefs about small stock systematic risk. The sum of all 8 (the contemporaneous plus 7 lagged) betas is 1.430, which is consistent with the monthly results and with commonly held beliefs about beta. This analysis again suggests the need for a Scholes and Williams (1977)-type adjustment in weekly returns and explains why betas measured using daily, weekly, monthly, and quarterly returns differ from each other (see, for example, Statman (1981) and Levy and Gunthorpe (1992)).

The second and third columns of Table V report the results of specification (3) after conditioning on up and down markets, respectively. The cross-autocorrelation discussed in the literature is evident in both up, $\beta_1^{\mathrm{UP}} = 0.176$, and down, $\beta_1^{\mathrm{DN}} = 0.253$, markets. The new finding is that the point estimates for the concurrent beta and first lagged beta are higher for down than for up markets. Beyond the second lag, the "up betas" are generally larger. This evidence suggests that some small stocks respond with a delay to *both* good

[6] Table V results do not include returns from the first or final weeks of the year, which are excluded because of the turn-of-the-year effects. The White correction for heteroskedasticity is used for weekly returns in place of the ARCH regressions because of the complications associated with overlapping observations and the skipping of the turn-of-the-year weeks. Results including turn-of-the-year weeks are similar, although the differences between β_j^{UP} and β_j^{DN} are generally not as pronounced (i.e., directional asymmetry is partly obscured by large turn-of-the-year returns on small stocks).

and bad news, but the delay to bad news is at most a week or two, while the delay to good news can be much longer. The directionally symmetric lag in the first week with the asymmetric lags for longer periods suggest that a full solution to the cross-autocorrelation puzzle may require multiple explanations. We now analyze potential solutions in light of our new empirical finding.

II. Analysis of Explanations Using Time Series Data on Portfolio Returns

Thus far, we have confirmed the size asymmetry in cross-autocorrelations and documented a new directional asymmetry in the relationship using portfolio returns. We now use this directional asymmetry to gauge the validity of extant theories regarding the cause of the cross-autocorrelation between returns on large and small stocks. To do so, we follow BRW's (1994) categorization of the explanations.

A. Loyalists

Lo and MacKinlay (1990a and 1990b) ruled out nonsynchronous trading as the only explanation of cross-autocorrelation, since unreasonably high levels of nontrading are needed to explain the correlation if nontrading is homogeneous (see also Atchison, Butler, and Simonds (1987)). However, BRW develop a model that allows for heterogeneous nontrading, giving new hope to the nonsynchronous trading explanation. Nevertheless, we observe that neither Lo and MacKinlay's (1990b) original model nor BRW's revised model predicts directional asymmetry. Furthermore, Mech (1993) finds that the cross-autocorrelation exists in Nasdaq stock returns, even after he controlled for nonsynchronous trading.

Table VI examines the effect of nonsynchronous trading on monthly (Panel A) and weekly (Panel B) returns of NYSE stocks using Mech's synchronous portfolio methodology. The first row in Panels A and B of Table VI report base-case coefficients from Tables III and V for monthly and weekly returns, respectively. Results from the base case use returns measured from the close on the last trading day of the respective holding period regardless of whether these stocks are actually traded on that given day. To control for this fact, we differentiate nonsynchronous trading that occurs because stocks trade at different times during the day from nonsynchronous trading that occurs because stocks do not trade at all during the day. We begin by eliminating the first day in the holding period horizon to calculate monthly (weekly) returns. Calculating returns in this way eliminates cross-autocorrelations due to stocks trading at different times during the same day. Unfortunately, it also eliminates cross-autocorrelations from one day to the next due to any other causes. Thus, the effect of this first correction is likely to overstate the effects of nonsynchronous trading. The results, labeled "First Day Skip," of this first adjustment are reported in the second row of Panels A and B in Table VI. To control for the effects of complete nontrading, we eliminate stocks in the smallest quintile

Table VI

Monthly and Weekly Synchronous Portfolio Regressions of Small Stock Portfolio Returns on Contemporaneous and Lagged Large Stock Portfolio Returns (January 1963 to December 1994)

See notes in Tables III and V. t-statistics are in parentheses. Panel A reports only the "all months" coefficients and omits the January and December incremental and ARCH coefficients; Panel B omits the coefficients for lags greater than one week. These ancillary coefficients are not materially affected by changing from nonsynchronous to synchronous portfolios.

Base Case = Base case from Table III (monthly) and Table V (weekly).
First Day Skip = Monthly (weekly) portfolio returns do not include the return on the first day of the month (week).
Fully Synchronous = First Day Skip adjustment plus the exclusion of stocks that did not trade on the first day of the month (week) from the small stock portfolio.

	β_0^{UP}	β_0^{DN}	β_1^{UP}	β_1^{DN}
Panel A: Monthly (See Specification in Table III)				
Base case	0.870	1.437	0.434	−0.102
	(13.0)	(22.1)	(6.6)	(1.5)
First day skip	0.810	1.460	0.408	−0.119
	(12.5)	(23.5)	(6.4)	(1.9)
Fully synchronous	0.816	1.473	0.406	−0.124
	(12.4)	(23.3)	(6.3)	(2.0)
Panel B: Weekly (See Specification in Table V)				
Base case	0.803	0.993	0.176	0.253
	(18.4)	(18.2)	(5.0)	(4.5)
First day skip	0.762	0.985	0.159	0.172
	(15.5)	(13.4)	(5.0)	(3.9)
Fully synchronous	0.773	1.001	0.158	0.170
	(15.6)	(13.4)	(4.9)	(3.9)

portfolio that did not trade during the first day of the holding period horizon as well as eliminating all first day returns. The cumulative effects of both adjustments will render portfolios that do not suffer from problems of nonsynchronous trading. Results for these "Fully Synchronous" portfolios are reported in the third row of Panels A and B in Table VI.

In the monthly regressions, the cross-autocorrelations decline monotonically as the portfolios become sequentially more synchronous. This finding is consistent with the hypothesis that nonsynchronous trading accounts for part of the cross-autocorrelations in the base case. However, the effects of nonsynchronous trading are quite small. β_1^{UP}, for the fully synchronous portfolio (0.406) is over 90 percent as large as β_1^{UP} for the nonsynchronous portfolio (0.434), and the fully synchronous portfolio estimate is still highly significant (t-statistic = 6.3).

Synchronizing portfolio returns also induces a monotonic decline in the weekly cross-autocorrelation coefficients (Panel B). Nevertheless, these coefficients remain significant, and the point estimate for β_1^{UP} in the fully synchronous portfolio is approximately 90 percent as large as the point estimate for the nonsynchronous portfolio. In addition, most of the decline in β_1^{UP} occurs with the first adjustment, which may overstate the effect of nonsynchronous trading. The decline from the second adjustment, which is exclusively from nontrading, is quite small. Thus, the nonsynchronous trading hypothesis is an incomplete explanation of the cross-autocorrelation puzzle. It explains little of the monthly and weekly cross-autocorrelation and fails (using current models) to explain why the degree of cross-autocorrelation differs in up and down markets.

We further illustrate the limits of the Loyalist nonsynchronous trading arguments by partitioning all months into high volume (above average) and low volume (below average) periods. The Loyalist nonsynchronous trading position implies that cross-autocorrelation would be strongest in low volume months. Such is not the case, however. Without conditioning, the monthly symmetric cross-autocorrelation coefficient is 0.262 (see Table III). When the prior month's small stock portfolio had high volume, the coefficient actually increases slightly to 0.295; but conditional on low volume, the coefficient decreases to 0.238.[7] Thus, higher volume does not diminish the slow response of small stocks to macroeconomic news.

Another Loyalist explanation for the cross-autocorrelation between returns on large and small firm stocks is a transactions cost argument. Specifically, Mech (1993) argues that more impactful shocks will be required to move small stock prices outside their relatively wider bid-ask boundaries than to move large stocks outside their boundaries. One implication of this argument is that observed prices of small firms' stocks will not respond to *minor* contemporaneous movements in large firms' stock prices but should adjust fully to *major* macroeconomic events that are large enough to move all stocks, large and small, outside of their bid-ask bounds. Therefore, the transactions cost argument implies that $r_{1,t}$ should be independent of $r_{5,t-1}$ when $r_{5,t-1}$ is large. To test this implication, we divide $r_{5,t}$ and $r_{5,t-1}$ into three ranges: below -2 percent, -2 percent to 2 percent, and above 2 percent. The extreme ranges (positive and negative) relate to "major" economic events; the inner ranges relates to "minor" events. Then, we test the transaction cost hypothesis implication that β_0 and β_1 are different for minor market moves than major market moves.[8] Test results, not reported here, indicate no statistically significant differences in coefficients for "minor" and "major" events. In fact, small stocks actually respond more dramatically to minor news than to major positive news.

[7] We define volume as the percent of shares outstanding that trade during the month, averaged across all stocks in the smallest quintile.

[8] The definition of minor market moves as moves between positive and negative 2 percent is arbitrary. Alternative definitions (e.g., 1 percent or 3 percent) give similar results.

Although nonsynchronous trading and transaction cost arguments provide, at best, partial explanations for the directional asymmetries in the cross-autocorrelations we document, there are other Loyalist arguments based on information flows and setup costs. For example, Chan (1993) assumes that market makers receive noisy signals about the value of their own stocks that cannot be instantaneously verified by signals that contain market-wide information. Thus, market makers' adjustments to stock prices after the arrival of corroborating market-wide signals induce positive own- and cross-autocorrelations. Though plausible, Chan's model implies an adjustment process that takes at most a *day* since market-wide movements are observable over very short horizons. Moreover, Chan's model remains silent regarding differences in information flow or setup costs that could induce the *directional* asymmetries we observe. Furthermore, Sias and Starks (1994) find that stocks held primarily by institutions—which presumably have lower transaction costs and better access to timely information—are more likely to respond to news with a delay measured in days. Thus, we conclude that existing Loyalist models provide incomplete explanations of the cross-autocorrelations between returns on large and small firms' stocks. Some of the Loyalist explanations may explain part of the symmetric cross-autocorrelation across a day or week but not the asymmetric cross-autocorrelation evident at longer lags.[9]

B. Revisionists

Conrad and Kaul (1988 and 1989), among others, point out that predictable portfolio returns do not violate market efficiency if expected returns vary over time in a predictable fashion. Essentially, relabeling predictable returns as expected returns allows Revisionists to explain all, or part, of the predictability in long-horizon returns (see Fama and French (1988) and Poterba and Summers (1988)) in monthly returns (see Conrad and Kaul (1989)) and in weekly returns (see Lo and MacKinlay (1988) and Conrad, Kaul, and Nimalendran (1991)).[10]

However, this reasoning is subject to the following criticisms. First, Mech (1993) shows that for the weekly return predictability to be explained by time-varying expected returns, large and frequently *negative* expected returns must be accepted.[11] Second, returns are more predictable for small rather than large stocks. Thus, the Revisionist explanation is limited to the time-varying

[9] Fargher and Weigand (1995) find that the cross-autocorrelation at one-day lags has weakened with time and suggest this is due to information technology improvements. Such Loyalist market frictions and imperfections may explain some of the symmetric small stock slowness, as well as the recent improvements in speed, that is evident in a day or even a week, but not the directional asymmetries and longer lags we document.

[10] McQueen (1992) shows that the long-horizon predictability is actually insignificant; thus, no "explanation" is needed.

[11] Boudoukh, Richardson, and Smith (1993) explain that ex ante risk premiums can be negative when the marginal rate of substitution and the excess return on the market are positively related. Harvey and Siddique (1994) show how negative ex ante risk premiums can arise from positive conditional skewness in returns.

risk premiums of small stocks only. Third, Brennan, Jegadeesh, and Swaminathan (1993) and Sias and Starks (1994) find that the predictability is related to the number of analysts following a stock or to the proportion of stocks held by institutional investors, neither of which should alter movements in time-varying risk premiums that instead should be related to movements in macroeconomic variables. Fourth, the volatility in forecasted weekly and monthly rates of return on small stocks is too high to be caused by risk premiums tied to presumably slow-moving consumption preferences and other macroeconomics variables.

Consistent with the first two criticisms, the cross-autocorrelations we document predict negative total small stock returns. For example, following a negative return on the large stock portfolio, the small stock portfolio's average weekly return is significantly negative, -0.0031 (t-statistic of 3.1) and, following a large stock return over two standard deviations below its mean, the small stock portfolio's average weekly return is -0.0116, below -1.0 percent. Thus, a Revisionist explanation would require that market participants frequently expect to be "rewarded" with very negative weekly returns on their small stock investments. Despite the arguments by Boudoukh, Richardson, and Smith (1993) and Harvey and Siddique (1994), such negative expected weekly returns seem unreasonable. Moreover, our evidence shows that the negative expected returns are not limited to periods of high expected inflation or downward-sloping term structures, periods when the model of Boudoukh, Richardson, and Smith (1993) predicts that negative expected returns are compatible with economic theory.

Despite the above critiques, we formally test the hypothesis that time-varying risk premiums explain the directional asymmetry in cross-autocorrelations, although, to our knowledge, such models do not suggest a difference in the decay structure of coefficients after good and bad economic news. The new test examines the degree of cross-autocorrelation after including variables previously shown to be associated with time-varying expected returns. Specifically, we use the following modification to specification (2):

$$\begin{aligned} r_{1,t} = {} & \alpha + \beta_0 r_{5,t} + \beta_1 r_{5,t-1} + \text{JAN}(\alpha^J + \beta_0^J r_{5,t} + \beta_1^J r_{5,t-1}) \\ & + \text{DEC}(\alpha^D + \beta_0^D r_{5,t} + \beta_1^D r_{5,t-1}) + \delta_{\text{TERM}}\text{TERM}_{t-1} + \delta_{D/P} D/P_{t-1} \\ & + \delta_{\text{DEF}}\text{DEF}_{t-1} + \delta_{\text{INF}}\text{INF}_t + \epsilon_t \\ & \epsilon_t \sim N(0, h_t), \qquad h_t = \gamma_0 + \text{JAN}\gamma_0^J + \text{DEC}\gamma_0^D + \gamma_1 \epsilon_{t-1}^2, \end{aligned} \tag{4}$$

where TERM is the term spread, D/P is the dividend yield, DEF is the default spread, INF is the continuously compounded inflation rate, and where binary variables allow the beta coefficients to take on a different value conditional on r_5 being greater than or less than zero.[12] TERM, D/P, DEF, and INF are

[12] As in Fama and French (1989), TERM is the difference in yield-to-maturity between the Ibbotson Associates' AAA Corporate Bond Portfolio and the one-month Treasury bill; D/P is the

Table VII

Monthly ARCH Regression with Time Varying Risk-Premia Explanatory Variables (January 1963 to December 1994)

See notes in Table III. t-statistics are in parentheses. Binary variables allow each coefficient in the specification to take on different values depending on the sign of r_5. TERM is the term spread, D/P is the dividend yield, DEF is the default spread, and INF is the inflation rate, all as defined by Fama and French (1989).

Specification: $r_{1,t} = \alpha + \beta_0 r_{5,t} + \beta_1 r_{5,t-1} + \text{JAN}(\alpha^J + \beta_0^J r_{5,t} + \beta_1^J r_{5,t-1}) +$
$\text{DEC}(\alpha^D + \beta_0^D r_{5,t} + \beta_1^D r_{5,t-1}) + \delta_{\text{TERM}}\text{TERM}_{t-1} + \delta_{\text{D/P}}\text{D/P}_{t-1} + \delta_{\text{DEF}}\text{DEF}_{t-1} + \delta_{\text{INF}}\text{INF}_{t-1} + \epsilon_t$
$\epsilon_t \sim N(0, h_t), \quad h_t = \gamma_0 + \text{JAN}\ \gamma_0^J + \text{DEC}\ \gamma_0^J + \gamma_1 \epsilon_{t-1}^2$

	α	β_0^{UP}	β_0^{DN}	β_1^{UP}	β_1^{DN}	$\gamma_0 \times 100$
All months	−0.010	0.828	1.459	0.423	−0.087	0.062
	(1.4)	(12.2)	(22.0)	(6.3)	(1.3)	(9.1)
JAN	0.033	0.380	−1.112	0.298	1.351	0.131
	(1.8)	(1.5)	(2.9)	(0.9)	(1.7)	(2.3)
DEC	0.005	0.518	−1.427	−0.711	0.804	0.007
	(0.4)	(2.1)	(2.4)	(3.0)	(4.0)	(0.3)
	δ_{TERM}	$\delta_{\text{D/P}}$	δ_{DEF}	δ_{INF}	γ_1	
	−0.225	0.305	−0.036	0.265	0.379	
	(2.1)	(1.4)	(0.1)	(0.5)	(4.1)	

included because Fama and French (1989) and/or Boudoukh, Richardson, and Smith (1993) find that these variables are useful in predicting time-varying risk premiums. Thus, specification (4) allows us to test for the cross-autocorrelation and its symmetry *after* allowing for the predictability associated with time-varying risk premiums.

Table VII reports the results of specification (4) using the monthly returns reported in Table III. Except TERM, the variables associated with time-varying risk premiums are not significant. Similarly, Fama and French (1989) found these variables to be significant for long-horizon but not for monthly returns. After including the additional explanatory variables, the concurrent beta for all months in up markets is still "too low," $\beta_0^{\text{UP}} = 0.828$, and the lagged up beta is "too high," $\beta_1^{\text{UP}} = 0.423$. Thus, even after allowing for variables to explain any time variation in expected returns, the cross-autocorrelation puzzle persists, and it remains directionally asymmetric.

value-weighted NYSE portfolios' dividend yield calculated by dividing the sum of the prior 12 monthly dividends by the current price; DEF is the difference in yield-to-maturity between the Ibbotson Associates' portfolio of all-corporate bonds and the portfolio of AAA bonds. TERM, D/P, and DEF are measured at the end of the prior month, $t - 1$. INF is calculated from the Consumer Price Index for all urban consumers, not seasonally adjusted, 1992–1994 = 100.

C. Heretics

Several articles show that abnormal profits are available based on the predictability of returns (see, for example, Lehman (1990), Jegadeesh (1990), and Brock, Lakonishok, and LeBaron (1992)). Jegadeesh and Titman (1994) find that most of the predictability is attributable to overreaction to firm-specific news rather than to delayed reaction to macroeconomic news. However, Jegadeesh and Titman do not address the directional asymmetry we document. Thus, excess returns apparently available from cross-autocorrelations may still violate the efficient markets hypothesis and Heretic claims must be considered.

Despite their label, Heretic explanations for cross-autocorrelation are often based on rational traders who respond either to institutional constraints and reward structures or to the behavior of another group of irrational or uninformed traders.[13] Given our new empirical finding, the validity of Heretic models no longer rests solely on their ability to explain the slow response of some small stocks to news in general. Rather, they must explain why small stocks respond quickly to "bad" news but slowly to "good" news. Since Heretic explanations related to herding, noise, and feedback trading typically include a role for more informed but often constrained institutional traders, we explore the influence of institutions on cross-autocorrelation following BKN and Sias and Starks (1994).

BKN develop a model based on information setup costs and penalties for imprudent investing that may explain why returns on stocks of "informationally unfavored" firms lag returns on stocks of "informationally favored" firms. Firms are defined as informationally favored (unfavored) if a relatively large (small) fraction of their shares are held by institutions. The BKN model may belong in the Loyalist camp since the information setup costs it presupposes are a type of market friction that impedes market efficiency.[14] However, our portfolio results and our cross-sectional tests both challenge BKN's interpretation of their findings. Thus, we address the institutional ownership issue here in the Heretic section.

We create and test the influence of institutional portfolios, controlling for size, following BKN. Data on total shares and shares held by institutions are from the January issues of Standard and Poor's *Security Owner's Stock Guide* in odd numbered years from January 1983 to January 1993. The January issues report end-of-year data. INST is defined as the percentage of total shares outstanding that are held by institutions. BKN (Tables III to VI) find that the INST variable is reasonably stable over time.[15] We create five port-

[13] See, for example, DeLong et al. (1990), Cutler, Poterba, and Summers (1990), Scharfstein and Stein (1990), Schleifer and Summers (1990), and Lakonishok, Shleifer, and Vishny (1992).

[14] In fact, none of the articles we cite perfectly conform to just one of the "three schools." However, BRW's (1994) classification scheme is descriptive and useful in organizing our paper.

[15] See Sias and Starks (1994) and BKN (1995) for details of the institutional data and its limitations. See the latter article and McQueen, Pinegar, and Thorley (1995) for specifics on the portfolio sorting procedure used to create institutional ownership portfolios that control for size.

folios having similar sizes but different degrees of institutional ownership using the double sorting procedure of BKN. For convenience, we label the portfolio with the smallest (largest) degree of institutional ownership Portfolio S (L). We also form five size-sorted portfolios that control for institutional ownership.

To test the influence of institutions and size we regress the monthly returns on a portfolio of stocks in the lowest quintile of institutional ownership (size), $r_{S,t}$, on the concurrent and four lagged returns on a portfolio of stocks in the highest quintile of institutional ownership (size), $r_{L,t}$ to $r_{L,t-4}$, controlling for size (institutional ownership) using the following ordinary least squares specification:

$$r_{S,t} = \alpha + \beta_0 r_{L,t} + \beta_1 r_{L,t-1} + \beta_2 r_{L,t-2} + \beta_3 r_{L,t-3} + \beta_4 r_{L,t-4} + E_t \tag{5}$$

Our results differ slightly from BKN's results because: 1) our sample periods differ, 2) we use nominal returns rather than excess returns, and 3) we use Standard and Poor's *Security Owner's Stock Guide* as our source of institutional data rather than CDA Investment Technologies, Inc. Nevertheless, the results are similar, particularly between our 1983 to 1988 subperiod, which closely matches BKN's 1981 to 1988 sample period.

Panel A of Table VIII reports the results of specification (5) for the high and low institutional ownership portfolios that control for size. Panel B reports results for the large and small capitalization portfolios that control for institutional ownership. In the first row of Panel A, we report the 1983 to 1988 subsample and confirm BKN's finding of a significantly positive β_2 (t-statistic of 3.1) and also report a significantly negative β_3. Based on the β_2 coefficient, BKN conclude that even after controlling for size, high institutional ownership portfolios lead low institutional ownership portfolios. However, BKN appear somewhat uncomfortable with this finding because, despite its significance, the lead-lag relationship ". . . is not observed until two months . . . ," whereas "One would expect the time taken by uninformed investors to incorporate past price data into their current demand to be fairly short."

We share BKN's discomfort for three additional reasons. First, a reasonable prediction of the informationally favored stock theory is a slow decay in the lagged betas—not a spike after two months with a reversal in the third. Second, we find (in regressions not reported in Table VIII) that β_2 is significant only for *bad* news, yet our earlier results suggest that the puzzle is driven by good news. Finally, the daily tests by Sias and Starks (1994 and 1995) and our cross-sectional tests suggest that, if anything, institutional ownership is positively correlated with delay.

To examine the robustness of β_2, we extend the analysis six years beyond BKN's original sample (i.e., from 1989 to 1994) and repeat the tests reported in the first row of Panel A. For this more recent period reported in the second row, β_2 equals 0.003 with a t-statistic of only 0.1, suggesting that the earlier coefficient could have existed only by chance.

Table VIII

The Effect of Institutional Ownership and Size on the Cross-autocorrelation Puzzle (January 1983 to December 1994)

t-statistics are in parentheses. In Panel A (B), $r_{S,t}$ is the monthly return on a quintile portfolio of New York Stock Exchange (NYSE) stocks with the smallest degree of institutional ownership (size) controlling for size (the degree of institutional ownership) at time t. $r_{L,t}$ is the monthly return on a quintile portfolio of NYSE stocks with the largest degree of institutional ownership (size) controlling for size (the degree of institutional ownership) at time t. The portfolios are created following Badrinath, Kale, and Noe (1995). A double (single) asterisk ** (*) indicates significance at the 0.01 (0.05) level.

Specification: $r_{S,t} = \alpha + \beta_0 r_{L,t} + \beta_1 r_{L,t-1} + \beta_2 r_{L,t-2} + \beta_3 r_{L,t-3} + \beta_4 r_{L,t-4} + E_t$

	β_0	β_1	β_2	β_3	β_4
Panel A: High Institutional Ownership Leading Low Institutional Ownership (Controlling for Size)					
1983–1988 (6 years)	0.693**	−0.016	0.099**	−0.062*	0.037
	(21.9)	(0.5)	(3.1)	(2.0)	(1.2)
1989–1994 (6 years)	0.528**	0.027	0.003	0.089*	−0.028
	(12.5)	(0.6)	(0.1)	(2.1)	(0.7)
1983–1994 (12 years)	0.628**	0.002	0.055*	−0.009	0.013
	(23.6)	(0.1)	(2.0)	(0.3)	(0.5)
Panel B: Large Size Leading Small Size (Controlling for Institutional Ownership)					
1983–1988 (6 years)	1.232**	0.199*	0.033	−0.048	−0.041
	(13.4)	(2.2)	(0.4)	(0.5)	(0.5)
1989–1994 (6 years)	1.115**	0.747**	0.272	−0.012	−0.139
	(6.2)	(4.2)	(1.5)	(0.1)	(0.8)
1983–1994 (12 years)	1.183**	0.370**	0.084	−0.035	−0.058
	(12.8)	(4.1)	(0.9)	(0.4)	(0.6)

As indicated above, "Heretics" derive their name from their insistence that cross-autocorrelations provide trading profits. A particularly interesting question in this context is whether such profits are available when differences in information are eliminated by holding institutional ownership constant. We examine this issue by comparing the risk-return characteristics of a buy-and-hold strategy to the risk-return characteristics of a simple trading rule suggested by our directional asymmetry. Specifically, the buy-and-hold strategy requires investors to hold Portfolio S from the beginning of 1983 through the end of 1994. The trading rule requires that investors hold Portfolio S only *after* observing a positive return on Portfolio L. Otherwise, investors hold Portfolio L. Under the buy-and-hold strategy, investors earn a mean monthly return of 1.03 percent with a standard deviation of 6.46 percent. Under the trading rule, they earn 1.58 percent with a standard deviation of 5.59 percent. The (modified) reward-to-variability ratios for the buy-and-hold strategy and the trading rule are 0.159 and 0.282, respectively. Given its risk, the trading rule could have earned 0.89 percent (annualized rate of 10.69 percent) less a month before it would have produced the same reward-to-variability ratio as the buy-and-hold strategy. Since the rule required, on average, only six trades per year, abnormal returns may have been available.

Regarding the segmented information theory, it is important to note that institutional ownership may be a poor proxy for information and that alternative proxies, such as the number of analysts (see Brennan, Jegadeesh, and Swaminathan's (1993)) or the period of listing (see Barry and Brown (1984)) may lend greater support to the theory. However, as with institutional ownership, the onus for these proxies is not merely to explain the delayed reaction, but to explain why the delay is directionally asymmetric. Absent such explanations, Heretic explanations gain greater credence. Thus, we remain "reluctant Heretics" in search of future models that can explain our findings. To aid in the development of such models and to examine the validity of existing explanations further, we now reexamine the cross-sectional determinants of individual stocks' cross-autocorrelations.

III. Analysis of Explanations Using Cross-Sectional Tests

Thus far, we have examined the previously reported size asymmetry and the new directional asymmetry of the cross-autocorrelation puzzle. Our results have been obtained with portfolios and have been used to gauge the validity of explanations proffered by the three schools of thought. In this section, we perform cross-sectional tests to shed further light on these extant explanations and to find the characteristics of firms that respond to news with a delay. The cross-sectional tests that follow are similar in nature to Mech's (1993) tests on weekly returns of Nasdaq stocks.

A. Cross-Sectional Data

To perform cross-sectional tests, we use measures of delay for individual stocks as the dependent variable and other firm characteristics hypothesized to cause delay as the independent variables. Our measure of delay, DELAY, is:[16]

$$\mathrm{DELAY}_i = f\left(\frac{a_{i1}}{a_{i0} + a_{i1}}\right), \tag{6}$$

where $f(x)$ is the logit transformation, $f(x) = 1/(1 + e^{-x})$, and where a_{i0} and a_{i1} are ordinary least squares estimates of a regression of individual stock returns on concurrent and lagged large stock portfolio returns,

$$r_{it} = a_i^* + a_{i0} r_{5,t} + a_{i1} r_{5,t-1} + E_{it}. \tag{7}$$

[16] We modify Mech's (1993) measure of delay since in McQueen, Pinegar, and Thorley (1995), we document a bias and several deficiencies. The deficiencies include first, the inability of Mech's measure to distinguish between predictability due to a delayed response from predictability due to a correction for overreaction, and second, an underweighting of delays that are distributed over multiple weeks.

The logit transformation serves two purposes. First, in practice for some stocks, the sum of the current and lagged regression coefficients is very close to zero. Dividing by this small number yields extreme values that are moderated by the transformation. Second, the transformation yields values between 0 and 1 which is consistent with Mech's measure, which gives the intuitively appealing interpretation of DELAY as the proportion of the response attributable to old news.[17]

In our sensitivity analysis we use a second measure of delay, geometric lag, based on the observation that the response of some small stocks to news (primarily good news) is distributed over several months. In particular, our measure of an individual firm's delay is the decay parameter, λ_i, of the following geometric lag model:

$$r_{it} = \alpha + \beta_i^*(1 - \lambda_i)(r_{5,t} + \lambda_i r_{5,t-1} + \lambda_i^2 r_{5,t-2} + \ \ldots\ ) + \epsilon_{it} \tag{8}$$

where β^* estimates the total or true effect of the index return, r_5, on a stock's return, r_i, and where lambda, $0 \leq \lambda \leq 1$. This allows the lagged response to extend indefinitely, albeit with the impact declining in a fixed proportion. Maximum likelihood estimates of β^* and λ are found using numerical estimation since no closed-form solution exists.

Based on the hypothesized causes of the cross-autocorrelation, on prior empirical research, and on data availability, our base case cross-sectional regressions use the following five independent variables:

ln SIZE = the log of the average market value of equity, in millions of dollars,
ln (1/PRICE) = the log of the inverse of the average price per share, in dollars,
ln VOLUME = the log of the average percentage of shares outstanding traded each day,[18]
ln STDRET = the log of the standard deviation of the monthly stock returns,
INST = the average percent of total shares outstanding held by institutions, based on biannual observations of ownership over the 12-year sample period.

[17] In our sensitivity analysis, the weekly measure of DELAY equals $1/(1 + e^{-x})$ where:

$$x = \sum_{k=1}^{7} \hat{a}_k \Big/ \sum_{k=0}^{7} \hat{a}_k,$$

and where the a coefficients are estimated from an OLS regression of an individual security's weekly return on the concurrent (a_0) and seven lagged (a_1 to a_7) large stock weekly returns.

[18] A percentage variable like VOLUME is bounded by 0 and 1 and typically would not need to be logged. However, the actual distribution has a very low mean, 0.00245, and is highly skewed, motivating the log transformation.

Additionally, in our sensitivity analysis we also use the following two independent variables:

ln MMCNT = the log of the average number of market makers, and
ln SPREAD = the log of the average relative bid-ask spread measured in basis points [100(ask price − bid price)/average of bid and ask prices].

SIZE, PRICE, VOLUME, MMCNT, and SPREAD are calculated as averages for each security based on mid-month observations over the entire 12-year sample period. The reciprocal of PRICE is used as a proxy for the relative bid-ask spread. Most of the cross-sectional variation in SPREAD in our sample is driven by differences in price (denominator), not the differences between the bid and ask prices (numerator). Thus, the reciprocal of price should be a good proxy for spread. We obtained bid and ask data for the smallest quintile of NYSE firms from Bob Wood at the ISSM at Memphis State University. For the subsample for which both variables are available, the logs of SPREAD and 1/PRICE have a correlation coefficient of 0.832. We report sensitivity analyses for alternative time periods, holding periods, markets, and variable definitions.

B. Monthly NYSE Cross-Sectional Results

In Table IX, we report the results of our cross-sectional test using our base case of monthly returns on a sample of 1,077 NYSE common stocks that are not in the largest size quintile and that traded for at least 50 percent of the months (6 years) from January 1983 to December 1994. This 12-year period is shorter than the period used in the prior portfolio tests, but it corresponds to the data available to us on institutional holdings and bid and ask prices for a subset of NYSE stocks.

Panel A of Table IX reports summary statistics on the five independent variables used in our base case. The first row in Panel B reports the cross-sectional results for our base case. Specifically Panel B reports ordinary least squares estimates of

$$\begin{aligned}\text{DELAY}_i = \delta_0 + \delta_{\text{SIZE}} \ln \text{SIZE}_i + \delta_{\text{PRICE}} \ln(1/\text{PRICE})_i + \delta_{\text{VOL}} \ln \text{VOLUME}_i \\ + \delta_{\text{STD}} \ln \text{STDRET}_i + \delta_{\text{INS}}\, \text{INS}_i + E_i. \qquad (9)\end{aligned}$$

The most significant and robust result from the cross-sectional tests is that volatility is positively related to the delay. The base case coefficient for ln STDRET, $\delta_{\text{STD}} = 0.035$, is significant at the 0.01 level (t-statistic = 6.0). The higher a stock's volatility, the slower the price adjusts to news. This finding does not support the transaction-based explanation of Mech (1993), since volatile stocks are more likely than less volatile stocks to move outside their bid-ask bounds and reflect news in a timely fashion. On the other hand, one implication of Chan's (1993) model is that stocks with noisy signals are likely to respond slowly to news and only respond completely after corroborating evidence arrives from other securities. Since volatility is related to noise, our volatility finding may be consistent with Chan's model. However, corroborat-

Table IX

Cross-Sectional Analysis of Delay using Monthly Returns (January 1983 to December 1994)

t-statistics are in parentheses. The sample consists of 1,077 New York Stock Exchange (NYSE) common stocks that are not in the largest size quintile and that meet minimum data requirements. DELAY_i is a security-specific measure of delay calculated using equation (6), excluding Januarys and Decembers. SIZE is the average market value of equity in millions of dollars, PRICE is the average share price in dollars, and VOLUME is the average daily trading volume as a fraction of total shares outstanding. The SIZE, PRICE, and VOLUME averages for each security are based on mid-month observations over the entire 12-year sample period. STDRET is the sample standard deviation of monthly returns. INST is the average fraction of total shares outstanding held by institutions, based on biannual observations over the 12-year sample period. The independent variables SIZE, 1/PRICE, VOLUME, and STDRET are logged in the cross-sectional regression. Share price is inverted to facilitate its interpretation as a proxy for transaction costs. The first row reports the results of a regression of delay on all five independent variables. The subsequent lines are the results of regressions of delay on SIZE and one other independent variable. R^2 is the multiple correlation coefficient corrected for degrees of freedom.

Panel A: Independent Variable Descriptive Statistics

	Mean	Minimum	Maximum
Size ($ millions)	441.3	5.7	1,680.5
Price ($)	20.78	0.65	137.19
Volume (basis points)	24.5	1.0	108.2
STDRET (%)	10.6	2.1	36.4
Institutions (%)	32.8	0.1	91.4

Panel B: Cross-Sectional Ordinary Least Squares (OLS) Regressions

$$\text{DELAY}_i = \delta_0 + \delta_{\text{SIZE}} \ln \text{SIZE}_i + \delta_{\text{PRICE}} \ln(1/\text{PRICE})_i + \delta_{\text{VOL}} \ln \text{VOLUME}_i + \delta_{\text{STD}} \ln \text{STDRET}_i + \delta_{\text{INS}} \text{INS}_i + E_i,$$

Independent Variable Coefficients

δ_{SIZE}	δ_{PRICE}	δ_{VOL}	δ_{STD}	$\delta_{\text{INST}} \times 100$	R^2
−0.014	−0.004	−0.002	0.035	0.043	0.12
(5.6)	(0.7)	(0.6)	(6.0)	(2.9)	
−0.013	−0.001				0.05
(5.3)	(0.3)				
−0.015		0.015			0.07
(8.5)		(4.6)			
−0.009			0.038		0.11
(4.9)			(8.5)		
−0.021				0.079	0.08
(10.1)				(6.4)	

ing signals can be observed daily and are presumably symmetric. The second most significant variable associated with delay is size itself, which remains significant ($\delta_{\text{SIZE}} = -0.014$ with a t-statistic of 5.6), even after allowing for the other four explanatory variables.

INST is significantly *positively* correlated with DELAY (δ_{INS} = 0.043, *t*-statistic = 2.9), although this result is less significant in the base case and less robust in the sensitivity analysis than the volatility and size results. Nevertheless, the positive coefficient contrasts sharply with the predictions of the Loyalist theory of informationally unfavored stocks. Although not significant, the negative coefficient on lnVOLUME is consistent with the nonsynchronous trading explanation of the delay puzzle, since higher volume stocks exhibit less delay. Contrary to Mech's (1993) conclusions, after improving on the measure of delay, we do not find that the delay in monthly returns increases with our proxy for the bid-ask spread ($\delta_{\text{PRICE}} = -0.004$, *t*-statistic = 0.7).

Before examining the sensitivity analysis, we note that the independent variables are highly collinear. The two strongest correlation coefficients are between ln SIZE and ln(1/PRICE), −0.700, and between ln SIZE and INST, 0.512. To illustrate the effects of this problem, we retest the base case regression four times using lnSIZE and each other independent variable—one at a time. When size and volume are examined in isolation, for example, the coefficient on ln VOLUME, δ_{VOL} = 0.015, is highly significant (*t*-statistic = 4.6). However, conclusions based on this regression alone would be misleading because at least three known left-out variables are significantly correlated with size, volume, or both. Likewise, tests based on portfolios sorted first by size, then by volume, or vice versa, may yield conclusions that are partially driven by other causes, such as volatility.

Given that caveat, we now examine the sensitivity of the base case findings to perturbations in the dependent and independent variables, sample periods, and portfolio compositions. Results of this analysis are reported in Table X. Case 1 repeats the base case for comparison purposes. In Cases 2 and 3, a binary variable is included in the cross-sectional tests to differentiate up and down markets. Given the directional asymmetry documented in Section 2, it is not surprising that the cross-sectional independent variables are only significant in up markets.

In Case 4, the dependent variable DELAY is replaced with λ, the geometric lag parameter as specified in equation (8). The coefficient values change due to the new dependent variable but, with one exception, the sign and significance levels are basically unchanged. The exception is that the positive coefficient on INST becomes insignificant, although the sign is still contrary to the hypothesis that "informationally favored" stocks experience only short or no delays. In Case 5, a_1 is used as a simple measure of delay as in Brennan, Jegadeesh, and Swaminathan (1993). The advantage of this measure is that it is not subjected to logit transformations or the geometric decay assumptions. The disadvantage is that a_1 is not normalized for systematic risk. Nevertheless, this simple measure of delay yields results similar to the base case.

In Case 6, a smaller sample of 238 firms is used. This sample includes firms in the smallest quintile for which we received bid and ask price data from Bob Wood. The advantage of this subset is that the proxy variable 1/PRICE can be replaced by SPREAD, the average bid-ask spread as a fraction of the share price. The disadvantage is that the sample size drops and is limited to the smallest firms which, due to the multicollinearity, limits the range of all the

Table X

Independent Variable Coefficients for a Cross-Sectional Sensitivity Analysis (January 1983 to December 1994)

t-statistics are in parentheses. The following regressions explore the sensitivity of the cross-sectional regression in Table IX.

	ln SIZE	ln(1/PRICE)	ln VOLUME	ln STDRET	INST
1) Base case	−0.014 (5.6)	−0.004 (0.7)	−0.002 (0.6)	0.035 (6.0)	0.043 (2.9)
2) Up delay	−0.017 (3.6)	−0.011 (1.2)	−0.008 (1.1)	0.049 (4.3)	0.007 (0.2)
3) Down delay	−0.009 (1.5)	−0.004 (0.3)	0.004 (0.4)	−0.009 (0.6)	−0.003 (0.1)
4) λ	−0.047 (5.0)	−0.004 (0.2)	−0.019 (1.3)	0.149 (7.0)	0.053 (1.0)
5) a_1	−0.047 (4.5)	0.003 (0.2)	0.008 (0.5)	0.224 (9.4)	0.010 (0.2)
6) Spread	−0.012 (2.0)	−0.003 (0.3)	−0.002 (0.2)	0.058 (4.2)	0.058 (1.8)
7) 3 Years	−0.013 (4.4)	0.011 (2.0)	−0.008 (2.1)	0.023 (3.5)	0.051 (3.0)
8) 9 Years	−0.016 (5.6)	−0.024 (4.2)	−0.013 (2.8)	0.074 (9.3)	0.040 (2.3)
9) With Jan. & Dec.	−0.012 (4.9)	0.004 (0.8)	0.002 (0.5)	0.030 (5.3)	−0.003 (0.2)
10) Weekly 1	−0.018 (7.2)	−0.015 (2.8)	−0.027 (6.6)	0.084 (12.8)	0.031 (2.0)
11) Weekly 2	−0.011 (4.4)	−0.006 (1.2)	−0.014 (3.5)	0.063 (9.9)	0.007 (0.5)
12) Subperiod A	−0.015 (6.2)	−0.012 (2.7)	−0.014 (4.0)	0.040 (4.8)	
13) Subperiod B	−0.005 (2.1)	−0.015 (3.3)	−0.020 (5.8)	0.088 (11.8)	
14) Subperiod C	−0.013 (5.1)	−0.010 (2.3)	0.001 (0.2)	0.041 (7.5)	

1) Base Case: The regression results in Table IX.

2) Up Delay: The base case with delay measured with respect to upside market movements.

3) Down Delay: The base case with delay measured with respect to downside market movements.

4) λ: The base case dependent variable, DELAY, is replaced by the measure, λ, from equation (8).

5) a_1: The base case dependent variable, DELAY, is replaced by the measure, a_1, from equation (7).

6) Spread: A sample of 309 small size quintile NYSE stocks for which bid-ask spread data is available. (1/PRICE) is replaced by SPREAD, where SPREAD is the average bid-ask spread as a fraction of the share price. Due to data availability, the sample ends in December 1992.

7) 3 Years: The base case with the minimum data requirements set at 3 years, not 6 years, $N =$ 1772.

8) 9 Years: The base case with the minimum data requirements set at 9 years, not 6 years, $N =$ 701.

9) With Jan. and Dec.: The base cases including turn-of-the-year months.

10) Weekly 1: The base case sample period and securities, but with DELAY based on concurrent and seven lagged weekly market returns. DELAY is the logit function of the ratio of the seven lagged coefficients to the sum of the concurrent and seven lagged coefficients.

11) Weekly 2: Similar to Weekly 1, using the ratio of six lagged coefficients (the first lag is excluded) to the sum of the concurrent and seven lagged coefficients.

12) Subperiod A: The base case for the 1963 to 1972 period, without the INST independent variable.

13) Subperiod B: The base case for the 1973 to 1982 period, without the INST independent variable.

14) Subperiod C: The base case (1983 to 1994) without the INST independent variable.

independent variables, not just size. Nevertheless, contrary to the Loyalist transaction cost explanation, both size and volatility remain significant and SPREAD, like 1/PRICE, is insignificant.

In the base case, a stock was included in the sample if it had return data in at least 6 out of the 12 years examined in the cross-sectional tests. In Case 7, only 3 years of data are required (N = 1,772) to be included in the sample and in Case 8, 9 years of data are required (N = 701). As with the base case, volatility, size, and institutional ownership are significantly correlated with our measure of delay. Additionally, volume becomes significant in Cases 7 and 8, consistent with nonsynchronous trading explaining a portion of the cross-autocorrelation. The base case results exclude the turn-of-the-year months. When these months are included in Case 9, the size and volatility results are confirmed, but the positive coefficient on institutional ownership is shown to be less robust.

Cases 10 and 11 use the base case sample period and securities but use weekly returns. In Case 10, DELAY is calculated using the equation in footnote 17. In Case 11, DELAY uses the same equation, but the numerator is the sum of coefficients a_2 to a_8, not a_1 to a_8. Given the size of a_1 relative to the other a's, Case 10 DELAY primarily measures delays of a week or less. In Case 11, the dependent variable represents delays of over one week. For Case 10, all five dependent variables become statistically significant. The increased significance is not surprising since, presumably, more stocks exhibit delays across the first week than across two or more weeks. Interestingly, the significance of the coefficient on ln VOLUME is particularly pronounced in Case 10. This finding suggests that nontrading explains more of the puzzle for short horizons, such as a week, but less of the puzzle at longer horizons, such as a month. The significant negative coefficient or the spread proxy further discredits any explanation based on transaction costs.

The last three cases explore alternative sample periods. Since the institutional data is not available to us before 1983, we repeat the base case sample period, labeled SUBPERIOD C, without INST for comparison purposes. Case 12 is for the 1963 to 1972 period, labeled SUBPERIOD A, and Case 13 is for the 1973 to 1982 period, labeled SUBPERIOD B. The key base case results are robust to sample changes although volatility drops in significance in the 1960s and size drops in significance in the 1970s.

Overall, the sensitivity analysis suggests that the size and volatility results are quite robust. The delayed response to news is associated with small and volatile stocks. Less robust is the evidence that a larger proportion of institutional investors is also associated with the delay.

IV. Conclusions

This article extends the work of Lo and MacKinlay (1990a, 1990b), Mech (1993), Boudoukh, Richardson, and Whitelaw (1994), Badrinath, Kale, and Noe (1995), and others concerning the ability of past returns for a portfolio of large stocks to explain returns for a portfolio of small stocks. The prior work points out a size asymmetry in the cross-autocorrelation relationship—small stock returns do not lead large stock returns. Boudoukh, Richardson, and Whitelaw (1994) categorize the extant explanations for the cross-autocorrelation puzzle into three camps: "Loyalists," "Revisionists," and "Heretics." Loyalists relate the puzzle to market imperfections, Revisionists to time-varying risk premiums, and Heretics to fads, bubbles, etc.

Our article extends the prior research in two ways. First, we document a new empirical characteristic of the data—directional asymmetry—which poses a new challenge to those seeking to explain the cross-autocorrelation puzzle. Specifically, the cross-autocorrelation is asymmetric in up and down markets with small stocks responding much more slowly to increases in large stocks than to decreases. Additionally, we find the delay to be evident in monthly as well as weekly returns. In general, directional asymmetry is inconsistent with the Revisionist and Loyalist explanations which implicitly assume symmetric responses to good and bad news.

Second, the article performs a number of time-series and cross-sectional tests of explanations from all three camps. Using time-series data on portfolios, we find evidence inconsistent with explanations based on time-varying risk premiums, transaction costs, and institutionally unfavored stocks. Additionally, we find that nonsynchronous trading explains only a portion of the puzzle. Using cross-sectional tests and an improved measure of delay, we find further evidence inconsistent with Loyalist theories of transaction and information costs. Our cross-sectional tests find that the delay is most significantly related to small stocks and to stocks with high standard deviations. Again, we find that stocks with these characteristics respond to good news much more slowly than to bad news, and that the slowness is evident even in monthly returns. We conclude that some Loyalist explanations may explain part of the directionally symmetric cross-autocorrelation evident over a day or even a week, but not the asymmetric cross-autocorrelation evident in monthly returns we document.

Our finding of directional asymmetry is compatible with the empirical findings of Grinblatt, Titman, and Wermers (1995) and Keim and Madhavan (1995).[19] Grinblatt, Titman, and Wermers (1995) find that mutual fund managers follow momentum investment strategies asymmetrically. Specifically, the managers follow positive feedback strategies only after good news—buying past winners but not selling past losers. Keim and Madhavan (1995) find that institutions' "motivation for the trade decision is often not symmetric for buys versus sells." Furthermore, they find that institutions typically place smaller buy orders that take longer to execute relative to sell orders. One

[19] Related forms of directional asymmetries are also reported elsewhere in the literature. Odier and Solnik (1993) and Bae and Karolyi (1994) find, respectively, that correlations and volatility spillovers among international markets are different for good and bad news environments. Similarly, Domian, Gilster, and Louton (1995) find the anomalous relationship between inflation and stock returns is driven primarily by positive responses to unexpected decreases in inflation rather than by negative responses to unexpected increases. Furthermore, McQueen and Thorley (1993) find directional asymmetries in measures of the U.S. economy, and the asymmetry of "sticky" prices is often used to explain stagflation. This growing body of evidence suggests that relationships in good economic environments may be quite different from relationships in bad environments.

possible story consistent with our findings is that investors attempt to sell all stocks quickly when news of the economy is bad. When the news is good, the market participants quickly buy large, easy to price stocks but take their time and "shop around" before buying smaller, more volatile stocks. Our directional asymmetry results, combined with the asymmetry findings of Grinblatt, Titman, and Wermers (1995), Keim and Madhavan (1995), and others, suggest a need for further work that formalizes this story into trading models that allow for asymmetries. Such models need to explain both the size and the directional asymmetries in cross-autocorrelations and why the cross-autocorrelations are more pronounced for volatile stocks. The new models must also make new testable predictions in order to be validated. Pending the arrival of such models, we remain "reluctant Heretics" so far as historical cross-autocorrelations are concerned. However, we anxiously await the development of plausible models of trading and return asymmetries that will convert us back to the Loyalist camp.

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