Industry Information Diffusion and the Lead-Lag Effect in Stock Returns

Kewei Hou*

Department of Finance
Fisher College of Business, Ohio State University

* Department of Finance, Fisher College of Business, Ohio State University, 2100 Neil Avenue, Columbus, OH 43210. Phone: (614)292-0552. Email: hou.28@osu.edu. An earlier version of this paper was titled "Information Diffusion and Asymmetric Cross-Autocorrelations in Stock Returns." I thank Jonathan Arnold, Nicholas Barberis, Nicole Boyson, George Constantinides, Douglas Diamond, Eugene Fama, Milton Harris, Owen Lamont, Richard Leftwich, Lubos Pastor, David Robinson, Rene Stulz, Andrew Wong, and especially Tobias Moskowitz, as well as seminar participants at the University of Chicago, the University of Texas at Austin, Emory University, MIT, Yale University, the University of North Carolina, Vanderbilt University, the University of Southern California, Cornell University, and the Ohio State University for helpful comments and suggestions. Research support from the Sanford J. Grossman fellowship in honor of Arnold Zellner is gratefully acknowledged; any expressions expressed herein are the author's and not necessarily those of Sanford J. Grossman or Arnold Zellner. Any remaining errors are my responsibility.

Industry Information Diffusion and the Lead-Lag Effect in Stock Returns

Abstract

This paper argues that slow diffusion of common information is a leading cause of the lead-lag effect in stock returns. I find that the lead-lag effect is predominantly an intra-industry phenomenon: returns on big firms lead returns on small firms within the same industry. Once this effect is accounted for, little evidence of predictability across industries can be found. Furthermore, this effect is largely driven by sluggish adjustment to negative information. Industry leaders lead industry followers; value firms lead growth firms (within the same industry); firms with low idiosyncratic volatility lead their highly volatile industry peers, controlling for firm size. Small, volatile, less competitive and neglected industries experience a more pronounced lead-lag effect. Finally, the intra-industry lead-lag effect drives the industry momentum anomaly.

Introduction

Recent literature has identified lead-lag cross-autocorrelations as an important component of stock return dynamics. Lo and MacKinlay (1990a) find that weekly stock returns are positively cross-autocorrelated with a distinct lead-lag pattern between firms of different size: lagged returns on big firms are correlated with current returns on small firms, but not vice versa. Subsequent studies have documented other determinants of the lead-lag effect, including the number of analysts following a firm (Brennan, Jegadeesh and Swaminathan (1993)), the level of institutional ownership (Badrinath, Kale and Noe (1995)), and trading volume (Chordia and Swaminathan (2000)).

Even though the magnitude and statistical significance of the lead-lag effect seem beyond doubt, its source has been subject to debate. Extant explanations include nonsynchronous trading (Lo and MacKinlay (1990b) and Boudoukh, Richardson and Whitelaw (1994)), time-varying expected returns (Conrad and Kaul (1988 and 1989) and Hameed (1997)), and slow diffusion of information (Lo and MacKinlay (1990a) and Chordia and Swaminathan (2000)).

This paper largely focuses on the third group of explanations that the lead-lag effect arises because some firms' stock prices react more sluggishly to common information than others. What economic forces are responsible for this slow diffusion of information in the equity market? The list of potential candidates includes information costs, noise traders, transaction costs, asymmetric information, short sale constraints, ERISA restrictions, as well as other types of market frictions and institutional constraints.[1]

I explore the above information diffusion hypothesis through several channels. First, I study the lead-lag effect by conditioning on industry membership because slow diffusion of common information should be more prevalent for firms from the same industry: these firms compete in the same product market, and move closely with each other regarding product and technology innovations. They react similarly to permanent shifts in supply and demand conditions, as well as the regulatory environment. In addition, as the industry goes through expansions and contractions, their growth opportunities and investing and financing decisions are correlated. These commonalities lead to information clustering at the industry level, so that shocks to firms convey more information about future prospects of firms within, rather than outside their own industry. Therefore, if the lead-lag effect is due to slow diffusion of information, then we should see more of a lead-lag effect within industries than across industries.

To test this hypothesis, I decompose the lead-lag effect into an intra-industry and an inter-industry component. The result shows that the intra-industry component drives the effect: returns on big firms lead returns on small firms from the same industry. Once this effect is controlled for, little evidence of cross-predictability across industries can be

[1] Merton (1987) is among the first to recognize the importance of information costs and institutional restrictions in the information acquisition and dissemination process. Extending the work in Kyle (1985), Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) demonstrate that the presence of more informed investors leads to faster stock price adjustment to new information. Diamond and Verrecchia (1987) argue that short sale constraints can slow down the response of stock prices to new information, especially when the information is negative. Mech (1993) shows that stock prices respond to new information more rapidly when price changes are large relative to the bid-ask spread. Chan (1993) presents an incomplete information model in which cross-sectional differences in the signal quality can give rise to asymmetric cross-autocorrelations. Badrinath, Kale and Noe (1995) develop a multi-period model in which the information set-up cost and/or prudence restrictions (as postulated by Merton (1987)) lead to a lead-lag relation between institutionally "favored" firms and "unfavored" firms. Finally, Peng

found. This result is robust to different weighting schemes (equal weight vs. value weight), alternative specifications of the vector-auto regressions (4-week lags, 1-week lag, controlling for contemporaneous returns, and skipping a week), and different subsamples (NYSE/AMEX/NASDAQ vs. NYSE firms) and subperiods (196307-198206 and 198207-200112).

Second, if market frictions and institutional forces are responsible for delayed response of stock prices to new information, then there might exist an asymmetry in the price adjustment process as certain market imperfections become more pronounced when bad news arrives (for example, as the short sale constraint becomes more and more distortionary). My results confirm this hypothesis. I find that the intra-industry lead-lag effect is largely driven by slow diffusion of bad news between firms. The ability of lagged returns on big firms to predict current returns on small firms is much greater when those big firms' returns are negative.

Prior research argues that firm size affects the speed of stock price adjustment through its correlation with variables such as the number of analysts following a firm, institutional ownership, and trading volume.[2] Since we have already known that analyst coverage, institutional holdings, and trading volume tend to cluster at the industry level, I re-examine these prior research results after conditioning on industries. My findings confirm that analyst coverage, institutional holdings, and trading volume contain important information regarding intra-industry news dissemination that is independent from firm size. Then I examine whether there is a lead-lag effect related to market share,

(2002) constructs a learning model in which incomplete information, in the form of an information capacity constraint faced by the representative investor, causes a delay in the price adjustment process.

[2] See Admati and Pfleiderer (1988), Brennan, Jegadeesh and Swaminathan (1993), Badrinath, Kale and Noe (1995), and Chordia and Swaminathan (2000).

as new information usually gets incorporated into the stock prices of industry leaders before spreading to other firms in the industry. The evidence supports my conjecture: returns on firms with big market share (industry leaders) lead returns on firms with smaller market share (industry followers), controlling for size. In addition, returns on high BE/ME firms lead returns on low BE/ME firms, controlling for size. This result is consistent with several theories predicting that firms with high BE/ME ratio react more rapidly to new information than their industry peers. Furthermore, consistent with that idiosyncratic volatility is related to the speed of information flow, I find that returns on firms with low idiosyncratic volatility lead returns on firms with high idiosyncratic volatility.

Additional support for the information hypothesis is obtained by studying how the significance of the lead-lag effect varies across industries. I find a more pronounced lead-lag effect in industries that are smaller and less competitive, as well as those with lower levels of analyst coverage, institutional ownership and trading volume, and higher levels of idiosyncratic volatility and analyst dispersion. These are the industries in which one would expect, *a priori*, information to disseminate more slowly.

Finally, I link the intra-industry lead-lag effect to the industry momentum anomaly. In a paper investigating the sources of profits to momentum trading strategies, Moskowitz and Grinblatt (1999) show that there is a strong momentum effect in industry portfolios. I interact the intra-industry lead-lag effect with the industry momentum effect in a cross-sectional regression framework. The result reveals that the lead-lag effect between small firms and big firms explains virtually all of the industry momentum effect.

This result indicates that slow diffusion of common information contributes significantly to the profitability of the industry momentum strategies.

There are certainly other plausible explanations of the data. For example, the lead-lag effect could be the result of data measurement errors, such as when stock prices are incorrectly assumed to be sampled simultaneously (this is also known as the nonsynchronous trading or thin trading problem).[3] If this were the case, the lead-lag effect would have little economic consequence. In this paper, I employ weekly, instead of daily returns, in my analysis, and take other measures to address the nontrading problem. The fact that the intra-industry lead-lag effect remains significant when I use value-weighted returns, employ only NYSE firms, skip a week in the vector-auto regressions, and examine different subperiods demonstrates that nonsynchronous trading does not drive my results.[4]

Differences in the level of time variation of expected returns can also, in theory, give rise to lead-lag patterns across stocks (Conrad and Kaul (1988 and 1989), Conrad, Kaul and Nimalendran (1991), Boudoukh, Richardson and Whitelaw (1994) and Hameed (1997)). Specifically, it has been argued that asymmetric cross-autocorrelations can be better explained by portfolio autocorrelations coupled with high contemporaneous correlations across portfolios. I address this hypothesis by including lagged returns on the

[3] Cohen, Maier, Schwartz and Whitcomb (1986) and Lo and MacKinlay (1990b) demonstrate that a model of nonsynchronous trading can generate positive cross-autocorrelations across stocks.

[4] Others who have examined the nonsynchronous trading problem also show that attributing all of the observed cross-autocorrelations to nonsynchronous trading would require unrealistically thin markets (Lo and MacKinlay (1990a)), even after allowing for extreme heterogeneity in nontrading probability and beta (Boudoukh, Richardson and Whitelaw (1994)). Furthermore, Mech (1993) and McQueen, Pinegar and Thorley (1996) test the nonsynchronous trading hypothesis using return series that have been adjusted for nontrading, and conclude that only a small portion of the observed cross-autocorrelations can be attributed to nonsynchronous trading. Kadlec and Patterson (1999) study the nontrading problem by sampling stock returns from transaction data where the actual trade times can be obtained. They estimate that the proportion of autocorrelation (and cross-autocorrelation) due to nonsynchronous trading is roughly 25 percent.

portfolio of small firms in the vector-auto regression test of the lead-lag effect, and find that lagged returns on big firms can reliably predict current returns on small firms within the same industry, above and beyond the predictive power of lagged returns on small firms. Therefore, it seems unlikely that time-varying expected returns can fully explain the observed lead-lag effect.

Understanding the source of the lead-lag effect has important implications for market efficiency and asset pricing, as one of the paramount concerns of financial economics is understanding how firms transmit information to markets, and how markets in turn impound this information into stock prices. Traditional asset-pricing theories typically assume that information diffusion takes place instantaneously in a complete and frictionless market. Yet, ample empirical evidence suggests that information can and do sometimes transfer slowly in the market place. This paper presents extensive evidence on the information transmission mechanism that is consistent with industries being the primary channel for news dissemination in the equity market. Additionally, this paper contributes to the broader literature in several other directions.

First, the findings in this paper coincide with a growing literature which uses industry membership as conditioning information to explore whether certain asset-pricing phenomena are attributable to industry effects.[5] The fact that the lead-lag effect is almost entirely driven by firms within the same industry supports the idea that industries are important for understanding the behavior of stock returns.

Second, my findings can also help determine the validity of different theories that have been proposed for the momentum anomaly in stock returns. Insofar as the intra-industry lead-lag effect drives the industry momentum effect, my results are consistent with the explanation which attributes the momentum effect to gradual diffusion of information (Hong and Stein (1999), and Hong, Lim and Stein (2000)).

Third, understanding the source of the lead-lag effect is important for policy considerations. To the extent that information frictions and investment restrictions are responsible for introducing delays in the price adjustment process, my results suggest that increased disclosure and improvement in information communication, as well as market mechanisms, can help stock prices become informationally more efficient.

The rest of the paper is organized as follows. Section I introduces the data. In section II, I decompose the unconditional lead-lag effect into inter- and intra-industry components, and demonstrate that the intra-industry component drives much of the effect. I also show that this effect is largely driven by stock prices' sluggish adjustment to negative information. Section III explores additional determinants of the intra-industry lead-lag effect, while section IV studies cross-industry differences in the lead-lag effect. Section V examines the link between the intra-industry lead-lag effect and the industry momentum anomaly. Section VI concludes.

I. Data

I obtain daily stock price and trading volume data for all publicly traded firms with sharecodes 10 or 11 (e.g., excluding ADR's, closed-end funds and REIT's) on the NYSE/AMEX/NASDAQ daily tapes maintained by the Center for Research in Security

[5] For example, Asness and Stevens (1996) decompose size and book-to-market factors into inter- and intra-industry components and find that intra-industry factors have greater explanatory power in the cross-section. Moskowitz and Grinblatt (1999) show that industry portfolios exhibit significant momentum.

Prices (CRSP) for the period beginning in July 1963 and ending in December 2001. Weekly stock returns are calculated by compounding daily returns between adjacent Wednesdays.[6] I employ weekly, instead of daily returns, in my analysis to avoid the substantial bias associated with nonsynchronous trading and other microstructure effects at the daily level.[7] I then match the weekly return series with balance sheet and income statement data from the COMPUSTAT industrial annual file, institutional ownership data from Standard & Poors, as well as analyst coverage data from Institutional Brokers Estimate System (I/B/E/S).[8]

To ensure that accounting information is known before the return series it is measured against, I match CRSP weekly returns between July of year t and June of year t+1 with accounting information for fiscal year ending in year t-1, as in Fama and French (1992). Book equity is stockholder's equity plus balanced sheet deferred tax and investment tax credit minus the book value of preferred stock. COMPUSTAT market equity is stock price times shares outstanding at fiscal year end in year t-1. Book-to-market ratio is calculated by dividing book equity by COMPUSTAT market equity. Sales is COMPUSTAT net sales. Size (CRSP market equity) is measured by multiplying shares outstanding by share price for June of year t. Turnover is measured by averaging, from July of year t-1 to June of year t, the ratio of the number of shares traded in a week to the number of shares outstanding at the end of the week. In addition, institutional ownership is in percentage terms recorded at the end of year t-1. Number of analysts is the average

[6] Calculating weekly returns from *Wednesday to the following Wednesday* is the convention in studying short horizon return dynamics. For example, see Keim and Stambaugh (1984), Bessembinder and Hertzel (1993), Boudoukh, Richardson and Whitelaw (1994) and Chordia and Swaminathan (2000).

[7] Forester and Keim (1998) estimate the likelihood for a typical stock going untraded for five consecutive days to be 0.42 percent.

[8] The data on institutional ownership is available from 1981 and on, and the data on analyst coverage is available from 1976 and on. They are generally biased towards larger firms.

number of investment analysts following a firm from July of year t-1 to June of year t. Finally, for some of my tests, I also employ idiosyncratic volatility which is measured by estimating a market model regression using weekly returns from July of year t-1 to June of year t.

II. Intra-Industry Lead-lag Effect

At the end of June of each calendar year from 1963 to 2001, I assign all firms in my sample to one of twelve Fama-French industries based on the firms' 4-digit Standard Industrial Classification (SIC) code, following the industry definitions obtained from Ken French's website.[9] Firms in each industry are then sorted into three size portfolios (bottom 30%, middle 40%, and top 30%) according to end-of-June market capitalization. Equal-weighted weekly returns are calculated for each portfolio from July of year t to June of year t+1.

Table I reports summary statistics of the intra-industry size portfolios. For brevity, only results on the portfolios of the smallest 30% firms (Pi,1, i=1 to 12) and the largest 30% firms (Pi,3, i=1 to 12) within each industry are presented. For every industry, the average return of the small firm portfolio is always higher than that of the big firm portfolio. For instance, the average return on P3,1 (the portfolio of the smallest 30% firms from industry 3) is 41 basis points per week whereas it is only 24 basis points per

[9] The twelve industries are: (1) Consumer Nondurables; (2) Consumer Durables; (3) Manufacturing; (4) Oil, Gas, and Coal Extraction and Products; (5) Chemicals and Allied Products; (6) Business Equipment; (7) Telephone and Television Transmission; (8) Utilities; (9) Wholesale, Retail, and Some Services; (10) Healthcare, Medical Equipment, and Drugs; (11) Finance and (12) Others. Detailed definitions are available on Ken French's website. Assigning firms into twelve industries is mainly the result of compromising between having a reasonable number of distinct industries and having enough firms within each industry so that sorting within industries will not produce portfolios that are too thin. My results remain largely unchanged when employing alternative industry classification procedures.

week for P3,3 (the portfolio of the largest 30% firms from industry 3). The first-order autocorrelation coefficient decreases with size within each industry – $\rho_1(1,1)$ is bigger than $\rho_1(3,3)$ in each of the 12 cases. Higher order autocorrelations also decline with size and decay over time.

A. *Cross-Autocorrelations and VAR test of the Lead-Lag Effect*

Table I also reports, for each industry, the first through fourth order correlation coefficients between *lagged* returns on the big firm portfolio and *current* returns on the small firm portfolio ($\rho_m(1,3)$, m=1 to 4), and between *lagged* returns on the small firm portfolio and *current* returns on the big firm portfolio ($\rho_m(3,1)$). We can clearly see that the lead-lag effect, which was first documented in Lo and MacKinlay (1990a), also exists intra-industry. The cross-autocorrelations between lagged returns on big firms and current returns on small firms within the same industry are always greater than those between lagged returns on small firms and current returns on big firms.

The observed asymmetric cross-autocorrelations are certainly consistent with the hypothesis that the stock prices of small firms react more sluggishly than big firms to new information. However, it could also be consistent with the alternative hypothesis based on time varying expected returns. That is, the cross-autocorrelations between size portfolios is a restatement of the autocorrelations of the small firm portfolio and the high contemporaneous correlation between the small firm and the big firm portfolio.[10] In other words, under this explanation, lagged returns on big firms are simply noisy proxies for lagged returns on small firms and, once the latter are controlled for, the lead-lag effect will become insignificant.

[10] In my sample, the contemporaneous correlation between the small firm portfolio and the big firm portfolio is greater than 0.50 in all but one industry.

To address this hypothesis and test the lead-lag effect between big firms and small firms within the same industry formally, I estimate the following vector-auto regressions jointly across all twelve industries:[11]

$$R_{i,1}(t) = a_{i,0} + \sum_{k=1}^{K} a_k R_{i,1}(t-k) + \sum_{k=1}^{K} b_k R_{i,3}(t-k) + e_{i,1}(t), \tag{1}$$

$$R_{i,3}(t) = c_{i,0} + \sum_{k=1}^{K} c_k R_{i,1}(t-k) + \sum_{k=1}^{K} d_k R_{i,3}(t-k) + e_{i,3}(t). \tag{2}$$

$R_{i,1}(t)$ is the equal-weighted week t return on the portfolio of the smallest 30% firms in industry i, whereas $R_{i,3}(t)$ is the equal-weighted week t return on the portfolio of the largest 30% firms from industry i. Autoregressive and cross-autoregressive coefficients are restricted to be identical across all industries in the joint regression system. Estimations are conducted with both 1 lag (K=1) and 4 lags (K=4).[12]

If the asymmetric cross-autocorrelations between $R_{i,1}$ and $R_{i,3}$ are merely a restatement of $R_{i,1}$'s own autocorrelations coupled with high contemporaneous correlation between $R_{i,1}$ and $R_{i,3}$, then once the explanatory power of the lagged values of $R_{i,1}$ is controlled for, the cross-autoregressive coefficients in the VAR should not be significantly different from zero. On the other hand, if the lead-lag effect between big firms and small firms is driven by the stock prices of big firms responding more rapidly to common information than those of small firms, then lagged returns on big firms should have independent predictive power for current returns of small firms, above and beyond that of lagged returns on small firms. In addition, this predictive power should be greater than the ability of lagged returns on small firms to predict current returns of big firms. In

[11] Similar regression models are employed in Brennan, Jegadeesh and Swaminathan (1993), and Chordia and Swaminathan (2000) to examine the lead-lag relations between stocks with different levels of analyst coverage and trading volume, respectively.

the context of the VAR (equation (1) and (2)), the above hypothesis predicts that the sum of the coefficients on $R_{i,3}(t\text{-}k)$ in equation (1) ($\sum_{k=1}^{K} b_k$) is significantly different from zero, and is greater than the sum of the coefficients on $R_{i,1}(t\text{-}k)$ in equation (2) ($\sum_{k=1}^{K} c_k$), i.e. $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$.[13]

The VAR estimation results are presented in Panel A of Table II. $\sum_{k=1}^{K} b_k$ is positive and statistically significant at the 1% level for both the 4-lag and 1-lag regressions.[14] Thus, lagged returns on big firms do contain information about current returns on small firms that is independent from that in lagged returns of small firms. Meanwhile, $\sum_{k=1}^{K} c_k$ is not different from zero in either regression, and the F-statistic (F_1) easily rejects the cross-equation restriction of $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ at the 1% level. The above results clearly indicate a lead-lag relation between big firms and small firms within the same industry.

B. *Inter- versus Intra-Industry Effects: the Intra-Industry Component Dominates*

The central proposition of this paper is that if the lead-lag effect is caused by slow diffusion of common information between firms, it should be stronger between firms

---

[12] The advantage of using only one lag is that it is easy to interpret, but it does not allow for time-series dependency beyond one week in weekly returns. VAR test with four lags eliminates this problem to a large extent, but at the expense of possibly adding noise to the estimation procedure.

[13] See the appendix in Brennan, Jegadeesh and Swaminathan (1993) for the derivation of this cross-equation restriction based on a simple model of lagged price adjustment. They also show that the sum of the c_k's in equation (2) can be negative, if variance of the residual terms in (1) and (2) is sufficiently small.

[14] It is equal to 0.2629 in the 4-lag regressions and 0.1836 in the 1-lag regression, which suggests that there is still some delayed price reaction beyond one week.

within the same industry than across different industries. Firms tend to move more closely with their industry peers as they operate in the same product market and face the same supply and demand shocks. They respond similarly to changing economic conditions, and their growth opportunities, investing and financing policies, and capital structure tend to be similar. This implies that news regarding big firms conveys more information about the future prospects of small firms within, rather than outside their own industry. Hence, lagged returns on big firms from industry i should be more important than those from other industries in explaining current returns on small firms of industry i.

To investigate the above hypothesis, for every industry, I include past four weeks' returns on an equal-weighted portfolio of the largest 30% firms from all other eleven industries as additional forecasting variables for current returns on the small firm portfolio. More precisely, the following two-equation system is estimated jointly across all industries:

$$R_{i,1}(t) = a_{i,0} + \sum_{k=1}^{K} a_k R_{i,1}(t-k) + \sum_{k=1}^{K} b_k R_{i,3}(t-k) + \sum_{k=1}^{K} f_k R_{\Sigma j,3}(t-k) + e_{i,1}(t), \qquad (3)$$

$$R_{i,3}(t) = c_{i,0} + \sum_{k=1}^{K} c_k R_{i,1}(t-k) + \sum_{k=1}^{K} d_k R_{i,3}(t-k) + e_{i,3}(t), \qquad (4)$$

where $R_{\sum j,3}(t-k)$ is the equal-weighted week t-k return on the portfolio of the largest 30% firms from the other eleven industries. A stronger lead-lag effect within industry would imply that $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} f_k$ in equation (3).

The regression results are reported in Panel B of Table II. First, the lead-lag effect between big firms and small firms within the same industry remains large and highly significant even after controlling for lagged returns of big firms from other industries.

$\sum_{k=1}^{K} b_k$ only drops slightly for both the 4-lag and 1-lag regressions, whereas $\sum_{k=1}^{K} c_k$ remains insignificant for both regressions. The F-statistic (F_1) for the cross-equation restriction ($\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$) again easily rejects the null at the 1% level. More importantly, the ability of lagged returns on big firms from the same industry ($R_{i,3}(t-k)$) to predict current returns on small firms ($R_{i,1}(t)$) is greater than that of lagged returns on big firms from other industries ($R_{\sum j,3}(t-k)$). Examining the 4-lag regressions, for example, $\sum_{k=1}^{K} b_k$ is 0.2304 and significant at the 1% level, while $\sum_{k=1}^{K} f_k$ is only 0.0294 and statistically insignificant, and the F-statistic (F_2 in Panel B) rejects the null of $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} f_k$ at the 1% significance level.

C. *Robustness Checks*

Panel C of Table II demonstrates the robustness of the results in Panel B under different weighting schemes, alternative regression specifications, as well as different subsamples and subperiods. First, I re-estimate the simultaneous regression system using value-weighted returns on the size-ranked portfolios. Employing value-weighed returns, instead of equal-weighed returns, would bias my results towards larger firms, and therefore alleviate the impact of microstructure effects such as nonsynchronous trading and bid-ask spread that are usually associated with smaller firms. I obtain results that are very similar to those in Panel B. Past returns on the value-weighted portfolio of big firms can still reliably predict current returns on the value-weighted portfolio of small firms within the same industry (but not vice versa). Moreover, this predictability is much stronger than that of lagged returns on the portfolio of large firms from other industries.[15] To further address the concern of the potential influence of nontrading, I skip a week when estimating the regression system, i.e. the explanatory variables are weekly returns on the size-ranked portfolios between week t-5 and week t-2. Again, my results remain largely unchanged. I also split the entire sample period (July 1963 – December 2001) into two subperiods (July 1963 – June 1982 and July 1982 – December 2001), and find a strong intra-industry effect and a much weaker inter-industry effect in both of them. Furthermore, in order to ensure that my findings are not entirely driven by the small firms on AMEX and NASDAQ, I restrict my sample to only firms listed on NYSE. Both equal-weighted and value-weighted regression results clearly indicate a strong lead-lag relation between firms within the same industry. The last model of this panel shows that including contemporaneous returns on big firms in equation (3) does not affect the significance of the intra-industry lead-lag effect.[16]

D. *Does Bad News Travel Slowly?*

If market frictions and institutional constraints are responsible for slow dissemination of information, then we should observe an asymmetry in the response of small firms to past returns on big firms since the impact of market frictions is usually more pronounced when bad news arrives. For example, the short sale constraint can delay

---

[15] For example, in the 4-lag regressions, $\sum_{k=1}^{K} b_k$ is 0.1713 and significant at the 1% level, whereas $\sum_{k=1}^{K} c_k$ is only 0.0052 and $\sum_{k=1}^{K} f_k$ equals -0.0199, both are statistically insignificant. The F-statistics (F_1 and F_2) reject the coefficient restrictions $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ and $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} f_k$ both at the 1% significance level.

[16] The hypothesis examined here is that the strong intra-industry lead-lag effect is due to higher contemporaneous correlation between big firms and small firms within the same industry, and once this effect is accounted for, there is little difference in the predict power between lagged returns of intra-

the incorporation of negative information into stock prices (Diamond and Verrecchia (1987). To test this hypothesis, I add dummy variables for positive and negative lagged returns to the 1-lag VAR regressions:

$$R_{i,1}(t) = a_{i,0} + a_1 R_{i,1}(t-1) D_{i,1}(t-1) + a_2 R_{i,1}(t-1) + b_1 R_{i,3}(t-1) D_{i,3}(t-1) + b_2 R_{i,3}(t-1) + e_{i,1}(t), \quad (5)$$

$$R_{i,3}(t) = c_{i,0} + c_1 R_{i,1}(t-1) D_{i,1}(t-1) + c_2 R_{i,1}(t-1) + d_1 R_{i,3}(t-1) D_{i,3}(t-1) + d_2 R_{i,3}(t-1) + e_{i,3}(t). \quad (6)$$

$D_{i,1}$(t-1) ($D_{i,3}$(t-1)) equals one if $R_{i,1}$(t-1) ($R_{i,3}$(t-1)) is positive and zero otherwise. Equation (5) and (6) are again estimated simultaneously across all twelve industries. A slower response by small firms to negative information on big firms within the same industry would imply that b_1 is negative and significantly different from zero.

The regression results are presented in Panel D of Table II. As predicted, good news is diffused rather quickly between small and big firms, and it is mainly the slow adjustment of small firm stock prices to bad news on big firms that is driving the observed lead-lag effect. b_1 is –0.1558 and significant at the 1% level, and the sum of b_1 and b_2 (0.1283) is less than half of b_2 (0.2841), indicating that the ability of past returns on big firms to forecast current returns on small firms is much greater when the returns on big firms are negative.

Thus far, this paper has shown that the lead-lag effect is a predominantly intra-industry phenomenon: lagged returns on big firms reliably predict current returns on small firms in the same industry, but not vice versa, and there is little evidence of predictability between firms from different industries once this intra-industry effect is accounted for. The evidence suggests that industry is important for understanding the

industry large firms and inter-industry large firms. If this hypothesis is true, then the lead-lag effect is not primarily an intra-industry effect.

process by which new information gets disseminated in the stock market. In the next section, I consider alternative determinants of the intra-industry lead-lag effect.

III. More on Intra-Industry Lead-Lag Effect: Alternative Determinants

In the previous section, I obtain results on the intra-industry lead-lag effect by sorting firms into portfolios based on firm size. A number of researchers have proposed alternative determinants of the lead-lag effect, including the number of investment analysts following a firm (Brennan, Jegadeesh and Swaminathan (1993)), the level of institutional ownership (Badrinath, Kale and Noe (1995)), and trading volume (Chordia and Swaminathan (2000)). Since analyst coverage, institutional holdings and trading volume tend to cluster at the industry level, I will first test whether these variables have explanatory power on their own right, or whether they are subsumed by industry considerations. Then I will explore several other measures which, *a priori*, should also be related to the intra-industry lead-lag effect.

A. *Analyst Coverage, Institutional Ownership and Trading Volume*

Because number of analysts, institutional ownership and trading volume are all positively correlated with firm size, I must control for the size effect in the analysis. Thus, when I form portfolios within each industry based on those characteristics, I first sort firms into three portfolios (top 30%, middle 40% and bottom 30%) according to their size. I then divide each size portfolio into three portfolios (top 30%, middle 40% and bottom 30%) according to analyst coverage (the average number of analysts following the firms over the previous year), institutional ownership (the level of institutional ownership measured at the end of year t-1), or trading volume (the average weekly share turnover over the previous year).[17] As a result of this two-way sort, I have nine portfolios within each industry. Finally, firms from the same characteristic-ranked portfolio from each of the three size groups are placed into one portfolio. This gives me, within each industry, three intra-industry characteristic-ranked portfolios while holding size approximately fixed. In addition, an inter-industry portfolio is formed, for each industry of interest, by grouping firms with the highest characteristic rank from the other 11 industries. Returns on the highest and lowest characteristic-ranked portfolio ($R_{i,3}$ and $R_{i,1}$, respectively) from each industry and the corresponding inter-industry portfolio ($R_{\sum j,3}$) are used to estimate equation (3) and (4) jointly across all industries.[18] The estimation results, reported in Panels A-C of Table III, show that there exist strong lead-lag effects based on analyst coverage, institutional ownership and trading volume. Furthermore, these effects are independent from the size effect, and are primarily intra-industry phenomena. Controlling for firm size, returns on firms with the highest levels of analyst coverage (institutional ownership, or trading volume) continue to predict returns on firms with lower levels of analyst coverage (institutional ownership, or trading volume) from the same industry, and this intra-industry predictability is much stronger than that of high analyst coverage (institutional ownership, or trading volume) firms from other industries.

B. *Industry "Leaders" versus "Followers"*

I propose another proxy of the speed of information flow – market share, as there might exist a lead-lag relation between industry leaders and other firms within the

---

[17] Because of the institutional differences between NYSE/AMEX and NASDAQ (specialist market vs. dealer market), the recorded trading volume is not directly comparable between them. Also the trading volume data is not available on the NASDAQ tape prior to 1983. I therefore employ NYSE/AMEX firms for tests related to trading volume.

[18] Note that the VAR system ((1) and (2)) is nested in (3) and (4) which also allow us to test whether a lead-lag effect is primarily an intra-industry effect.

industry. A new piece of information usually affects firms with big market share (industry leaders) first. However, this information will not be impounded into the prices of other firms in the same industry instantaneously due to information cost and institutional restrictions. As investors of those firms take time to re-evaluate their shares by extracting information from past price movements of industry leaders, a lead-lag relation between industry leaders and followers arises.

In investigating the intra-industry lead-lag effect related to market share, I control for firm size since the two variables are likely to be highly correlated. Similar to the portfolio formation procedure implemented in Section III.A, within each industry I first sort firms into three size portfolios, and within each size portfolio into three portfolios based on net sales. Then firms from the same sales-ranked portfolio from each of the three size portfolios are grouped into one portfolio, resulting in three intra-industry sales-ranked portfolios holding size fixed. An inter-industry portfolio is also formed by grouping together firms with big market share from the other 11 industries. Panel D presents results of the intra-industry lead-lag test (equation (3) and (4)), using returns on the two extreme sales-ranked portfolios within each industry and the corresponding inter-industry portfolio. These results show that, holding size constant, returns on firms with the biggest market share lead returns on firms with smaller market share from the same industries, and there is little evidence of cross-industry predictability related to market share. For both the 4-lag and 1-lag regressions, $\sum_{k=1}^{K} b_k$ from equation (3) is greater than $\sum_{k=1}^{K} c_k$ from equation (4) and $\sum_{k=1}^{K} f_k$ from equation (3), and the coefficient restrictions $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ and $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} f_k$ are both rejected at the 1% significance level.

C. *"Value" versus "Growth" Firms*

Fama and French (1992) postulate that the premium associated with high BE/ME firms is related to the relative distress effect in Chan and Chen (1991). This argument is further supported by these firms' persistent poor earnings and return performance in the past (Fama and French (1995)). Under this explanation, the future profitability of high BE/ME firms is more sensitive to changes in surrounding economic environment, and consequently, these firms' stock prices would adjust to aggregate shocks more rapidly. Moreover, when a firm becomes distressed (all else being equal), it will usually come under closer scrutiny by (informed) investors, possibly because it is forced to raise capital more frequently via external markets (Eastrbrook (1984), and Almazan, Suarez and Titman (2002)). As a result, a larger amount of information will be produced on it. This again suggests that the stock prices of high BE/ME firms will adjust more rapidly to new information, and their returns lead those of low BE/ME firms. In this section, I investigate this hypothesis by conditioning on industry.

It is important to control for the impact of firm size when investigating the lead-lag effect related to BE/ME because size and BE/ME are negatively correlated. If not accounted for, the lead-lag effect between big firms and small firms will surely confound our inferences on the BE/ME effect. Therefore, I construct within each industry three BE/ME-ranked portfolios, holding size constant.[19] Panel E of Table III reports the

[19] Consistent with the hypothesis that high BE/ME firms are subject to greater scrutiny by informed investors, I find that they are followed by an average of 3.83 analysts and have an average institutional ownership of 18%, whereas the corresponding numbers for low BE/ME firms are 2.16 (analyst coverage) and 10% (institutional ownership). The test for equal mean between the two groups produces a t-statistic of 4.30 for analyst coverage and 3.94 for institutional ownership, indicating rejections of the null at the 1% significance level. Also not tabulated are the results of Fama-MacBeth (1973) cross-sectional regressions of ln(BE/ME) on ln(SIZE), analyst coverage and institutional ownership, in which the time series means of the coefficients on analyst coverage and institutional ownership are both positive and highly statistically significant.

regression coefficients for equation (3) and (4), estimated jointly across all industries. These coefficients are consistent with an intra-industry lead-lag effect based on BE/ME. Lagged returns on high BE/ME firms strongly predict current returns on low BE/ME firms, and this ability to predict is significantly greater than that of low BE/ME firms' lagged returns for current returns on high BE/ME firms. Moreover, the predictive power is much stronger for high BE/ME firms from the same industry than from other industries.

D. *Idiosyncratic Volatility*

Finally, I postulate that the firm-specific component of return variance (idiosyncratic volatility) may also contain information about the lead-lag effect within industries. The bigger the idiosyncratic volatility, the noisier the signal on a stock. In addition, many investors, especially institutional investors, tend to avoid stocks with high idiosyncratic volatility. Accordingly, there is a slower diffusion of new information into the stock prices of firms with higher levels of idiosyncratic volatility, and these firms' returns lag those of their less volatile industry peers.

I estimate the idiosyncratic volatility with a market model regression using weekly returns from July of year t-1 to June of year t, matched with returns from July of year t to June of year t+1.[20] Within each industry, I sort stocks into three portfolios (top 30%, middle 40%, and bottom 40%) based on the inverse of estimated idiosyncratic volatility while holding size constant. Weekly returns on the two extreme portfolios and the corresponding inter-industry portfolio are used to conduct the intra-industry lead-lag test. The results in Panel F clearly show that returns on firms with the lowest level of

[20] The market portfolio is proxied by the value-weighted portfolio of NYSE/AMEX/NASDAQ firms.

idiosyncratic volatility lead returns on their peers with higher levels of idiosyncratic volatility, even after controlling for size. This effect is again primarily an intra-industry effect. The evidence supports my hypothesis that idiosyncratic volatility is related to the speed of information diffusion.

Each of the variables discussed above adds a unique perspective to the intra-industry lead-lag effect in stock returns. They demonstrate the complexity of the information structure in the equity market. For the rest of this paper, I return to the effect associated with size and use it to explore cross-industry differences in the lead-lag effect, and link the intra-industry lead-lag effect with the industry momentum anomaly.

IV. Cross-Industry Differences in Lead-Lag Effect

In this section, I investigate whether industries exhibit different levels of the lead-lag effect. To address this question, I add an interaction term to the 1-lag vector-auto regressions, allowing the ability of lagged returns on big firms to predict current returns on small firms to vary with the characteristic of the industry in question:

$$R_{i,1}(t) = a_{i,0} + a_1 R_{i,1}(t-1) + b_1 R_{i,3}(t-1) + b_2 R_{i,3}(t-1) \times IC_i(\mathrm{t}) + e_{i,1}(t), \qquad (7)$$

$$R_{i,3}(t) = c_{i,0} + c_1 R_{i,1}(t-1) + d_1 R_{i,3}(t-1) + e_{i,3}(t). \qquad (8)$$

IC_i refers to characteristic of industry i. The first four panels of Table IV employ the industry median values of a set of measures, which have been previously shown to be positively related to the speed of information diffusion within an industry: firm size, analyst coverage, institutional ownership, and share turnover. The coefficients on all four interaction terms are negative and statistically significant at the 1% level, indicating a stronger lead-lag effect in industries that are smaller, followed by fewer investment analysts, not significantly owned by institutional investors, and having lower levels of trading volume. The results are consistent with the lagged information diffusion story, as these industries are the ones in which we would expect information to transmit more slowly.

I also find a more pronounced effect in industries where information is noisier. In Panel E, I interact industry median idiosyncratic volatility with lagged returns on big firms. The interaction term is positive with a t-statistic of 2.65. Additionally, I measure the quality of information using the analyst dispersion variable in Diether, Malloy and Scherbina (2001), which is calculated by dividing the standard deviation of analysts' annual earnings forecast by the absolute value of the mean forecast.[21] Once again, the interaction term is positive and statistically significant.

Product market competition may also have an impact on the speed of information diffusion in an industry. In concentrated industries, the dramatic difference in market position between big and small firms makes it more difficult for investors of small firms to interpret the effect that past price movements of big firms have on their share prices. As a result, news diffuses very slowly between big and small firms. This diffusion is less sluggish in competitive industries, where it is relatively easy for investors of small firms to extract relevant information from past price changes on big firms. I measure product market competitiveness with the Herfindhal index, which is the sum of the squared market share of all firms in an industry. The results in Panel G confirm my conjecture. Indeed, there is a positive relationship between the Herfindhal index and the significance of the lead-lag effect, as evidenced by the positive and statistically significant coefficient on the interaction term.

V. Lead-Lag Effect and Industry Momentum Anomaly

Despite considerable research efforts, the profitability of momentum trading strategies (Jegadeesh and Titman (1993)) remains one of the most controversial issues during current debate between market efficiency and behavioral finance. A large number of theories have been put forth to account for this persistence in stock returns. In a recent study, Moskowitz and Grinblatt (1999) report that there is a strong and prevalent momentum component in industry portfolio returns. Recall that the autocovariance of an industry portfolio is merely the sum of the autocovariances of the individual stocks in that industry and the cross-autocovariances between them. Since individual stock returns are on average negatively autocorrelated, the industry momentum effect has to be due to a lead-lag effect within industries, and once controlled for, the industry momentum effect should become insignificant.[22]

In this section, I interact the industry momentum effect with the intra-industry lead-lag effect in a Fama-MacBeth (1973) cross-sectional regression framework. Each week, I estimate a cross-sectional regression on the smallest 70 percent firms from every industry.[23] Individual stock returns are regressed on ln(size), ln(BE/ME), various industry momentum variables (industry returns over past one month, six months and twelve months) and intra-industry lead-lag variables (lagged returns from week t-4 to week t-1 on the portfolio of the largest 30 percent firms in the industry to which each small firm

[21] I thank Chris Malloy for providing the data on analyst dispersion.
[22] See also Grundy and Martin (2001).
[23] I obtain similar results when I employ all firms in the cross-sectional regressions.

belongs).[24] The coefficients from the weekly regressions are averaged over time and reported in Table VII, along with their time-series t-statistics.

The table shows that each industry momentum variable, taken alone, is highly significant in cross-sectional regressions. However, when they are employed simultaneously as independent variables, the significance of the six-month and twelve-month industry momentum variables is weakened by the one-month industry momentum variable. This finding is consistent with Moskowitz and Grinblatt (1999), which shows that the industry momentum strategy is strongest at one-month horizon. However, once I include past four weeks' returns on large firms within the same industry, all three industry momentum variables lose their significance, consistent with the intra-industry lead-lag effect driving the industry momentum effect. This finding suggests that slow diffusion of information between firms contributes significantly to the profitability of the industry momentum strategies. Furthermore, to the extent that the lead-lag effect is more prevalent for negative news (as shown in Section II), the result in this section is broadly consistent with the explanation of the momentum anomaly based on slow diffusion of bad news (Hong and Stein (1999), and Hong, Lim and Stein (2000)). Finally, the results also suggest that the lead-lag effect has implications for longer horizon returns and anomalies.

[24] In my sample, the industry momentum strategies that are based on past one-month, six-month and twelve-month industry returns generate average weekly profits of 25 basis points (t-statistic=7.24), 18

VI. Conclusion

I find that the previously documented lead-lag effect (Lo and MacKinlay (1990a)) is driven by a persistent intra-industry component. Returns on big firms lead returns on small firms within the same industry. Once this effect is controlled for, little evidence of predictability across industries can be found. The intra-industry lead-lag effect is robust to alternative test specifications, different weighting methods, and different subsamples and subperiods. Moreover, this effect is primarily caused by stock prices' sluggish response to negative information. Other known determinants of the lead-lag effect remain significant intra-industry: returns on firms with the highest level of analyst coverage (institutional ownership, or trading volume) lead returns on firms with lower levels of analyst coverage (institutional ownership, or trading volume) from the same industry, controlling for firm size. Furthermore, returns on industry leaders lead returns on industry followers; returns on value firms lead returns on growth firms; returns on less volatile firms lead returns on highly volatile firms from the same industry. The significance of the intra-industry lead-lag effect varies with the characteristics of the industry in question. The effect is more pronounced in industries that are smaller and less competitive, as well as those with lower levels of analyst coverage, institutional ownership and trading volume, and higher levels of residual volatility and analyst dispersion. Finally, I find that the intra-industry lead-lag effect drives the industry momentum anomaly. My findings cannot be fully explained by nonsynchronous trading or time varying expected returns, and are most consistent with slow information diffusion between firms within the same industry.

---

basis points (t-statistic=5.10) and 22 basis points (t-statistic=5.85), respectively.

It is very important to get a clear understanding on the mechanism by which information is diffused among firms and into stock prices, as it has profound implications for market efficiency and asset pricing. This paper takes a first step towards that direction. There are several venues worth pursuing in the future.

First, although this paper has checked the slow information diffusion story against a number of alternatives, the list is far from exhaustive, and there certainly exist other explanations that are not addressed directly in this paper. For instance, could the lead-lag effect be caused by correlated sentiment (Lee, Shleifer and Thaler (1991)) or specific trading patterns of investors, such as style investing (Barberis and Shleifer (2003))? One potential way of differentiating this "trading-based" view from the information diffusion story is to link the lead-lag effect in returns to other sources of information about a firm's future prospect. Indeed, Hou (2002) finds that the lead-lag effect between big and small firms within the same industry is related to the response of small firms to past earnings surprises on big firms. This finding suggests that the behavioral explanations mentioned above cannot be the whole story. Further work along this line to identify other alternative theories and exploring the extent to which they can explain the additional evidence on the lead-lag effect presented in this paper, can not only help us determine the relevancy of these alternatives, but also promote further understanding of the lagged information diffusion process between firms.

Second, more work on measuring and distinguishing the impact of various market frictions and investment constraints on the information diffusion process, and studying the extent to which these frictions prevent the lead-lag effect from being arbitraged away could lead to richer predictions and empirical tests.

Third, we can also benefit from more work on investigating the effect of slow information diffusion on the *level* of expected returns, and therefore linking time series return predictability to cross-sectional return predictability. This could provide additional insights on some of the puzzling issues in asset return dynamics and is currently pursued in Hou and Moskowitz (2003).

Fourth, I have presented some stylized facts linking the significance of the intra-industry lead-lag effect to the characteristics of the industry in question. Further investigations along this line, on how the differences across industries in product market and financial market characteristics, legal environment, as well as growth opportunities influence the way that information is transmitted within industries, may also prove to be a fruitful area of future research.

References

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, *Review of Financial Studies* 1, 3-40.

Asness, Clifford, and Ross Stevens, 1996, Intra-industry and inter-industry factors in the cross-section of expected stock returns, Working Paper, Goldman Sachs Asset Management.

Almazan, Andres, Javier Suarez, and Sheridan Titman, 2002, Capital structure and Transparency, Working Paper, The University of Texas at Austin.

Badrinath, S.G., Jayant R. Kale, and Thomas H. Noe, 1995, Of shepherds, sheep, and the cross-autocorrelations in equity returns, *Review of Financial Studies* 8, 401-430.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, forthcoming, *Journal of Financial Economics*.

Bessembinder, Hendrik, and Michael G. Hertzel, 1993, Return autocorrelations around non-trading days, *Review of Financial Studies* 6, 155-190.

Boudoukh, Jacob, Matthew P. Richardson, and Robert F. Whitelaw, 1994, A tale of three schools: insights on autocorrelations of short-horizon stock returns, *Review of Financial Studies* 7, 539-573.

Brennan, Michael J., Narasimhan Jagadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799-824.

Chan, Kalok, 1993, Imperfect information and cross-autocorrelation among stock prices, *Journal of Finance* 48, 1211-1230.

Chan, K.C., and Nai-fu Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467-1484.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, *Journal of Finance* 55, 913-935.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1986, *The Microstructure of Securities Markets*, Prentice-Hall, Englewood Cliffs, N.J.

Conrad, Jennifer, and Gautam Kaul, 1988, Time varying expected returns, *Journal of Business* 61, 409-425.

Conrad, Jennifer, and Gautam Kaul, 1989, Mean-reversion in short-horizon individual security return, *Journal of Financial Economics* 29, 365-384.

Conrad, Jennifer, Gautam Kaul, and M. Nimalendran, 1991, Components of short-horizon individual security returns, *Journal of Financial Economics* 29, 365-384.

Diamond, Douglas, and Robert Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277-311.

Diether, Karl, Christopher Malloy, and Anna Scherbina, 2002, "Differences of opinion and the cross-section of stock returns," *forthcoming Journal of Finance*.

Easterbrook, Frank H., 1984, Two agency-cost explanations of dividends, *American Economic Review* 74, 650-659.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131-155.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Forester, Stephen R., and Donald B. Keim, forthcoming, Direct evidence of non-trading of NYSE and AMEX stocks; in W. Ziemba and D.B. Keim, eds: *Security Market Imperfections in Worldwide Equity Markets* (Cambridge University Press, New York).

Foster, F. Douglas, and S. Viswanathan, 1993, The effect of public information and competition on trading volume and price volatility, *Review of Financial Studies* 6, 23-56.

Foster, George, 1981, Intra-industry information transfers associated with earnings release, *Journal of Accounting and Economics*, 201-232.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies*, 14, 29-78.

Hameed, Allaudeen, 1997, Time-varying factors and cross-autocorrelations in short-horizon stock returns, *Journal of Financial Research* 20, 435-458.

Holden, Craig W., and Avanidhar Subrahmanyam, 1992, Long-lived private information and imperfect competition, *Journal of Finance* 47, 247-270.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hou, Kewei, 2002, Information diffusion and asymmetric cross-autocorrelations in stock returns, Unpublished Ph.D. dissertation, The University of Chicago.

Hou, Kewei, and Tobias J. Moskowitz, 2003, Market frictions, price delay, and the cross-section of expected returns, Working Paper, The Ohio State University.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kadlec, Gregory B., and Douglas M. Patterson, 1999, A transactions data analysis of nonsynchronous trading, *Review of Financial Studies* 12, 609-630.

Keim, Donald B., and Robert F. Stambaugh, 1984, A further investigation of the weekend effect in stock returns, *Journal of Finance* 39, 819-834.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lee, Charles, Andrei Shleifer, and Richard Thaler, 1991, Investor sentiment and the close-end fund puzzle, *Journal of Finance* 46, 75-110.

Lo, Andrew W., and A. Craig MacKinlay, 1990a, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.

Lo, Andrew W., and A. Craig MacKinlay, 1990b, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181-211.

McQueen, Grant, Michael Pinegar, and Steven Thorley, 1996, Delayed reaction to good news and the cross-autocorrelation of portfolio returns, *Journal of Finance* 51, 889-919.

Mech, Timothy S., 1993, Portfolio return autocorrelation, Journal of Financial Economics 34, 307-344.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483-510.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance 54*, 1249-1290.

Peng, Lin, 2002, Learning with Information Capacity Constraints, Working paper, Duke University.

Table I: Summary Statistics for the Intra-Industry Size Portfolios

Table I reports summary statistics for intra-industry size portfolios from July 1963 to December 2001 (2008 weekly observations). At the end of June of year t, firms on CRSP NYSE/AMEX/NASDAQ tapes with sharecodes 10 or 11 are assigned into one of twelve Fama-French industry portfolios based on their 4-digit Standard Industrial Classification (SIC) codes, following the industry definitions obtained from Ken French's website. Firms within each industry portfolio are then sorted into three size portfolios (bottom 30%, middle 40% and top30%) according to their end-of-June market capitalization. Equal-weighted weekly returns are computed for each portfolio from July of year t to June of year t+1. Pi,j, i=1 to 12 and j=1 or 3, refers to the j^{th} size-ranked portfolio from industry i, j=1 for the portfolio of the smallest 30% firms and j=3 for the portfolio of the largest 30% firms. N refers to the average number of firms in each portfolio. Mean and median size are calculated first across stocks within each portfolio, and then averaged across time. They are in billions of dollars. $\rho_m(j,k)$, m=0 to 4, j=1 or 3, and k=1 or 3, refers to the m^{th} order correlation coefficient between returns on j^{th} size-ranked portfolio and returns on k^{th} size-ranked portfolio within each industry. For instance, ρ_1 (1,3) denotes the correlation between week t return on the small firm portfolio and week t-1 return on the large firm portfolio, whereas ρ_1 (3,1) denotes the correlation between week t return on the large firm portfolio and week t-1 return on the small firm portfolio. Cross correlation and cross-autocorrelation coefficients are in *italic*. Asymptotic standard errors for the correlation coefficients are equal to 0.0223 under the i.i.d. null.

Portfolio industry, size	N	Mean Return	Std. dev. Return	Mean Size	Median Size	ρ_0 (j,1)	ρ_0 (j,3)	ρ_1 (j,1)	ρ_1 (j,3)	ρ_2 (j,1)	ρ_2 (j,3)	ρ_3 (j,1)	ρ_3 (j,3)	ρ_4 (j,1)	ρ_4 (j,3)
P1,1	102	0.0034	0.0225	0.0085	0.0077	1.0000	*0.6204*	0.3528	*0.3312*	0.2040	*0.1739*	0.1607	*0.1341*	0.0997	*0.0962*
P1,3	102	0.0027	0.0196	2.1222	0.6566	*0.6204*	1.0000	*0.1009*	0.1611	*0.0641*	0.0893	*0.0092*	0.0705	*-0.0091*	0.0086
P2,1	45	0.0036	0.0290	0.0096	0.0090	1.0000	*0.6122*	0.2708	*0.3179*	0.1652	*0.1558*	0.1098	*0.1081*	0.0972	*0.0847*
P2,3	45	0.0026	0.0244	3.2086	0.5185	*0.6122*	1.0000	*0.0862*	0.1851	*0.0668*	0.0667	*0.0247*	0.0561	*0.0287*	0.0299
P3,1	193	0.0041	0.0229	0.0105	0.0097	1.0000	*0.7094*	0.3789	*0.3428*	0.2234	*0.1786*	0.1580	*0.1482*	0.1100	*0.1096*
P3,3	193	0.0024	0.0230	1.3927	0.5623	*0.7094*	1.0000	*0.1038*	0.1765	*0.0381*	0.0509	*0.0063*	0.0583	*-0.0025*	-0.0035
P4,1	67	0.0056	0.0313	0.0128	0.0118	1.0000	*0.5828*	0.2566	*0.2900*	0.1400	*0.1163*	0.0746	*0.0630*	0.0567	*0.0398*
P4,3	67	0.0022	0.0270	3.4527	1.0951	*0.5828*	1.0000	*0.0501*	0.1106	*-0.0022*	-0.0037	*-0.0001*	-0.0012	*0.0073*	-0.0019
P5,1	34	0.0039	0.0271	0.0135	0.0116	1.0000	*0.5054*	0.2647	*0.2454*	0.1338	*0.0894*	0.1117	*0.0899*	0.0534	*0.0525*
P5,3	34	0.0025	0.0220	3.7118	1.3395	*0.5054*	1.0000	*0.0770*	0.0950	*0.0086*	-0.0022	*0.0312*	0.0277	*-0.0049*	-0.0066
P6,1	179	0.0058	0.0313	0.0084	0.0079	1.0000	*0.6739*	0.3953	*0.3784*	0.2286	*0.1502*	0.1582	*0.1402*	0.0868	*0.1061*
P6,3	179	0.0028	0.0370	1.7546	0.3446	*0.6739*	1.0000	*0.0974*	0.1238	*0.0638*	0.0295	*0.0436*	0.0783	*-0.0490*	-0.0169

Table I, continued

Portfolio industry, size	N	Mean Return	Std. dev. Return	Mean Size	Median Size	ρ_0 (j,1)	ρ_0 (j,3)	ρ_1 (j,1)	ρ_1 (j,3)	ρ_2 (j,1)	ρ_2 (j,3)	ρ_3 (j,1)	ρ_3 (j,3)	ρ_4 (j,1)	ρ_4 (j,3)
P7,1	25	0.0054	0.0392	0.0258	0.0222	1.0000	*0.4887*	0.1918	*0.2304*	0.1124	*0.1159*	0.0810	*0.1256*	0.0433	*0.0239*
P7,3	25	0.0026	0.0263	5.8785	1.3375	*0.4887*	1.0000	*0.0488*	0.0662	*-0.0027*	0.0080	*0.0207*	0.0501	*0.0025*	-0.0271
P8,1	47	0.0028	0.0122	0.0625	0.0571	1.0000	*0.5540*	0.2570	*0.2831*	0.1347	*0.1332*	0.0803	*0.1032*	0.0334	*0.0471*
P8,3	47	0.0019	0.0176	2.3228	1.8308	*0.5540*	1.0000	*0.0493*	0.1151	*0.0033*	0.0156	*-0.0159*	0.0308	*-0.0153*	0.0067
P9,1	138	0.0039	0.0229	0.0079	0.0075	1.0000	*0.6652*	0.4121	*0.3558*	0.2583	*0.1828*	0.2083	*0.1530*	0.1474	*0.1125*
P9,3	138	0.0028	0.0248	1.2016	0.3525	*0.6652*	1.0000	*0.1317*	0.1864	*0.0624*	0.0698	*0.0505*	0.0620	*0.0249*	0.0390
P10,1	82	0.0054	0.0303	0.0189	0.0169	1.0000	*0.5874*	0.3380	*0.2894*	0.1858	*0.1062*	0.1447	*0.0895*	0.1101	*0.1091*
P10,3	82	0.0030	0.0275	2.1075	0.6816	*0.5874*	1.0000	*0.0328*	0.0817	*0.0296*	-0.0085	*-0.0055*	0.0363	*-0.0219*	-0.0133
P11,1	275	0.0037	0.0202	0.0140	0.0135	1.0000	*0.6651*	0.3676	*0.3190*	0.2180	*0.1680*	0.1764	*0.1530*	0.1096	*0.0985*
P11,3	275	0.0025	0.0196	1.3046	0.4213	*0.6651*	1.0000	*0.1240*	0.1923	*0.0309*	0.0403	*0.0187*	0.0447	*-0.0012*	0.0097
P12,1	165	0.0051	0.0250	0.0087	0.0081	1.0000	*0.6778*	0.3744	*0.3622*	0.2143	*0.1673*	0.1586	*0.1393*	0.1032	*0.1150*
P12,3	165	0.0025	0.0254	0.8081	0.3422	*0.6778*	1.0000	*0.1004*	0.1728	*0.0436*	0.0507	*0.0213*	0.0442	*-0.0160*	-0.0030

Table II: Test of Intra-Industry Lead-Lag Effect, Jointly Estimated across All Industries

In Panel A, the following 4-lag and 1-lag vector-auto regressions are estimated jointly across all industries using weekly returns on the intra-industry size portfolios (see Table I for the details on portfolio formation), from July 1963 to December 2001:

$$R_{i,1}(t) = a_{i,0} + \sum_{k=1}^{K} a_k R_{i,1}(t-k) + \sum_{k=1}^{K} b_k R_{i,3}(t-k) + e_{i,1}(t), \qquad (1)$$

$$R_{i,3}(t) = c_{i,0} + \sum_{k=1}^{K} c_k R_{i,1}(t-k) + \sum_{k=1}^{K} d_k R_{i,3}(t-k) + e_{i,3}(t), \qquad (2)$$

with i=1 to 12 and K=1 or 4. $R_{i,1}(t)$ is the equal-weighted week t return on the portfolio of the smallest 30% firms in industry i. $R_{i,3}(t)$ is the equal-weighted week t return on the portfolio of the largest 30% firms of industry i. Autoregressive and cross-autoregressive coefficients are restricted to be identical across all industries in the joint estimation. $R_{i,1}$(t-1:t-K), K=1 or 4, reports $\sum_{k=1}^{K} a_k$ from equation (1) or $\sum_{k=1}^{K} c_k$ from equation (2), depending on the left-hand-side variable. Similarly, $R_{i,3}$(t-1:t-K), K=1 or 4, reports $\sum_{k=1}^{K} b_k$ from equation (1) or $\sum_{k=1}^{K} d_k$ from equation (2). In *italic* are the F-Statistics (t-statistics) for the hypothesis that the sum of the regression coefficients equals 0 in the 4-lag (1-lag) vector-auto regressions. F_1 refers to the F-statistic for the cross-equation hypothesis that $R_{i,3}$(t-1:t-k) from equation (1) equals $R_{i,1}$(t-1:t-k) from equation (2), i.e. $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$. *** denotes significant at the 1 percent level. ** denotes significant at the 5 percent level. * denotes significant at the 10 percent level.

In Panel B, for industry i, i=1 to 12, lagged weekly returns on an equal-weighted portfolio of the largest 30% stocks from the other 11 industries ($R_{\sum j,3}$(t-k), k=1 to 4) are added to the right-hand-side of regression equation (1):

$$R_{i,1}(t) = a_{i,0} + \sum_{k=1}^{K} a_k R_{i,1}(t-k) + \sum_{k=1}^{K} b_k R_{i,3}(t-k) + \sum_{k=1}^{K} f_k R_{\sum j,3}(t-k) + e_{i,1}(t), \qquad (3)$$

$$R_{i,3}(t) = c_{i,0} + \sum_{k=1}^{K} c_k R_{i,1}(t-k) + \sum_{k=1}^{K} d_k R_{i,3}(t-k) + e_{i,3}(t). \qquad (4)$$

Equation (3) and (4) are again estimated jointly across all 12 industries. $R_{\sum j,3}$(t-1:t-k) reports the sum of the corresponding regression coefficients. F_2 refers to the F-statistic for the hypothesis $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} f_k$.

In Panel C, as robustness checks, the 4-lag and 1-lag regression system in Panel B (equation (3) and (4)) are repeated with value-weighted portfolio returns, skipping a week between lagged returns on the right-hand-side and the returns they are explaining, and for two subperiods (196307-198206 and 198207-200112) and the subsample of NYSE firms, as well as controlling for contemporaneous terms.

In Panel D, dummy variables for positive and negative lagged returns are added to the 1-lag VAR.

$$R_{i,1}(t) = a_{i,0} + a_1 R_{i,1}(t-1) D_{i,1}(t-1) + a_2 R_{i,1}(t-1) + b_1 R_{i,3}(t-1) D_{i,3}(t-1) + b_2 R_{i,3}(t-1) + e_{i,1}(t), \quad (5)$$

$$R_{i,3}(t) = c_{i,0} + c_1 R_{i,1}(t-1) D_{i,1}(t-1) + c_2 R_{i,1}(t-1) + d_1 R_{i,3}(t-1) D_{i,3}(t-1) + d_2 R_{i,3}(t-1) + e_{i,3}(t). \quad (6)$$

$D_{i,1}$(t-1) takes the value of one if $R_{i,1}$(t-1) >0, and zero otherwise. $D_{i,3}$(t-1) equals one if $R_{i,3}$(t-1) >0, and zero otherwise.

Panel A: Intra-Industry Lead-Lag Effect

	4-Lag Regressions			1-Lag Regressions		
LHS	$R_{i,1}$(t-1:t-4)	$R_{i,3}$(t-1:t-4)	F_1	$R_{i,1}$(t-1)	$R_{i,3}$(t-1)	F_1
$R_{i,1}$(t)	0.3027	0.2629	204.37***	0.2137	0.1836	309.77***
	*565.55****	*302.30****		*28.21****	*24.02****	
$R_{i,3}$(t)	-0.0183	0.1946		-0.0031	0.1414	
	2.14	*150.23****		*-0.42*	*17.80****	

Panel B: Intra- versus Inter-Industry Lead-Lag Effects

	4-Lag Regressions				1-Lag Regressions			
LHS	$R_{i,1}$(t-1:t-4)	$R_{i,3}$(t-1:t-4)	$R_{\sum j,3}$(t-1:t-4)	F_1 (F_2)	$R_{i,1}$(t-1)	$R_{i,3}$(t-1)	$R_{\sum j,3}$(t-1)	F_1 (F_2)
$R_{i,1}$(t)	0.2937	0.2304	0.0294	125.08***	0.2025	0.1482	0.0376	146.91***
	*487.58****	*157.94****	*2.05*	(40.66***)	*25.85****	*14.72****	*3.10****	(31.51***)
$R_{i,3}$(t)	-0.0183	0.1946			-0.0031	0.1414		
	2.14	*150.23****			*-0.42*	*17.80****		

Table II, continued

Panel C: Intra-Industry Lead-Lag Effect, Robustness Checks

	4-Lag Regressions				1-Lag Regressions			
LHS	$R_{i,1}$(t-1:t-4)	$R_{i,3}$(t-1:t-4)	$R_{\sum j,3}$(t-1:t-4)	F_1 (F_2)	$R_{i,1}$(t-1)	$R_{i,3}$(t-1)	$R_{\sum j,3}$(t-1)	F_1 (F_2)
				Value-Weighted Returns				
$R_{i,1}$(t)	0.3562	0.1713	-0.0199	61.92***	0.2430	0.1115	0.0201	94.59***
	*860.09****	*90.09****	*1.02*	(32.67***)	*32.96****	*11.92****	*1.97***	(26.73***)
$R_{i,3}$(t)	0.0052	0.0545			0.0001	0.0452		
	0.22	*12.67****			*0.01*	*6.09****		
				Skipping One Week				
$R_{i,1}$(t)	0.1861	0.1644	-0.0012	62.36***	0.1596	0.0647	-0.0215	13.72***
	*175.09****	*72.37****	*0.00*	(24.43***)	*19.35****	*6.12****	*-2.04***	(20.20***)
$R_{i,3}$(t)	-0.0182	0.0876			0.0170	0.0357		
	2.06	*29.79****			*2.24***	*4.16****		
				196307-198206				
$R_{i,1}$(t)	0.2467	0.3173	0.0540	95.30***	0.1651	0.1973	0.0587	91.01***
	*140.96****	*103.33****	*3.47**	(23.91***)	*13.81****	*10.94****	*3.34****	(17.81***)
$R_{i,3}$(t)	-0.0283	0.2878			0.0025	0.1740		
	*2.87**	*154.81****			*0.27*	*14.68****		
				198207-200112				
$R_{i,1}$(t)	0.3334	0.1835	0.0227	56.25***	0.2389	0.1289	0.0316	84.84***
	*379.38****	*71.80****	*1.24*	(18.74***)	*23.00****	*11.14****	*2,79****	(21.81***)
$R_{i,3}$(t)	-0.0327	0.1253			-0.0208	0.1186		
	*2.95**	*32.74****			*-1.84**	*11.07****		
				NYSE Firms				
$R_{i,1}$(t)	0.1686	0.2035	0.0217	49.22***	0.0963	0.1306	0.0439	90.63***
	*105.93****	*88.72****	*0.96*	(22.76***)	*10.92****	*11.66****	*3.65****	(17.47***)
$R_{i,3}$(t)	0.0229	0.0670			0.0017	0.0712		
	*2.71**	*14.52****			*0.22*	*8.38****		
				NYSE Firms, Value-Weighted Returns				
$R_{i,1}$(t)	0.2033	0.1422	-0.0432	33.78***	0.1275	0.1009	0.1613	55.71***
	*173.77****	*62.20****	*3.46**	(29.26***)	*15.06****	*9.74****	*1.38*	(18.71***)
$R_{i,3}$(t)	0.0198	0.007			0.0058	0.0209		
	2.14	*0.17*			*0.79*	*2.57***		

Controlling for Contemporaneous Terms

LHS	$R_{i,1}$(t-1:t-4)	$R_{i,3}$(t-1:t-4)	$R_{\sum j,3}$(t-1:t-4)	$R_{i,3}$(t)	$R_{\sum j,3}$(t)	F_1 (F_2)
			4-Lag Regressions			
Ri,1(t)	0.3101	0.1402	0.0124	0.3317	0.3148	72.27***
	*972.90****	*105.88****	*0.91*	*46.74****	*44.15****	(29.16***)
Ri,3(t)	-0.0183	0.1946				
	2.14	*150.23****				
			1-Lag Regressions			
Ri,1(t)	0.2119	0.0900	0.0092	0.3337	0.3149	77.20***
	*36.24****	*12.06****	*1.24*	*46.50****	*43.73****	(34.59***)
Ri,3(t)	-0.0031	0.1414				
	-0.42	*17.80****				

Panel E: Intra-Industry Lead-Lag Effect, Good News versus Bad News

LHS	$R_{i,1}$(t-1)$D_{i,1}$(t-1)	$R_{i,1}$(t-1)	$R_{i,3}$(t-1)$D_{i,3}$(t-1)	$R_{i,3}$(t-1)
$R_{i,1}$(t)	0.1447	0.1004	-0.1558	0.2841
	*6.60****	*6.03****	*-6.86****	*17.83****
$R_{i,3}$(t)	0.0084	-0.0091	-0.0130	0.1571
	0.41	*-0.59*	*-0.57*	*9.88****

Table III: Intra-Industry Lead-Lag Effect: Alternative Determinants

At the end of June of calendar year t from 1963 to 2001 (the sample period starts in 1976 for analyst coverage and 1981 for institutional ownership), all firms with sharecodes 10 or 11 on CRSP NYSE/AMEX/NASDAQ (NYSE/AMEX for turnover) tapes are assigned into one of twelve Fama-French industry portfolios based on their 4-digit Standard Industrial Classification (SIC) codes, following the industry definitions obtained from Ken French's website. Firms within each industry portfolio are first sorted into three size-ranked portfolios (bottom 30%, middle 40%, and top 30%) and within each size portfolios into three characteristic-ranked portfolios (bottom 30%, middle 40%, and top 30%). Then firms from the three size portfolios that have the same characteristic ranking are placed into one portfolio. This procedure generates, within each industry, three characteristic-ranked portfolios while holding size fixed. Equal-weighted weekly returns are computed for each portfolio from July of year t to June of year t+1.

Matched with individual stock returns from July of year t to June of year t+1, analyst coverage is the average number of analysts following a firm, from July of year t-1 to June of year t. Institutional ownership is in percentage terms measured in December of year t-1. Turnover is the average share turnover per week, defined as the ratio of the number of shares traded in a week to the number of shares outstanding at the end of the week, averaged from July of year t-1 to June of year t. It is calculated for NYSE/AMEX firms only. Sales is net sales for fiscal year ending in year t-1, as reported by COMPUSTAT. BE/ME is book equity divided by market capitalization at fiscal year end in year t-1. Book equity is COMPUSTAT stockholders' equity plus investment tax credit and balance sheet deferred tax minus the book value of preferred stock. Idiosyncratic volatility is estimated by running a market model regression using weekly returns from July of year t-1 to June of year t.

The following 4-lag and 1-lag regression system are estimated jointly across all industries:

$$R_{i,1}(t) = a_{i,0} + \sum_{k=1}^{K} a_k R_{i,1}(t-k) + \sum_{k=1}^{K} b_k R_{i,3}(t-k) + \sum_{k=1}^{K} f_k R_{\sum j,3}(t-k) + e_{i,1}(t), \qquad (3)$$

$$R_{i,3}(t) = c_{i,0} + \sum_{k=1}^{K} c_k R_{i,1}(t-k) + \sum_{k=1}^{K} d_k R_{i,3}(t-k) + e_{i,3}(t). \qquad (4)$$

with i=1 to 12 and K=1 or 4. $R_{i,1}(t)$ is the equal-weighted week t return on the portfolio of the lowest-ranked 30% firms in industry i. $R_{i,3}(t)$ is the equal-weighted week t return on the portfolio of the highest ranked 30% firms of industry i. $R_{\sum j,3}(t-k)$ is the equal-weighted week t-k (k=1 to 4) return on the portfolio of the highest ranked 30% firms from the other 11 industries. Autoregressive and cross-autoregressive coefficients are restricted to be identical across all industries. $R_{i,1}(t-1:t-K)$, K=1 or 4, refers to $\sum_{k=1}^{K} a_k$ from equation (3) or $\sum_{k=1}^{K} c_k$ from equation (4), depending on the right-hand-side variable. Similarly, $R_{i,3}(t-1:t-K)$, K=1 or 4, reports $\sum_{k=1}^{K} b_k$ in equation (3) or $\sum_{k=1}^{K} d_k$ in equation (4). $R_{\sum j,3}(t-1:t-k)$ reports $\sum_{k=1}^{K} f_k$ in equation (3). In *italic* are the F-Statistics (t-statistics) for the hypothesis that the sum of the regression coefficients equals 0 in the 4-lag (1-lag) vector-auto regressions. F_1 refers to the F-statistic for the cross-equation hypothesis that $R_{i,3}(t-1:t-k)$ from equation (1) equals $R_{i,1}(t-1:t-k)$ from equation (2), i.e. $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$. F_2 refers to the F-statistic for the hypothesis $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} f_k$. *** denotes significant at the 1 percent level. ** denotes significant at the 5 percent level. * denotes significant at the 10 percent level.

	4-Lag Regressions				1-Lag Regressions			
LHS	$R_{i,1}(t-1:t-4)$	$R_{i,3}(t-1:t-4)$	$R_{\sum j,3}(t-1:t-4)$	F_1 (F_2)	$R_{i,1}(t-1)$	$R_{i,3}(t-1)$	$R_{\sum j,3}(t-1)$	F_1 (F_2)
Panel A: Analyst Coverage, controlling for Size								
$R_{i,1}(t)$	-0.0075	0.2742	-0.0404	29.05***	0.0037	0.1554	0.0291	26.60***
	0.06	82.26***	3.23*	(56.79***)	0.24	10.31***	2.19**	(29.24***)
$R_{i,3}(t)$	0.0461	0.1569			0.0481	0.1052		
	2.43	28.01***			3.37***	7.37***		
Panel B: Institutional Ownership, controlling for Size								
$R_{i,1}(t)$	0.0284	0.2756	-0.0375	12.49***	-0.0182	0.1701	0.0338	33.43***
	0.79	65.90***	1.71	(33.16***)	-1.16***	9.81***	1.98**	(19.82***)
$R_{i,3}(t)$	0.1100	0.1297			0.0357	0.1347		
	11.56***	16.65***			2.32**	8.88***		

Table III, continued

LHS	4-Lag Regressions				1-Lag Regressions			
	$R_{i,1}$(t-1:t-4)	$R_{i,3}$(t-1:t-4)	$R_{\sum j,3}$(t-1:t-4)	F_1 (F_2)	$R_{i,1}$(t-1)	$R_{i,3}$(t-1)	$R_{\sum j,3}$(t-1)	F_1 (F_2)
Panel C: Turnover, controlling for Size								
$R_{i,1}$(t)	0.0663	0.2360	0.0346	9.03***	0.0150	0.1640	0.0570	23.17***
	*9.37****	*162.19****	*4.54***	(36.97***)	*1.39*	*18.83****	*6.16****	(24.87***)
$R_{i,3}$(t)	0.1361	0.1431			0.0831	0.1081		
	*20.87****	*40.81****			*5.70****	*10.39****		
Panel D: Sales, controlling for Size								
$R_{i,1}$(t)	0.1501	0.2702	-0.0265	40.88***	0.0817	0.1817	0.0341	49.25***
	*51.88****	*110.29****	*1.59*	(52.61***)	*7.38****	*13.11****	*2.61****	(38.08***)
$R_{i,3}$(t)	0.0738	0.2526			0.0640	0.1727		
	*16.19****	*150.91****			*6.69****	*16.27****		
Panel E: BE/ME, controlling for Size								
$R_{i,1}$(t)	0.1372	0.2324	-0.0132	19.65***	0.0927	0.1677	0.0391	18.59***
	*36.50****	*74.93****	*0.32*	(32.67***)	*7.70****	*10.22****	*2.66****	(21.49***)
$R_{i,3}$(t)	0.0877	0.2697			0.0956	0.1653		
	*22.31****	*168.01****			*10.07****	*15.11****		
Panel F: Inverse of Idiosyncratic Volatility, controlling for Size								
$R_{i,1}$(t)	0.2250	0.2232	*-0.0158*	12.57***	0.1174	0.1798	*0.0567*	22.87***
	*98.28****	*40.76****	*0.21*	(17.33***)	*9.75****	*9.30****	*2.62****	(12.37***)
$R_{i,3}$(t)	0.0921	0.2399			0.0824	0.1569		
	*60.33****	*149.55****			*13.22****	*14.93****		

Table IV: Cross-Industry Differences in Lead-Lag Effect

The 1-lag vector-auto regressions, with an interaction term between lagged return on big firms and industry characteristic added as an additional explanatory variable, are estimated jointly across all industries using weekly returns on the intra-industry size portfolios from July 1963 to December 2001 (the sample period starts in 1976 for analyst coverage and in 1981 for institutional ownership):

$$R_{i,1}(t) = a_{i,0} + a_1 R_{i,1}(t-1) + b_1 R_{i,3}(t-1) + b_2 R_{i,3}(t-1) \times IC_i(t) + e_{i,1}(t), \quad (7)$$

$$R_{i,3}(t) = c_{i,0} + c_1 R_{i,1}(t-1) + d_1 R_{i,3}(t-1) + e_{i,3}(t). \quad (8)$$

$R_{i,1}(t)$ is the equal-weighted return on the portfolio of the smallest 30% firms of industry i in week t. Similarly, $R_{i,3}(t)$ is the equal-weighted returns on the portfolio of the largest 30% firms of industry i in week t. See Table I for the details on the formation of these intra-industry size portfolios. IC_i denotes the characteristic of industry i.

Matched with individual stock returns from July of year t to June of year t+1, size is calculated by multiplying the number of shares outstanding by the share price at the end of June of year t. Analyst coverage is the average number of investment analysts following a firm, from July of year t-1 to June of year t. Analyst dispersion is defined in Diether, Malloy and Scherbina (2001). It is calculated by dividing the standard deviation of analysts' annual earnings forecast by the absolute value of the mean forecast. The average value of the variable from July of year t-1 to June of year t is employed. Institutional ownership is in percentage terms measure in December of year t-1. Turnover is the ratio of the number of shares traded in a week to the number of shares outstanding at the end of the week, averaged from July of year t-1 to June of year t. Idiosyncratic volatility of is estimated by running a market model regression from July of year t-1 to June of year t. HERF refers to the Herfindhal index of an industry. It is measured by the sum of squared market share of all firms within an industry.

Equation (9) and (10) are estimated jointly across all industries with coefficients restricted to be identical across industries. Reported are the coefficient estimates and their t-statistics (in *italic*). *** denotes significant at the 1 percent level. ** denotes significant at the 5 percent level. * denotes significant at the 10 percent level.

LHS	$R_{i,1}(t-1)$	$R_{i,3}(t-1)$	Interaction Term
	Panel A: IC=Industry Median ln(Size)		
$R_{i,1}(t)$	0.2062	0.6787	-0.0439
	*27.04****	*10.98****	*-8.08****
$R_{i,3}(t)$	-0.0031	0.1414	-
	-0.42	*17.80****	
	Panel B: IC=Industry Median Analyst Coverage		
$R_{i,1}(t)$	0.2449	0.2176	-0.0147
	*26.49****	*13.77****	*-5.17****
$R_{i,3}(t)$	-0.0248	0.1311	-
	*-2.48***	*13.50****	
	Panel C: IC=Industry Median Institutional Ownership		
$R_{i,1}(t)$	0.2236	0.1972	-0.0033
	*19.90****	*9.41****	*-3.45****
$R_{i,3}(t)$	-0.0249	0.1217	-
	*-2.07***	*10.52****	
	Panel D:IC=Industry Median Turnover		
$R_{i,1}(t)$	0.1574	0.2568	-8.8179
	19.71***	16.11***	-5.77***
$R_{i,3}(t)$	-0.0027	0.1050	-
	-0.39	12.96***	
	Panel E: IC=Industry Median Idiosyncratic Volatility		
$R_{i,1}(t)$	0.2008	0.1326	1.0973
	*23.85****	*5.92****	*2.65****
$R_{i,3}(t)$	-0.0053	0.1548	-
	-0.68	*17.87****	

Table IV, continued

LHS	$R_{i,1}(t-1)$	$R_{i,3}(t-1)$	Interaction Term
Panel F: IC=Industry Median Analyst Dispersion			
$R_{i,1}(t)$	0.2352	0.0885	0.4038
	*23.33****	*4.75****	*3.09****
$R_{i,3}(t)$	-0.0248	0.1311	-
	*-2.48***	*13.50****	
Panel G: IC=Industry HERF			
$R_{i,1}(t)$	0.2138	0.1851	0.1620
	*28.21****	*21.92****	*3.02****
$R_{i,3}(t)$	-0.0031	0.1414	-
	-0.42	*17.80****	

Table V: Fama-MacBeth Cross-Sectional Regressions: Industry Momentum Anomaly and Lead-Lag Effect

Fama-MacBeth (1973) cross-sectional regressions of individual stock returns on industry momentum variables and intra-industry lead-lag variables are estimated each week from July 1964 to December 2001 on the smallest 70 percent firms from each industry. R_i (-4:-1), R_i (-26:-1) and R_i (-52:-1) are the returns on the value-weighted industry portfolio, to which each small firm belongs, over the past 1 month, 6 months and 1 year, respectively. $R_{i,3}$(-1), $R_{i,3}$(-2), $R_{i,3}$(-3) and $R_{i,3}$(-4) are past four weeks' returns on the equal-weighted portfolio of the largest 30 percent firms from the industry to which each small firm belongs. Reported below are the time series averages of the coefficients from weekly regressions, as well as in *italics* the t-statistics calculated using the standard error of the mean.

ln(Size)	ln(BE/ME)	R_i (-4:-1)	R_i (-26:-1)	R_i (-52:-1)	$R_{i,3}$(-1)	$R_{i,3}$(-2)	$R_{i,3}$(-3)	$R_{i,3}$(-4)
-0.0009	0.0005							
-7.73	*3.85*							
-0.0009	0.0005	0.0642						
-7.57	*3.98*	*15.34*						
-0.0009	0.0005		0.0155					
-7.90	*3.91*		*10.82*					
-0.0009	0.0005			0.0094				
-7.85	*4.07*			*9.22*				
-0.0009	0.0005	0.0468	0.0030	0.0060				
-7.98	*4.33*	*8.937783*	*1.26*	*3.67*				
-0.0009	0.0005	-0.0105	0.0053	0.0035	0.1061	0.0784	0.0593	0.0355
-7.85	*4.95*	*-1.03*	*1.59*	*1.54*	*5.29*	*4.18*	*3.24*	*1.88*