Market Frictions, Price Delay, and the Cross-Section of Expected Returns*

Kewei Hou
Fisher College of Business, Ohio State University

and

Tobias J. Moskowitz
Graduate School of Business, University of Chicago and NBER

First Draft: March, 2002
Current Draft: April, 2003

*We thank John Cochrane, Gene Fama, John Heaton, David Hirshleifer, Andrew Karolyi, Owen Lamont, Lubos Pastor, René Stulz, Richard Thaler, Annette Vissing-Jørgensen, and seminar participants at Michigan State, Rochester, UCLA, USC, Columbia, Ohio State, the University of Chicago Finance lunch, and Fuller and Thaler Asset Management for valuable comments and suggestions as well as Martin Joyce for outstanding research assistance. Data provided by BARRA Associates, Lubos Pastor, and Soeren Hvidkjaer is gratefully acknowledged. Hou thanks the Dice Center for Research in Financial Economics for financial support. Moskowitz thanks the Center for Research in Security Prices, the Dimensional Fund Advisors Research Fund, and the James S. Kemper Foundation for financial support.

Correspondence to: Kewei Hou, Fisher College of Business, Ohio State University, 2100 Neil Ave., Columbus, OH 43210. E-mail: hou.28@osu.edu or Tobias Moskowitz, Graduate School of Business, University of Chicago, 1101 E. 58th St., Chicago, IL 60637. E-mail: tobias.moskowitz@gsb.uchicago.edu.

Market Frictions, Price Delay, and the Cross-Section of Expected Returns

Abstract

We parsimoniously characterize the severity of market frictions affecting a stock using the delay with which its share price responds to information. The most severely delayed firms command a large return premium that captures the size effect and half the value premium. Moreover, idiosyncratic risk is priced only among the most delayed firms. These results are not explained by other sources of return premia, microstructure, or pure liquidity effects, but appear most consistent with investor recognition and firm neglect. The very small segment of neglected firms (less than 0.02% of the market) captures a sizeable amount of cross-sectional variation in average returns.

Introduction

Predictability in the cross-section of returns has fueled much of the market efficiency debate. Whether such predictability is due to mismeasurement of risk or constitutes an efficient market anomaly remains unresolved, due in large part to the joint hypothesis problem. Complicating this debate, however, is the fact that traditional asset pricing theory assumes markets are frictionless and complete and investors are well-diversified, yet ample empirical evidence demonstrates the existence of sizeable market frictions and large groups of poorly diversified investors.

Both theoretically and empirically, researchers have discussed the importance of many market frictions, such as incomplete information (Merton (1987), Hirshleifer (1988), Basak and Cuoco (1998), Shapiro (2002)), asymmetric information (Kyle (1985), Jones and Slezak (1999), Easley, Hvidkjaer, and O'Hara (2002)), short sale constraints (Miller (1977), Chen, Hong, and Stein (2002), Jones and Lamont (2002)), taxes (Brennan (1970), Constantinides (1984), Grinblatt and Moskowitz (2002), Poterba and Weisbenner (2001)), liquidity (Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2002)), and noise trader or sentiment risk (DeLong, Shleifer, Summers, and Waldmann (1992), Shleifer and Vishny (1997)). In addition, from the early work of Blume and Friend (1973) to recent studies by Falkenstein (1996), Coval and Moskowitz (1999, 2001), Barber and Odean (2000), Benartzi and Thaler (2001), Benartzi (2001), Heaton and Lucas (1999, 2000), and Moskowitz and Vissing-Jørgensen (2002), a significant fraction of individual and institutional investors have been shown to hold poorly diversified portfolios.

How important are these features of the economy for understanding the cross-section of expected returns? We assess the impact of these market features for cross-sectional return predictability using a parsimonious measure of the severity of frictions facing a firm. Specifically, we characterize the degree to which market frictions affect a stock using the delay with which its share price responds to information. Firms whose stock prices respond sluggishly to news are those likely facing the most severe frictions. The link between the speed of information diffusion and market frictions is consistent with many theories. For instance, theories of incomplete markets and limited stock market participation (Merton (1987), Hirshleifer (1988), Basak and Cuoco (1998), Shapiro (2002)) or of neglected firms (Arbel and Strebel (1982), Arbel, Carvell, and Strebel (1983), Arbel (1985)) argue institutional forces and transactions costs can delay the process of information incorporation for less visible, segmented firms. Hong and Stein (1999) develop a model of gradual information diffusion and Peng (2002) shows that information capacity constraints can cause a delay in the response of asset prices to fundamental and firm-specific news. Similarly, price delay may result from lack of liquidity of an asset's shares, which can arise from many potential frictions and sources. Our measure of price delay parsimoniously captures the impact of these potential frictions on the price process of a stock.

We find that the most severely delayed firms (top decile) command a large return premium of more than 12% per year, after accounting for other return premia (most notably the market, size, book-to-market equity (BE/ME), and momentum), as well as microstructure and pure liquidity effects. More interestingly, the premium for delay subsumes entirely the effect of firm size on the cross-section of returns and about half of the value effect. These results are confirmed for both halves of the sample period (July, 1964 to June, 1983 and July, 1983 to December, 2001), for the month of January, and for a number of specifications, return adjustments, and subsamples. In addition, we find that idiosyncratic risk is priced only among severely delayed firms. We also find that post announcement drift to both earnings news and extreme market movements (top and bottom 5%) is present only for the most delayed firms.

The delay premium comes from the most delayed stocks, consistent with models of frictions where only the most constrained assets carry a premium. On a value-weighted basis, the most severely delayed firms comprise less than 0.02% of the market, yet this very small segment of firms captures a great deal of the cross-sectional variation in average returns.

We then investigate the types of firms most associated with price delay that are generating this cross-sectional predictability. First, we find that delayed firms are small, volatile, less visible, and neglected by many market participants. We then show that the premium associated with delay stems from more than just a liquidity effect. In particular, a premium for firm neglect seems to explain most of the return predictability associated with delay. Specifically, we instrument our price delay measure with traditional liquidity proxies, such as volume, price, number of trading days, and bid-ask spread and with proxies for investor recognition or attention, such as analyst coverage, regional exchange membership, number of shareholders, institutional ownership, and remoteness (average airfare from all airports to firm headquarters). We find that the explanatory power of delay for the cross-section of returns is driven entirely by the component of delay captured by the attention/recognition variables. There is no premium or predictability associated with traditional proxies for liquidity. We also show no relation between the delay premium and the aggregate liquidity risk premium of Pastor and Stambaugh (2002). Hence, either a strong premium associated with firm visibility exists, or the attention variables we employ are better proxies for liquidity than traditional measures. This provides a new interpretation of the size and (half of) the value effect. Small, value firms carry a premium because they respond slowly to information. Such sluggishness arises because these stocks are less visible and ultimately neglected.

In addition, the fact that idiosyncratic risk is priced only among the most delayed firms is consistent with a neglected firm premium. Since the most delayed firms are segmented from the rest of the market, residual volatility, as opposed to beta, is a better measure of risk for these firms since risk is not being shared efficiently. Merton (1987), Hirshleifer (1988), and Basak and Cuoco (1998) make similar predictions. Also, frictions associated with information asymmetry or sentiment risk do not appear to explain our findings. We find no relation between Easley, Hvidkjaer, and O'Hara's (2002) measure of informed trading risk and the delay premium. We also find little relation between high growth stocks and the delay premium or momentum and delay, which suggests delay is not likely associated with noise trader risk if sentiment is associated with growth and momentum as suggested by recent theory (Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)).

In the final part of the paper, we discuss the impediments to exploiting the price delay premium and why it may persist in markets. The delay premium resides among small, value stocks, recent losers, and stocks with low institutional ownership and high idiosyncratic risk. Consequently, trading and price impact costs may limit the ability to exploit this phenomenon.

The rest of the paper is organized as follows. Section I describes the data and measures of price delay. Section II examines how price delay predicts the cross-section of expected stock returns. We show how the premium associated with delay subsumes the size effect and half the value effect. We also show that idiosyncratic risk is priced only among the most severely delayed firms and that post-announcement drift occurs only among such firms. Section III then tests various hypotheses for what drives the delay premium. We examine the characteristics of firms associated with severe price delay and their relation to the cross-section of returns. Section IV discusses the tradeability of severely delayed firms and what frictions might be present. Finally, Section V concludes.

I. Data and Measures of Price Delay

Our sample employs every listed security on the Center for Research in Security Prices (CRSP) data files with sharecodes 10 or 11 (e.g., excluding ADR's, closed-end funds, REIT's) from July, 1963 to December, 2001. From 1963 to 1973, the CRSP sample includes NYSE and AMEX firms only, and post-1973 NASDAQ-NMS firms are added to the sample. For many of our tests, we require book value of common equity from the previous fiscal year available on COMPUSTAT. Book value of equity is defined as in Fama and French (1993) to be book value of stockholder's equity plus balance sheet deferred taxes and investment tax credits minus the book value of preferred stock. Weekly, as opposed to monthly or daily, returns are employed to estimate price delay. At monthly frequencies, there is little dispersion in delay measures since most stocks respond to information within a month's time. Also, estimation error is much higher. Although daily frequencies might provide more dispersion in delay, the cost of using daily (or even intra-daily) data in terms of confounding microstructure influences (such as bid-ask bounce and non-synchronous trading) can be large. In addition, we are primarily concerned with capturing stocks with the most severe delay (frictions), whose lagged response may take several weeks. We define weekly returns to be the change from Wednesday to Wednesday closing prices (plus dividends) as in Moskowitz (2002) and Hou (2002).[1] Measures of price delay require a year of prior weekly return history (firms with missing weekly return observations over the prior year are excluded). Hence, the trading strategy returns begin in July, 1964.

For some of our tests we also employ data on the number of employees and number of shareholders obtained from COMPUSTAT. These data items are not recorded for many firms, mostly small firms, and hence may introduce a selection bias into our analysis. However, this selection issue likely understates our results. We also supplement these data with institutional ownership information (available from January, 1981 on) from Standard & Poors and analyst coverage (available from January, 1976 on) from Institutional Brokers Estimate System (I/B/E/S). Analyst coverage is defined as the number of analysts providing current fiscal year annual earnings estimates each month as in Diether, Malloy, and Scherbina (2002). The I/B/E/S and S&P data also introduce a slight bias toward larger firms.

Finally, we augment our sample with the stock's headquarters location (obtained from *Disclosure* and matched to latitude and longitude coordinates from *Geographic Names Information System Digital Gazetteer* (GNISDG), published by the *U.S. Geological Survey*) to compute distances between locations as in Coval and Moskowitz (1999, 2001). This is used to identify nearest airport locations and to calculate average air route distances and airfare between all U.S. airports. The data are obtained from the *Intermodal Transportation Database* (ITDB) collected by various agencies within the U.S. Department of Transportation and the U.S. Bureau of the Census. We

[1]Wednesday to Wednesday closing prices are used to compute weekly returns since Chordia and Swaminathan (2000), Hou (2002), and others document high autocorrelations using Friday to Friday prices and low autocorrelations using Monday to Monday prices. Wednesday seems like an appropriate compromise.

also employ indicator variables for regional exchange membership, obtained from each U.S. regional stock exchange.[2]

A. *Measuring Price Delay*

To measure the delay with which a stock's price responds to information, we run, at the end of June of each calendar year, the following regression of weekly stock returns on contemporaneous and 4 weeks of lagged returns on the market portfolio plus 4-week lags of the stock's own return. We only employ up to 4 weekly lags since autocorrelation coefficients at 5 lags or greater are negligible and highly volatile. Also, 4 weeks seems like a fair amount of time for a stock to respond to news. Most of the significance on the lagged regressors occurs at 1 or 2 week lags. Specifically, for each stock j we estimate,

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \sum_{n=1}^{4} \delta_j^{(-n)} R_{m,t-n} + \sum_{n=1}^{4} \gamma_j^{(-n)} r_{j,t-n} + \epsilon_{j,t} \tag{1}$$

using the prior 52 weeks of return data, where $r_{j,t}$ is the return on stock j and $R_{m,t}$ is the return on the CRSP value-weighted market index at time t. If the stock responds immediately to market news, then β_j will be significantly different from zero, but none of the $\delta_j^{(-n)}$'s will differ from zero. If, however, stock j's price responds with a lag, then some of the $\delta_j^{(-n)}$'s will differ significantly from zero. Notice that this regression also controls for serial correlation in the stock's own return. If firm-specific information about the firm is immediately incorporated into prices, then the $\gamma_j^{(-n)}$'s will be no different from zero. However, if stock j responds with a lag to firm-specific news, then the $\gamma_j^{(-n)}$'s will be significantly different from zero. Hence, this regression identifies the delay with which a stock responds to both market-wide and firm-specific news if expected returns are relatively constant over these horizons. Mech (1993), Boudoukh, Richardson, and Whitelaw (1994), McQueen, Pinegar, and Thorley (1996), Chordia and Swaminathan (2000), and Hou (2002) find that time-varying expected returns explain a very small portion of short horizon return autocorrelations, suggesting that expected returns are relatively constant over short (less than one month) horizons.

Using the estimated coefficients from this regression, we compute three measures of price delay for each firm at the end of June of each year. The first measure is the fraction of variation of contemporaneous returns explained by the lagged regressors. This is simply one minus the ratio of the R^2 from regression (1) assuming $\delta_j^{(-n)} = 0$ and $\gamma_j^{(-n)} = 0$, $\forall n \in [1, 4]$, over the R^2 from

[2]The 7 regional U.S. stock exchanges are Arizona, Boston, Chicago, Cincinnati, Pacific, Philadelphia, and San Diego.

regression (1) with no restrictions.

$$D1 = 1 - \frac{R^2_{\delta_j^{(-n)}=0, \gamma_j^{(-n)}=0}}{R^2}. \tag{2}$$

This is similar to an F-test on the joint significance of the lagged variables scaled by the amount of total variation explained contemporaneously. The larger this number, the more return variation is captured by lagged returns, and hence the stronger is the delay in response to return innovations. This measure does not distinguish between market and own return innovations, and also does not distinguish between shorter and longer lags for explaining contemporaneous returns. The following two measures attempt to capture these effects (j subscripts are suppressed for notational ease):

$$D2 = \frac{\sum_{n=1}^{4} \frac{n\delta^{(-n)}}{se(\delta^{(-n)})}}{\frac{\beta}{se(\beta)} + \sum_{n=1}^{4} \frac{\delta^{(-n)}}{se(\delta^{(-n)})}} \tag{3}$$

$$D3 = \sum_{n=1}^{4} \frac{n\gamma^{(-n)}}{se(\gamma^{(-n)})}, \tag{4}$$

where $se(\cdot)$ is the standard error of the coefficient estimate. $D2$ measures the fraction of a stock's contemporaneous price movement attributed to delayed reaction to the market, with coefficients weighted by their precision and length of lag.[3] $D3$ similarly captures delayed response to own stock return innovations.

Note that all of these measures ignore the sign of the lagged coefficients. This is because most lagged coefficients are either zero or positive. We obtain nearly identical results if we redefine our delay measures using the absolute value of the coefficient estimates or ignore the few negative coefficients. This indicates that most of the lagged coefficients are indeed non-negative.

Firms we classify as having "high delay" by our measures do indeed have larger and positive lagged coefficients than other firms, consistent with our interpretation of these variables measuring price delay. For instance, stocks in the 90th percentile of delay measure $D1$ have an average contemporaneous β of only 0.77, but significant lagged market coefficients of 0.17, 0.035, and 0.025 on $\delta^{(-1)}$, $\delta^{(-2)}$, and $\delta^{(-3)}$, respectively. Conversely, stocks below the 90th percentile of delay have higher contemporaneous β's (0.92 on average) and lower lagged market coefficients (0.14, 0.006, and 0.008). These differences are statistically significant. Similar, though weaker, results are obtained when examining own lagged regressor coefficients (the $\gamma^{(-n)}$'s).

[3] Variants of this measure are employed by Brennan, Jegadeesh, and Swaminathan (1993) and Mech (1993) to measure the extent of lead-lag relations among stocks and the speed with which certain stocks respond to information. In addition, our results are unaltered if we do not weight the coefficients by their precision or length of lag.

A.1 Pre- and Post-Ranking Delay

Due to the volatility in weekly individual stock returns, the coefficients from equation (1) are estimated imprecisely. To mitigate an errors-in-variables problem, we assign firms to portfolios based on their market capitalization and individual delay measure. At the end of June of calendar year t we sort stocks into deciles based on their market capitalization. Within each size decile, we then sort stocks into deciles based on their pre-ranking individual delay measure, estimated using regression coefficients from equation (1) with weekly return data from July of year $t-1$ to June of year t.[4] Since size is highly correlated with both price delay and average returns, sorting within size deciles increases the spread in delay and average returns across the portfolios, and allows for variation in delay unrelated to size. The equal-weighted weekly returns of the 100 size-delay portfolios are computed from July of year t to June of year $t+1$. Hence, variables used to predict returns are at least a month to as much as a year old, ensuring their availability before portfolio formation, as well as rendering microstructure issues immaterial. We then estimate equation (1) using the entire sample of post-ranking weekly returns for each of the 100 portfolios and use the estimated coefficients to compute delay measures for each portfolio. These are the post-ranking delay measures which are then assigned to each stock within the portfolio.

This procedure mitigates the errors-in-variables problem by shrinking individual delay measures to a portfolio average, while at the same time, the use of post-ranking measures mitigates the regression phenomenon (i.e., that we may have ranked on noise). The improved precision of the post-ranking delay measures relative to the pre-ranking individual measures outweighs the reduction in information from assigning all stocks in a portfolio the same measure. Chan and Chen (1988) and Fama and French (1992) propose this method for estimating individual stock betas for the same reasons. Note that assigning the full period post-ranking delay measure to stocks does not mean a stock's delay measure is constant over time, since stocks will move across the 100 portfolios as their relative size and pre-ranking delay measures change.

The cross-sectional correlation between the common ($D2$) and own ($D3$) delay measures is around 0.53, suggesting that they capture slightly different components of a firm's response to information. Their correlation with $D1$ is around 0.80. In addition, we also employ annual *changes* in the delay measures for our analysis. The average cross-sectional correlation between changes

[4] June is chosen as the portfolio formation month simply because it is the earliest month beginning in 1963 when required data is available. Although there is no economic reason to suspect June to be an unusual formation month, we confirm that results in the paper are robust to other portfolio formation months.

in total delay ($\Delta D1$) and changes in the other delay measures is 0.46. The correlation between changes in common and own delay is -0.38.

II. Delay and the Cross-Section of Stock Returns

Table I reports the average returns of portfolios sorted on post-ranking delay measures ($D1$, $D2$, and $D3$). At the end of June of each year, stocks are ranked by delay, sorted into deciles, and the equal- and value-weighted monthly returns on the decile portfolios are computed over the following year from July to June. Since delay is likely correlated with other known determinants of average returns, we adjust returns using a characteristic-based benchmark to account for return premia associated with size, BE/ME, and momentum. The benchmark portfolio is based on an extension and variation of the matching procedure used in Daniel, Grinblatt, Titman, and Wermers (1997). All CRSP-listed firms are first sorted each month into size quintiles, based on NYSE quintile breakpoints, and then within each size quintile further sorted into BE/ME quintiles using NYSE breakpoints. Stocks are then further sorted within each of these 25 groupings into quintiles based on the firm's past 12-month return, skipping the most recent month (e.g., cumulative return from $t-12$ to $t-2$). Within each of these 125 groupings, we weight stocks both equally and by value (based on end-of-June market capitalization), forming two sets of 125 benchmark portfolios. The value weighted benchmarks are employed for delay portfolios that are value weighted and the equal weighed benchmarks are employed against equal weighted portfolios. To form a size, BE/ME, and momentum hedged return for any stock, we simply subtract the return of the benchmark portfolio to which that stock belongs from the return of the stock.[5] The expected value of this return is zero if size, book-to-market, and past year return are the only attributes that affect the cross-section of expected stock returns. We also note that although there is no direct hedging of beta risk, these hedged returns are close to having zero beta exposure (see Grinblatt and Moskowitz (2003)).

Average characteristic-adjusted monthly returns and t-statistics on the delay decile portfolios, as well as the difference in returns between decile portfolios 10 (highest delay) and 1 (lowest delay), are reported in Panel A of Table I. For the total delay measure $D1$, the average spread between the highest and lowest portfolio of delay firms is a striking 130 basis points per month when equal weighted and 99 basis points when value weighted. Sizeable return differences are also present for the common delay ($D2$) and own delay ($D3$) measures as well, although total delay $D1$ has slightly stronger predictive power.

[5]We do not exclude the stock itself from the benchmark portfolios. This, however, understates our results.

Interestingly, the $10 - 1$ characteristic adjusted spread derives mainly from the astounding performance of decile 10. This is in contrast to most long-short strategies where profits from the short side typically comprise the bulk of the strategy's profitability, such as momentum (Grinblatt and Moskowitz (2003)). Stocks with high price delay command large abnormal returns, while stocks with low delay do not exhibit significant underperformance. Hence, short-selling constraints will have little impact on this strategy. In fact, only deciles 9 and 10, the stocks with the highest delay, generate abnormal returns. This asymmetry is consistent with models of market frictions, where only the most constrained or inefficient assets carry a premium. This asymmetry can only exist if the most constrained firms comprise a small fraction of the market, which we show below.

A. *Robustness*

Our results are robust to other measures of delay, further adjustment in returns, subperiod and subsample analysis, and potential microstructure issues.

A.1 Pre-Ranking Delay

Since the post-ranking delay measures are not implementable in practice, Panel A of Table I also reports the value weighted characteristic-adjusted returns of decile portfolios formed from pre-ranking delay measures. Returns are reported for pre-ranking portfolio measures using the most recent past year of returns data, the past five years of data, and the entire past sample of data. Profits from the one- and five-year pre-ranking portfolio measures are smaller than those from post-ranking portfolio measures, but still highly significant. The noise from smaller sample pre-ranking measures reduces the information content of the sort. However, employing the entire past sample of data to measure delay generates profits almost as large as those from the post-ranking measures. All of the results in the paper are robust to employing pre-ranking measures.

A.2 Change in Delay

In addition, Panel A reports the value weighted characteristic-adjusted returns of decile portfolios formed from sorting on the *change* in delay from the previous year. The spread between decile portfolios sorted on the change in delay, $\Delta D1$, is a highly significant 52 basis points per month, after adjusting for size, BE/ME, and momentum premia.

A.3 Further Return Adjustment

To ensure our characteristic adjustment procedure is not contributing to the profitability of the strategies, we regress the time-series of the characteristic adjusted returns of the $10-1$ spread in value-weighted decile portfolios sorted on $D1$ and $\Delta D1$ on various factor models. Panel B of Table I reports the α or intercept (along with t-statistics) from these time-series regressions. The first factor model we employ is the Fama and French (1993) three-factor model, which uses the excess return on the market $R_M - r_f$, a small stock minus big stock portfolio SMB, and a high BE/ME minus low BE/ME portfolio HML as factor-mimicking portfolios. The next two columns report intercepts under the Carhart (1997) four factor model, which adds a momentum factor-mimicking portfolio $PR1YR$ to the Fama-French factors. The following two columns report α's under a model which adds the aggregate liquidity risk factor-mimicking portfolio of Pastor and Stambaugh (2002) to the aforementioned factors. Finally, the last two columns report intercepts under a model containing the other factors plus a factor-mimicking portfolio for the informed trader risk identified by Easley, Hvidkjaer, and O'Hara (2002).[6] In addition to providing further return adjustment, these last two factors indicate whether liquidity or asymmetric information drives the delay premium. As Panel B indicates, the intercepts are large and highly significant after adjusting returns using both the characteristic benchmarks and various factor models. The spreads in value-weighted $D1$ and $\Delta D1$ portfolios actually increase after adjusting for covariation with the various sets of factors. Thus, potentially inadequate risk adjustment from the characteristic benchmarks does not seem to be driving the profitability of these strategies.

In addition to the informed trading factor not having an effect on the profitability of delay, the loading on this factor for the spread in $D1$ ($\Delta D1$) portfolios is -0.05 (-0.13) with a statistically insignificant t-statistic of -0.38 (-0.94). This suggests that the premium associated with delay does not appear to be related to this proxy for information asymmetry.

[6]Details on the construction of these factors can be found in Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2002). We thank Lubos Pastor and Soeren Hvidkjaer for providing the aggregate liquidity risk and informed trading factors, respectively. The informed trading factor is formed at each year-end using independent sorts of stocks into three size and three "probability of facing an informed trader" (PIN) groups. Breakpoints are set at 30 and 70 percentiles. The equal-weighted returns of the intersection of the size-PIN portfolios are computed each month, where the difference in average returns across the 3 size portfolios between the low and the high PIN portfolios represents the informed trading factor-mimicking portfolio. These returns are only available after July, 1984.

A.4 Subperiods and Subsamples

Panel B reports the value weighted characteristic-adjusted spread in delay sorted portfolios across various subperiods and subsamples of stocks. The first column reports the profits excluding the month of January, since returns are on average higher in January and behave unusually at the turn of the year, particularly for small, illiquid stocks (see Grinblatt and Moskowitz (2003)) that likely have significant price delay. Profits from February through December are still highly significant. The next two columns report profits across the two subperiods of the sample. Profits are higher in the second half of the sample, but are significant in both subperiods. This may be due in part to the first half of the sample not containing NASDAQ firms. The last two columns report that NASDAQ firms exhibit higher profits, but profits are still significant for NYAM firms. Subperiod profits on NYAM stocks only (not reported) revealed higher profits in the second half of the sample as well. Hence, the higher profits in the latter half of the sample cannot be entirely attributed to the introduction of NASDAQ firms. The increase in the delay premium over time suggests that it is not entirely due to a size or liquidity effect since both the size and liquidity premiums have diminished over time. Later, we show more formally that delay is not an artifact of a size or liquidity effect, and, in fact, subsumes the premium associated with size.

A.5 Microstructure Issues

The returns of the delay portfolios do not seem to be tainted by microstructure effects such as bid-ask bounce or non-synchronous trading. First, stocks with missing weekly return observations over the prior year are excluded. Second, delay is measured from July of year $t-1$ to June of year t and portfolio returns are calculated from July of year t to June of year $t+1$. Hence, there is as much as an entire year gap between the measurement of delay and subsequent returns. Profits are also no higher in July than any other month. Since July is the month closest to the measurement of delay, returns in this month would be most likely to be affected by potential microstructure effects. We also note that skipping a month (e.g., excluding July) produces nearly identical results.

It is also worth noting that the trading strategy does not attempt to take advantage of delay by buying long delay firms with predicted price increases and shorting those with predicted price decreases, but rather just buys (shorts) all high (low) delay firms regardless of the sign of the information trend. Thus, stale prices are not an issue for our strategy. In addition, the difference in returns between equal- and value-weighted portfolios is small, suggesting that microstructure issues (which are more prevalent among small stocks) are not affecting our results. Furthermore, if we exclude all stocks with market capitalization below \$5 million, weekly dollar trading volume below \$200,000, and share prices below \$3, the trading strategy profits remain highly significant.

High delay firms are small, value firms, with poor past performance. Although we adjust returns for the premia associated with size, value, and momentum, one concern might be that delay simply represents a refined sort on size and value or an interactive effect between small, extreme value firms that is not fully captured by our return adjustment. The last two columns of Panel B report delay profits for firms with extreme value (BE/ME greater than two) and firms with BE/ME less than or equal to two, separately. The latter produces more profits (89 basis points per month) than firms with extreme BE/ME ratios (68 basis points per month). This suggests the most extreme value firms are not driving delay profits.

A.6 Interaction of Delay with Firm Characteristics

In addition to adjusting returns for size, BE/ME, and momentum premia, Table II reports delay profits within size, BE/ME, and momentum quintiles. This provides another control for these firm characteristics, isolating the delay premium, and highlights the interaction between delay and these firm characteristics. Average monthly characteristic-adjusted returns on value-weighted portfolios first sorted by each characteristic into quintiles, and then sorted into delay quintiles are reported. Within each characteristic quintile the average returns on the lowest (quintile 1), middle (quintile 3), and highest (quintile 5) delay portfolios, as well as the difference in returns between quintiles 5 and 1 are reported. Each row documents the prevalence of the delay effect within each characteristic group.

As the upper left portion of the table shows, the spread between high and low delay firms is prevalent only among the smallest stocks, but does not disappear after this additional control. Moving to the right, the table shows that the delay premium is strong and significant across all BE/ME categories, but is largest among value firms. Hence, value enhances the effect of delay on returns, but does not capture the delay premium. In addition, the lower left portion of the table shows that the delay premium is present across momentum categories, but is most pronounced among the worst past year performing stocks (e.g., losers). This is consistent with evidence of slower information diffusion regarding negative news found in Hong, Lim, and Stein (2000) and Hou (2002). While this may be consistent with short-sale constraints that hinder bad news from being incorporated immediately into prices, it is also consistent with poorly performing firms receiving less investor attention.

Finally, we examine the interaction between price delay and idiosyncratic risk. Market segmentation and investor recognition models such as Merton (1987), Hirshleifer (1988), Shapiro (2002), and Peng (2002) provide a direct pricing role for idiosyncratic risk. We measure idiosyncratic risk (σ_ϵ^2) as the variance of the residual from a market model regression of weekly stock returns on the contemporaneous returns of the market portfolio over the prior year for each firm.[7] As the lower right portion of Table II indicates, the delay premium monotonically increases with idiosyncratic risk, rising to an exceptional 2% per month among stocks with the most idiosyncratic volatility.

In unreported results, we perform the reverse double sort of first sorting on delay and then on each characteristic to assess the premia associated with each characteristic within a delay category. We find that the size premium exclusively resides among the highest delay firms. The value premium is weaker among low delay firms, but present across all delay categories. This suggests the value premium is not exclusive to high delay firms. Since high delay firms are the most neglected firms, this also suggests that the value premium is not purely a glamour versus neglect phenomenon as suggested by Lakonishok, Shleifer, and Vishny (1994). In addition, the relative flatness of the value premium across the delay quintiles suggests that delay may not be a good proxy for noise trader risk. A sentiment risk story would predict the largest premia among the highest delay firms. Momentum profits are also prevalent among all delay quintiles, exhibiting somewhat of a hump-shaped pattern in their magnitude. Again, this suggests delay is not a sentiment risk proxy, since the latter would predict increasing momentum profits with higher delay. Finally, idiosyncratic risk only exhibits a positive premium among the highest delay firms, but has no relation to average returns across the first four quintiles of delay. The quintile of firms with the most idiosyncratic risk outperform those with the least by a striking 118 basis points per month (t-statistic = 4.10) among firms suffering from severe price delay.

B. *Price Delay and the Size and Value Effects*

Since the early work of Banz (1981), Keim (1983), Stattman (1980), and Rosenberg, Reid, and Lanstein (1985) researchers have attempted to understand why small, value firms earn higher returns on average than large, growth firms. Since firms experiencing severe delay are small, value firms, it is interesting to examine how the delay premium relates to the premia associated with size

[7] In Merton's (1987) model of market segmentation the degree of participation is exogenous and the variance of residual returns is priced. In Hirshleifer's (1988) model where participation is endogenously determined, the residual standard deviation matters for asset pricing. Empirically, both residual variance and standard deviation give the same result. We employ residual variance, but results for residual standard deviation are available upon request.

and value. Tables I and II show that neither size nor value capture the premium associated with delay. We now examine how much of the size and value premia are captured by delay.

Panel A of Table III examines the returns of portfolios sorted by size. At the end of June of each year, stocks are ranked by their market capitalization and sorted into deciles using NYSE breakpoints. The equal-weighted and value-weighted monthly returns on these decile portfolios are computed over the following year from July to June. Average returns and t-statistics on deciles 1, 5, 10 and the difference between deciles 10 (largest) and 1 (smallest) are reported. Confirming previous evidence, there is a weak negative relation between average returns and size over the whole sample (June, 1964 to December, 2001), a strong negative relation in the first half of the sample (June, 1964 to June, 1983), no relation in the second half of the sample (July, 1983 to December, 2001), and a huge negative relation in January.

To examine the impact of delay on these size-sorted portfolios, we adjust returns for the delay premium by matching stocks with benchmark portfolios formed from their delay measure $D1$ and subtracting the benchmark return. (Value-weighted and equal-weighted benchmarks are used for the appropriate set of results.) When adjusting returns for delay, the average spread between the smallest and largest size deciles drops from 57 basis points to an insignificant 8 basis points when equal weighted and from 28 to 3 basis points when value weighted. Furthermore, the significant reduction in the size premium occurs even over periods where the size effect is strongest. From July, 1964 to June, 1983, the equal weighted (value weighted) size premium drops from 129 (104) basis points to 19 (6) after adjusting for delay. This is despite the fact that delay is a stronger economic effect in the latter half of the sample (Table I) as opposed to size. Likewise, the equal (value) weighted size premium in January drops dramatically from 8.9% (7.3%) to only 0.71% (0.41%) after adjusting for delay.

Finally, in addition to adjusting returns for the delay premium, we also form portfolios based on the component of a firm's size related to delay and the component orthogonal to delay. Specifically, we run a cross-sectional regression of each firm's size on its delay measure,

$$\text{Market Cap}_i \quad = \quad a + b(\text{Delay}_i) + e_i. \tag{5}$$

The predicted component of size related to delay is then $\widehat{Size}(Delay) = b(\text{Delay}_i)$ and the orthogonal component of size with respect to delay is $\widehat{Size}(Residual) = a + e_i$. As the bottom of Panel A of Table III indicates, only the component of size related to delay captures variation in average returns. The component of size unrelated to delay has no cross-sectional return predictability. Thus, the delay premium seems to dominate and largely capture the premium associated with firm size.

Panel B of Table III repeats the previous analysis for BE/ME-sorted portfolios. The first four rows confirm the value premium documented in the literature across subsample periods and January. When returns are adjusted for delay, the next four rows show that the value premium is halved. Over the entire sample period the equal (value) weighted premium declines from 101 (50) basis points to 66 (29) basis points. Similar reductions are shown for the first half of the sample period and for January. The last two rows of Panel B sort stocks into portfolios based on the components of BE/ME related and unrelated to delay. Consistent with the results in the first part of the panel, the component of BE/ME associated with delay and its orthogonal component contribute equally to the cross-sectional predictive power of BE/ME. Hence, the delay premium captures about half of the value effect.

C. *Fama-MacBeth Regressions*

Table IV examines the relation between price delay and the cross-section of average returns using Fama and MacBeth (1973) regressions. The regressions provide further robustness of our results since they employ all securities (without imposing decile breakpoints), allow for more controls in the cross-section of returns, and provide an alternative weighting scheme for portfolios.[8]

The cross-section of stock returns each month is regressed on the firm characteristics of log of size (market capitalization), log of BE/ME, the previous month's return on the stock $ret_{-1:-1}$, the previous year's return on the stock from month $t-12$ to $t-2$ ($ret_{-12:-2}$), the previous three year's return on the stock from month $t-36$ to $t-13$ ($ret_{-36:-13}$), market β, idiosyncratic variance, and price delay. The size, book-to-market, and delay variables are from the previous June of each year. Market beta is the sum of the coefficients from the market model regression (contemporaneous plus four weekly lags). Both residual variance (σ_ϵ^2) and beta (β) estimates are the post-ranking measures of these variables, where stocks are first sorted into size deciles and pre-ranking idiosyncratic risk (β) deciles, and the post-ranking variance of residual returns (β) from a market model regression of each portfolio's weekly return over the entire sample period is assigned to each stock at each date.

The first column of Table IV confirms the standard results found in the literature that average returns are negatively related to size, past 1 month, and past three year returns, and positively

[8]Each coefficient from a Fama-MacBeth regression is the return to the minimum variance portfolio with weights that sum to zero, weighted characteristic on its corresponding regressor that sums to one, and weighted characteristics on all other regressors that sum to zero (see Fama (1976)). The weights are tilted toward stocks with the most extreme (volatile) returns.

related to BE/ME and past year returns. The second column adds the delay measure $D1$ to the cross-sectional regression. Delay is strongly positively associated with average returns, consistent with our previous results. More interestingly, however, is the effect delay has on the importance of size for the cross-section of average returns. The coefficient on log of size changes from negative and statistically significant to positive. Both economically and statistically, it appears that delay subsumes the explanatory power of size. This is consistent with Merton (1987), who argues that controlling for visibility, firm size should be positively related to expected returns. Amihud and Mendelson (1989) also find a positive relation between size and average returns when controlling for trading volume, bid-ask spread, and residual variance, and interpret their findings as consistent with Merton's (1987) hypothesis.

Note that neither idiosyncratic risk nor beta is priced in the cross-section. In fact, beta has the wrong sign. This is consistent with the general findings in the literature on the weak role of idiosyncratic volatility and beta for describing cross-sectional average returns (Fama and MacBeth (1973), Fama and French (1992)). Empirically, idiosyncratic risk has had limited success in describing average stock returns. Prior research examining the pricing role of residual/idiosyncratic volatility has yielded mixed results.[9] One possible reason for this limited success is that most studies examine the relation between idiosyncratic risk and average returns for the average firm. However, the average firm may not face significant frictions and would therefore not be expected to have priced idiosyncratic risk. Idiosyncratic risk may only be priced among the most constrained or segmented firms, identified as those with significant price delay.

The next two columns repeat the regressions separately for firms in the highest delay decile and in deciles 1-9. As the table shows, idiosyncratic risk is significantly priced for the highest decile of delay firms only. For the other 90 percent of firms, there is a negative and insignificant relation between idiosyncratic risk and average returns. This highlights the fact that idiosyncratic risk is only priced among the most constrained (as measured by price delay) firms.

D. *Post-Event Drift*

Finally, as an additional test of the impact of delay on stock returns we analyze the price response of firms' equity to certain events. This also highlights how our delay measure captures the speed

[9] Fama and MacBeth (1973) and Tinic and West (1986) find no relation between idiosyncratic variance and average returns. Friend, Westerfield, and Granito (1978) find a slight positive relation. Recently, Malkiel and Xu (2002) also find some cross-sectional predictability. Studies of other markets have yielded some evidence linking idiosyncratic risk to pricing. Green and Rydqvist (1997) find some supporting evidence among Swedish lottery bonds. Bessembinder (1992) finds supporting evidence in the foreign currency and agricultural futures markets.

of information diffusion.

D.1 Surprise in Unexpected Earnings

The first set of events we consider are earnings announcements. There is a vast literature examining the equity price response to earnings announcements (Ball and Brown (1968), Bernard and Thomas (1989), among others), which demonstrates significant post-earnings announcement drift.

Earnings news is measured by the commonly used Standardized Unexpected Earnings (SUE) variable, which is the difference between current quarter's earnings and earnings four quarters ago divided by the standard deviation of unexpected earnings over the past eight quarters (obtained from COMPUSTAT). Firms are sorted independently into quintiles based on their SUE and delay rankings (where delay is measured in the prior year). Adjusted returns on the portfolio of event firms at each event date that intersect in the top and bottom quintiles of both delay and SUE rankings are computed monthly from six months before the event to 12 months after using the event study approach of Jaffe (1974) and Mandelker (1974). For each calendar month t, we calculate the abnormal return on each firm that had an earnings announcement in calendar month $t + k$, for $k = [-6, 12]$. Abnormal returns are estimated by benchmarking against a value-weighted portfolio of firms matched by size, BE/ME, and past one year returns. The value-weighted average of these abnormal returns across firms in each category are computed for each calendar month t and averaged across time.[10] This approach has the added advantage of accounting for the correlation of returns across event firms, thus providing robust standard errors (see Fama (1998)).

The average monthly adjusted return over the six months following the event is reported in Figure 1 along with its t-statistic. Significant post-announcement drift is present only for firms in the highest delay quintile. Firms with high prior delay experience significant drift in their returns following both positive and negative earnings surprises. Positive (negative) surprises yield 69 (-42) basis points per month with a t-statistic of 6.82 (-3.30) for high delay firms. For low delay firms, there is no evidence of post-announcement drift.

Figure 1 also plots the cumulative adjusted abnormal return (CAR) on the portfolio of event

[10] For example, suppose we want to measure the average price response of event firms in month 4 after the earnings announcement, where month 0 is the month when the earnings announcement takes place. For each calendar month t, we calculate the abnormal return on each firm that had an earnings announcement in calendar month $t-4$. We then calculate the value-weighted average of abnormal returns across firms to obtain the abnormal return for calendar month t on the portfolio of firms that had events in month $t-4$. Finally, we average the abnormal returns on this portfolio across time to estimate the average price reaction in month 4 after the earnings announcement. This exercise is repeated for each month from 6 months before to 12 months after the event, and for each SUE-ranked and delay-ranked event portfolio.

firms that intersect in the top and bottom quintiles of both delay and SUE from six months before the event to 12 months after. The figure plots the CAR's in event rather than calendar time, demonstrating post announcement drift only among high delay firms.

D.2 Extreme Market Movements

We also analyze the post-event response to extreme market movements, which are defined as the 5th (R_m^{95-}) and 95th (R_m^{95+}) percentile monthly return events on the CRSP value-weighted index. Unlike earnings surprises, which are firm-specific, these shocks apply to all firms. In addition, there is no evidence of post-announcement drift for the average firm following market-wide shocks.

Figure 1 reports that there is significant drift following extreme positive market movements, but only for high delay firms. Negative movements also exhibit some drift, but only for 2-3 months. By 6 months, the drift disappears. Low delay firms do not generate any post-event price response for either positive or negative news. These results provide reassurance that our delay measure captures the speed of information diffusion and indicate another link between delay and the cross-section of average returns.

III. What Drives the Delay Premium?

Price delay may result from a variety of market frictions and the cross-sectional return predictability of delay is consistent with a variety of models that incorporate these frictions. In this section we investigate several hypotheses for what drives delay and its associated premium. In particular, we distinguish between the investor recognition hypothesis and a pure liquidity effect that could arise from many sources.

A. *Determinants of Price Delay*

We begin by examining the determinants of price delay. Each year we run cross-sectional regressions of firms' delay on traditional liquidity variables and variables that better proxy for investor attention/recognition in the style of Fama and MacBeth (1973), where the time-series average of the yearly cross-sectional coefficient estimates are computed along with their time-series t-statistics. The regression is estimated as follows,

$$D1_j \quad = \quad a + \sum_{k=1}^{8} b_k M_{k,j} + \sum_{q=1}^{5} c_q L_{q,j} + \epsilon_j, \tag{6}$$

where M_k and L_q are 8 attention/recognition and 5 liquidity variables, respectively. The investor attention/recognition variables are the log of institutional ownership, log of number of analysts, a regional exchange dummy (to capture regional visibility given the local/regional portfolio biases documented by Coval and Moskowitz (1999)), and the log of number of shareholders and employees. Since there is substantial skewness in the number of analysts, shareholders, and employees, and since the impact of these variables on delay is likely to be decreasing at a decreasing rate, we use the natural logarithm of these variables in our analysis. Analyst coverage should be associated with a more recognizable firm and should improve the speed with which a stock's price responds to information. Brennan, Jegadeesh, and Swaminathan (1993) examine the relation between the speed of information diffusion and analyst coverage in the context of daily and weekly lead-lag effects. They find that returns on high coverage stocks lead returns on low coverage stocks. Badrinath, Kale, and Noe (1995) relate the speed of information flow to institutional ownership by showing that stocks with higher levels of institutional ownership lead stocks with lower levels of institutional ownership. Hong, Lim, and Stein (2000) examine information diffusion in the context of momentum in 6-month returns and find that low analyst coverage stocks exhibit the greatest momentum, particularly for poor past performance. The number of shareholders measures directly the breadth of the stock's investor base. Similarly, the number of employees may provide another measure of a firm's recognizability. We also employ measures of remoteness to characterize investor recognition. Using the latitude and longitude coordinates of each firm's headquarters location, we compute the average distance (in miles) between each stock's headquarters and a proxy for the location of the average investor using the arclength formula from Coval and Moskowitz (1999). Since we do not have data on the locations (or identity) of every investor in every stock, we compute the average distance between each firm's headquarters and all U.S. airports using data from the ITDB. We calculate the distance between each stock's headquarters and the nearest airport, and compute the average air distance and airfare between the nearest airport and all U.S. airports, weighted by the number of air routes (market share) each airport comprises. More remotely located stocks are likely to be the most segmented and least recognized by investors. All firms in the sample must have available data on each of these variables. This requirement tilts the sample toward larger more liquid firms. While the attention/recognition variables could potentially represent several types of frictions, they seem more related to visibility than either the degree of information asymmetry or noise trading.

The liquidity variables are the average monthly closing price of the stock over the prior year, number of trading days (days with trading volume and price changes), log of turnover (defined as the average weekly number of shares traded divided by number of shares outstanding over the prior year) for NYAM and NASDAQ stocks separately,[11] and a dummy variable for trading on NASDAQ. The regressions are estimated over the period July, 1981 to December, 2001 since some of the variables are only available post-1981.

The time-series averages and t-statistics of the regression coefficients are (j subscripts suppressed for notational ease):

$$
\begin{aligned}
\sum_{k=1}^{8} \hat{b}_k M_{k,j} = \; & \underset{(-8.10)}{-0.0010 \log(\text{Institutional Ownership})} + \underset{(-12.31)}{-0.0177 \log(\#\text{Analysts})} \\
& + \underset{(-7.62)}{-0.0056 \text{ Regional Exchange}} + \underset{(-4.73)}{-0.0013 \log(\#\text{Shareholders})} \\
& + \underset{(-7.55)}{-0.0028 \log(\#\text{Employees})} + \underset{(1.15)}{0.0101 \text{ Nearest Airport}} \\
& + \underset{(-0.01)}{-0.0017 \text{ Air Distance}} + \underset{(2.89)}{0.0252 \text{ Airfare}}
\end{aligned}
\tag{7}
$$

and

$$
\begin{aligned}
\sum_{q=1}^{5} \hat{c}_q L_{q,j} = \; & \underset{(-2.77)}{-0.0109 \text{ NASD}} + \underset{(7.51)}{0.0076 \log(\text{Turnover}_{NYAM})} \\
& + \underset{(1.77)}{0.0028 \log(\text{Turnover}_{NASD})} + \underset{(-6.63)}{-0.0007 \, \#\text{Trading Days}} \\
& + \underset{(-7.80).}{-0.0005 \text{ Average Price}}
\end{aligned}
\tag{8}
$$

The average adjusted R^2 from this regression is 56%, indicating that a substantial portion of the cross-sectional variation in delay is captured by the recognition and liquidity proxies. When running regressions for the liquidity and recognition variables separately, the average adjusted R^2's are 40% for the liquidity variables alone and 49% for the attention variables alone.

The regressions confirm a strong association between delay and investor recognition and liquidity. Delay is negatively related to analyst coverage, institutional ownership, regional exchange membership, and the number of shareholders and employees and is positively related to average air fare. These results control simultaneously for traditional measures of liquidity, which, not surprisingly are negatively associated with delay.[12]

[11]Due to the dealer system, each NASDAQ trade is generally counted twice and sometimes more, exaggerating trading volume relative to the traditional exchanges.

[12]We have also tried other attention/recognition variables with similar results. For example, as an exogenous

The average monthly bid-ask spread, which is available for NASDAQ firms primarily, is omitted from the regressions due to its limited availability in the data. However, results are similar including bid-ask spread, as well other liquidity variables such as number dealers in a stock, and number of trades executed per day, on a limited sample of NASDAQ firms. Bid-ask spread is positively related to delay, but does not alter the coefficients on the other variables in this smaller sample. The other two variables are insignificant. In addition, results are similar including firm size as a regressor. However, due to multicollinearity, firm size and many of the liquidity variables cannot be included simultaneously. Hence, we report results for the liquidity proxies only, omitting firm size. The effects are similar including firm size but omitting the liquidity variables.

B. *Decomposing the Impact of Delay*

We now employ the measures of liquidity and investor attention to instrument the level of price delay and examine the relation between these instrumented components of delay and the cross-section of average returns. Specifically, we define the component of delay associated with liquidity as $\widehat{Delay}(\text{Liquidity}) = \sum_{q=1}^{5} \hat{c}_q L_{q,j}$ and attention as $\widehat{Delay}(\text{Attention}) = \sum_{k=1}^{8} \hat{b}_k M_{k,j}$. Although neglected firms are less liquid, this approach separates the investor recognition effect from one of pure liquidity. If the former is what drives the delay premium, then we should see stronger cross-sectional return predictability from these variables than from the traditional liquidity measures. Despite the fact that low liquidity may be a consequence of investor recognition, it is therefore interesting to examine whether the component of delay attributable to each of these sets of variables is primarily responsible for its predictive power on the cross-section of returns.

The last three columns of Table IV report Fama-MacBeth regression coefficients employing the components of delay related to liquidity and attention, as well as the residual component. Since the liquidity and attention variables are only available after June, 1981, the results pertain to the July, 1981 to December, 2001 time period. For reference, the third to last and second to last columns report results with and without the total delay measure. Over this shorter time period, delay has a slightly stronger economic effect on returns. Once again, including delay reverses the sign of the coefficient on size, although the size effect is not statistically significant

measure of institutional ownership, we employ an S&P 500 index membership dummy, which is negatively related to delay. In addition, whether options are traded on the firm's equity and the annual level of option volume (for all calls and puts, obtained from the CBOE from 1986 to 1997) are both associated with lower delay, as are other measures of remoteness such as the population greater than 25 years of age, total vehicle miles traveled, and phone usage for the state in which the company is headquartered. Including these other measures does not alter any of the results in the paper, but limits the number of firms in our sample, since many of these variables cannot be matched to some fraction of firms.

in the post-1981 period. Decomposing delay into its liquidity, attention/recognition, and residual components, the last column shows that the attention/recognition variables are primarily driving the explanatory power of delay for average returns. The liquidity-instrumented component of delay has a slightly negative (statistically insignificant) effect on returns, and residual delay has a positive but insignificant effect. Thus, the explanatory power of delay derives mainly from the attention/recognition proxies. This suggests that the friction most likely associated with the delay premium is firm neglect or lack of investor recognition.

Table V reports the average monthly characteristic adjusted returns on the decile 1 (lowest delay) and 10 (highest delay) portfolios, as well as the difference in returns between them for the liquidity instrumented component of delay and the attention/recognition instrumented component of delay. Note that the liquidity and attention instruments are estimated simultaneously so that only the marginal impacts of these two sets of variables are considered (i.e., controlling for the other set of variables). As the table indicates, when the attention variables are used to instrument delay, substantial profits of 62 basis points per month are obtained. However, when using the traditional liquidity variables to instrument delay, there is no relation to expected returns. Liquidity-instrumented delay generates an insignificant 26 basis point spread per month.

For further robustness, we also examine the residual component of delay, after controlling for both liquidity and attention variables. Residual delay has little explanatory power. Although we may be missing other important indicators of investor attention/recognition, the relative weakness of the residual delay results suggests we are capturing a substantial portion of the explanatory power of delay using our instruments (this is also indicated by the high adjusted R^2's from the regressions). We obtain similar results for the change in delay (ΔD1), using as instruments the changes in the liquidity and attention variables (not reported).

C. *Somewhat versus Truly Neglected Firms*

In addition, because some of our variables of interest are only available on a limited sample of firms (such as analyst coverage and institutional ownership data), we also report results for delay sorted portfolios on two samples of stocks: those that have at least some analyst and institutional ownership coverage, which we refer to as "somewhat-neglected" firms, and those that have no analyst or institutional following ("truly neglected" firms). Since data on analyst and institutional coverage is only available after 1981, the results in both panels pertain to the July, 1981 to December, 2001 sample period. Firms with at least some analyst coverage and institutional ownership tend to be larger, more liquid, and by definition less neglected or more recognized. The delay profits from these "somewhat-neglected" firms are still an impressive 53 basis points per month (t-statistic of 2.52). Of course, the premium for delay is magnified among the "truly neglected" firms. The profits from delay portfolios formed from only these stocks, which did not have any analyst coverage or institutional ownership, are a striking 195 basis points per month, after adjusting for size, BE/ME, and momentum. Although we do not know whether all stocks not covered by I/B/E/S or having no S&P institutional ownership coverage actually have zero analyst or institutional following, it is likely that this is the case for the majority of such firms. In any case, this caveat understates our results.

IV. Trading Costs and Frictions Associated with Delay

Finally, while the delay premium appears to be related to investor recognition, the premium associated with delay poses a challenge. If firms facing significant frictions can be easily identified (by our delay or other measures), then investors can form well-diversified portfolios with little systematic risk exposure that exploit this premium. Hence, either this premium will be priced away or we need to identify the impediments or trading costs that would prevent exploitation.

An investor trying to take advantage of delay would need to account for trading costs. Since the profitability of our delay strategies comes mostly from the long side, short-selling constraints and costs should not be binding. In addition, the strategies are only updated once a year and there is persistence in the delay rankings from year to year. This results in a relatively low turnover of about 35 percent per year. However, firms with significant delay tend to be small, low priced, and less liquid, and therefore trading costs may be high.

To gain further insight into the premium associated with delay, Table VI reports the characteristics of the delay decile portfolios. We are particularly interested in what sorts of firms fall into decile 10, the portfolio of highest delay, since these are the firms that drive most of the associated premium. Panel A reports the value-weighted average characteristics of the decile portfolios over the July, 1964 to December, 2001 period. F-statistics on the difference in average characteristics across all decile portfolios as well as the first 9 deciles are reported in the last two columns. As the table indicates, the average delay measures across the first 9 deciles and across all 10 portfolios are significantly different, although the increase in delay from decile 9 to 10 is the most striking.

Delay is associated with small, low-priced, value firms, with low institutional ownership, and low dollar trading volume. Analyst coverage and number of shareholders (breadth of investor base) are also inversely related to delay, as noted previously. In addition, residual volatility σ_{ϵ}^2 is monotonically increasing with delay. Past performance (over the past year or three years) is relatively stable across the first 8 delay deciles and then drops significantly for the two deciles of highest delay.

Focusing on decile 10, it is not surprising that the highest delay firms are very small, with an average market capitalization of only \$5.48 million (nominal dollars from 1964 to 2001), dollar trading volume of \$314,000 per week, and average share price of \$4.74. Certainly the most neglected, least visible firms are going to be very small and have low trading volume. These firms comprise less than 0.02% of the total market capitalization of all publicly traded equity in the U.S. This may make trading on delay prohibitively costly.

In addition to large bid-ask spreads, price impact costs will be important. Thus, there may be a limit on the amount of capital one may potentially be able to invest in such securities. This could preclude many large institutional investors from exploiting delay.

On the other hand, an investor could downweight stocks with particularly high trading costs. For instance, focusing on stocks with at least some analyst and institutional coverage still generates 53 basis points per month and avoids extremely low priced and tiny firms. The average market capitalization for decile 10 is \$26 million, with an average share price of \$8.76 and \$1.8 million in weekly trading volume. While we do not attempt to analyze trading costs in depth, we consider how large these costs might have to be to wipe out profits. Adopting a strategy of going long decile 10 firms (with at least some analyst and institutional coverage), to wipe out the 53 basis point per month (6.4 percent per year) profit would require a round-trip cost of 9.1 percent (assuming turnover of 35 percent per year).

To address whether actual trading costs would exceed this estimate, we appeal to the results in Keim and Madhavan (1997), who estimate trading costs from the actual trades of 21 institutions from 1991 to 1993. For buys (sells) that consist of less than 0.0556% (0.0775%) of outstanding shares, average one-way trading costs in the smallest size quintile are 1.35% (0.67%) on the NYSE/AMEX and 2.68% (0.88%) on NASDAQ. For trade sizes larger than this, costs on the buy (sell) side are 2.35% (2.68%) on the NYSE/AMEX and 3.34% (4.08%) on NASDAQ. In the worst case, these costs would not entirely eliminate profits from delay, leaving at least 3.8 percent $(= 6.4 - [0.35(3.34) + 0.35(4.08)])$ risk-adjusted return.

Since trading costs depend on trade size, market capitalization, exchange, and need for immediacy, Keim and Madhavan (1997) estimate the following model for all trades (buys and sells),

$$\begin{aligned} TradingCost &= 0.687 + 0.239D^{Nasd} + 0.165Trsize - 0.076log(Mktcap) + 9.924(1/Price) \\ &\quad +0.607D^{Tech} + 0.451D^{Index} \end{aligned} \tag{9}$$

where D^{Nasd} is a NASDAQ stock dummy, $Trsize$ is the size of the trade (order size($) divided by market capitalization outstanding), $Mktcap$ is the stock's market capitalization in $thousands, $Price$ is price per share, and D^{Tech} and D^{Index} are dummies for technical and index managers, which Keim and Madhavan (1997) use as proxies for the need of trade immediacy (the omitted dummy is for value funds, who are most patient). Plugging in the average values for Decile 10 from Table VI Panel B, as well as the fraction of decile 10 trading on NASDAQ and assuming the greatest need for immediacy (e.g., $D^{Tech} = 1$) and trade size of 0.05% to be conservative, we estimate the average trading cost of going long decile 10 to be 2.52 percent. With 35% turnover per year, this would be 1.76 percent total round-trip cost.

However, even though the returns net of costs from a delay strategy seem large, the potential dollar profits may be small. For example, decile 10 of somewhat-neglected firms contain an average of 255 stocks. If we limit ownership to at most 5 percent of outstanding market capitalization in any firm, this would only allow $332 million dollars to be invested in such a strategy. With a return of 6.4 percent minus trading costs of 1.76 percent, this is only $15.4 million in profits. For a large institution, this is small and may not be worth the time and effort. Furthermore, since delayed firms have substantial idiosyncratic risk, such activity may be limited further for reasons suggested by Shleifer and Vishny (1997) and thus discourage institutions from exploiting the delay premium.

V. Conclusion

We propose a parsimonious measure of the severity of market frictions affecting a firm using the delay with which its stock price responds to information. Price delay is a powerful predictor of cross-sectional average returns that subsumes the size effect and half the value effect. Moreover, idiosyncratic risk is shown to be priced only among the most severely delayed firms. The delay premium is strongly associated with measures of stock visibility and investor recognition. This points to a new interpretation of the size effect and (half of) the value effect that is consistent with Merton's (1987) investor recognition hypothesis. Our results cannot be explained by microstructure, liquidity effects, market risk, or other known determinants of average returns. The very small segment of neglected/severely delayed firms (less than 0.02% of the market) captures a sizeable amount of cross-sectional variation in average returns.

These findings support recent evidence of non-news events such as advertising increasing visibility and investor attention (e.g., Grullon, Kanatas, and Weston (2002) and Frieder and Subrahmanyam (2002)). They may also help explain why corporate managers concern themselves with visibility, public relations, press releases, dual exchange listing (e.g., Kadlec and McConnell (1994), Foerster and Karolyi (1999), and Chaplinsky and Ramchand (2002)), and media coverage. Further investigating frictions associated with investor recognition and their impact is an interesting area of future study.

References

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Amihud, Yakov, and Haim Mendelson, 1989, The effects of beta, bid-ask spread, residual risk, and size on stock returns, *Journal of Finance* 44(2), 479-86.

Arbel, Avner, 1985, Generic Stocks: An old product in a new package, *Journal of Portfolio Management* 11, 4-13.

Arbel, Avner, and Paul Strebel, 1982, The neglected and small firm effects, *Financial Review* 17, 201-218.

Arbel, Avner, Steven Carvell, and Paul Strebel, 1983, Giraffes, institutions, and neglected Firms, *Financial Analysts Journal* 2-8.

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

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks," *Journal of Financial Economics* 6, 103-126.

Barber, Brad, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773-806.

Basak, Suleyman, and Domenico Cuoco, 1998, An equilibrium model with restricted stock market participation," *Review of Financial Studies* 11, 309-341.

Benartzi, Shlomo, 2001, Excessive extrapolation and the allocation of 401(k) accounts to company stock, *forthcoming Journal of Finance*.

Benartzi, Shlomo, and Richard Thaler, 2001, Naive diversification strategies in defined contribution savings plans, *American Economic Review* 91, 79-98.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27(Suppl), 1-36.

Bessembinder, Hendrik, 1992, Systematic Risk, hedging pressure, and risk premiums in futures markets, *Review of Financial Studies* 5, 637-667.

Blume, Marshall, and Irwin Friend, 1973, A new look at the capital asset pricing model, *Journal of Finance* 28, 19-33.

Brennan, Michael J., 1970, Taxes, market valuation, and corporate financial policy, *National Tax Journal* 23, 417-427.

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

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chan, K.C., and Nai-fu Chen, 1988, An unconditional asset-pricing test and the role of firm size as an instrumental variable for risk, *Journal of Finance* 43, 309-325.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *forthcoming Journal of Financial Economics.*

Chaplinsky, Susan, and Latha Ramchand, 2000, The impact of global equity offerings, *Journal of Finance* 55, 2767-2789.

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

Constantinides, George, 1984, Optimal stock trading with personal taxes, *Journal of Financial Economics* 13, 65-89.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045-2074.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy*, 109(4), 811-841.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russell Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

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

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara, 2002, Is Information Risk a Determinant of Asset Returns? *forthcoming Journal of Finance.*

Easley, David, and Maureen O'Hara, 2000, Information and the cost of capital, Working paper, Cornell University.

Falkenstein, Eric G., Preferences for stock characteristics as revealed by mutual fund holdings, 1996, *Journal of Finance* 51, 111-135.

Fama, Eugene, F., *Foundations of Finance*, 1976, Basic Books.

Fama, Eugene F., 1998, Market efficiency, long-term returns and behavioral finance, *Journal of Financial Economics* 49, 283-306.

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, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 53, 427-465.

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

Foerster, Stephen R., and G. Andrew Karolyi, 1999, The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States, *Journal of Finance* 54, 981-1013.

Frieder, Laura, and Avanidhar Subrahmanyam, 2002, Brand perceptions and the market for common stock, Working paper, UCLA.

Friend, Irwin, Randolph Westerfield, and Michael Granito, 1978, New evidence on the Capital Asset Pricing Model, *Journal of Finance* 33, 903-17.

Green, Rick, and Kristian Rydqvist, 1997, The valuation of non-Systematic risks and the pricing of swedish lottery bonds, *Review of Financial Studies* 10, 447-479.

Grinblatt, Mark, and Tobias J. Moskowitz, 2003, Predicting stock price movements from past returns: The role of consistency and tax-loss selling, *forthcoming Journal of Financial Economics.*

Grullon, Gustavo, George Kanatas, and James P. Weston, 2002, Advertising, breadth of ownership, and liquidity, Working paper, Rice University.

Heaton, John, and Lucas, Deborah, 2000, Portfolio choice and asset prices: The importance of entrepreneurial risk, *Journal of Finance* 2000, 1163-1198.

Hirshleifer, David, 1988, Residual risk, trading costs, and commodity futures risk premia, *Review of Financial Studies* 1, 173-193.

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, 265-296.

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, Industry information diffusion and the lead-lag effect in stock returns, Working paper, Fisher College of Business, Ohio State University.

Jaffe, Jeffrey F., 1974, Special information and insider trading, *Journal of Business* 47, 410-428.

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

Jones, Charles, and Owen Lamont, 2002, Short-Sale constraints and stock returns, *forthcoming Journal of Financial Economics.*

Jones, Charles, and Steve L. Slezak, 1999, The theoretical implications of asymmetric information on the dynamic and cross-sectional characteristics of asset returns, Working paper, UNC Chapel Hill.

Kadlec, Gregory B., and John J. McConnell, 1994, The effect of market segmentation and illiquidity on asset prices: Evidence from exchange listing, *Journal of Finance* 49, 611-636.

Keim, Donald, 1983, Size related anomalies and stock return seasonality: Further empirical evidence, *Journal of Financial Economics* 12, 13-32.

Keim, Donald B., and Ananth Madhavan, 1997, Transactions costs and investment style: An inter-exchange analysis of institutional equity trades, *Journal Financial Economics* 46, 265-292.

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

Mandelker, Gershon, 1974, Risk and return: The case of merging firms, *Journal of Financial Economics* 1, 303-336.

Mech, Timothy S., 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.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

Moskowitz, Tobias J., 2002, An analysis of covariance risk and pricing anomalies, *forthcoming Review of Financial Studies.*

Moskowitz, Tobias J., and Annette Vissing-Jørgensen, 2002, The returns to entrepreneurial investment: A private equity premium puzzle? *forthcoming American Economic Review.*

Pastor, Lubos, and Robert Stambaugh, 2002, Liquidity risk and expected stock returns, *forthcoming Journal of Political Economy.*

Peng, Lin, 2002, Learning with information capacity constraints, Working paper, Duke University.

Poterba, James, and Scott Weisbenner, 2001, Capital gains tax rules, tax loss trading, and turn-of-the-year returns, *Journal of Finance* 56, 353-368.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9-17.

Shapiro, Alexander, 2002, The investor recognition hypothesis in a dynamic general equilibrium: Theory and evidence, *Review of Financial Studies* 15, 97-141.

Shleifer, Andrei, and Robert W. Vishny, 1997, Limits of arbitrage, *Journal of Finance* 52, 35-55.

Stattman, Dennis, 1980, Book Values and stock returns, *The Chicago MBA: A Journal of Selected Papers* 4, 25-45.

Tinic, Seha M. and Richard R. West, 1986, Risk, return, and equilibrium: A revisit, *Journal of Political Economy* 94, 125-47.

Table I:
Price Delay and the Cross-Section of Expected Stock Returns

The equal and value-weighted monthly returns of decile portfolios formed from various measures of delay, their t-statistics (in parentheses), and the difference in returns between decile portfolios 10 (highest delay) and 1 (lowest delay) are reported over the period July, 1964 to December, 2001. Panel A reports characteristic-adjusted returns of the delay-sorted decile portfolios, using characteristic-based benchmarks which account for return premia associated with size, BE/ME, and momentum. Panel B reports the robustness of the spread in characteristic-adjusted average returns between decile portfolios 10 and 1 for delay sorted portfolios, which exclude the month of January, for the two subperiods of the sample, for NYAM and NASD stocks separately, for firms with book-to-market equity ratios (BE/ME) less than or equal to and greater than 2, for firms with average share prices above \$3, for firms with weekly dollar trading volume above \$200,000, and for firms with at least \$5 million (mm) in market capitalization. In addition, the intercepts, α, from time-series regressions of the characteristic-adjusted $10-1$ spread on the Fama-French 3-factor model, which contains the factor-mimicking portfolios associated with the market, a size factor (SMB), and a BE/ME factor (HML), a 4-factor model which adds $PR1YR$, the Carhart (1997) momentum factor-mimicking portfolio, to the previous factors, a 5-factor model which adds the Pastor and Stambaugh (2002) aggregate liquidity risk factor-mimicking portfolio, and a 6-factor model which adds the Easley, Hvidkjaer, and O'Hara (2002) informed trading risk factor-mimicking portfolio (available from July, 1984) are also reported.

	1	2	3	4	5	6	7	8	9	10	**10-1**
	Panel A: Delay Sorted Decile Portfolios – Characteristic-Adjusted Returns										
Equal Weighted Portfolios formed on post-ranking D1 measure											
$D1$	0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0004	-0.0010	0.0010	0.0027	0.0131	**0.0130**
	(0.24)	(-0.12)	(-0.21)	(-0.50)	(-0.13)	(-1.12)	(-2.68)	(1.75)	(3.22)	(8.82)	(8.43)
$D2$	0.0003	-0.0001	-0.0003	-0.0002	-0.0001	-0.0001	0.0005	0.0005	0.0049	0.0097	**0.0095**
	(0.94)	(-0.01)	(-1.31)	(-0.57)	(-0.07)	(-0.20)	(1.13)	(0.96)	(5.53)	(7.54)	(6.91)
$D3$	-0.0002	-0.0002	-0.0002	-0.0004	0.0001	0.0001	0.0016	0.0015	0.0042	0.0088	**0.0090**
	(-0.80)	(-0.73)	(-0.59)	(-1.39)	(-0.15)	(0.16)	(3.01)	(2.82)	(5.03)	(7.72)	(7.63)
Value Weighted Portfolios formed on post-ranking D1 measure											
$D1$	0.0001	-0.0002	-0.0003	-0.0001	-0.0002	-0.0004	-0.0012	0.0006	0.0022	0.0100	**0.0099**
	(0.66)	(-0.60)	(-1.35)	(-0.18)	(-0.74)	(-1.25)	(-3.12)	(1.19)	(2.77)	(7.44)	(7.34)
$D2$	-0.0001	0.0002	-0.0005	0.0005	-0.0001	-0.0004	0.0001	-0.0009	0.0013	0.0059	**0.0060**
	(-0.33)	(0.73)	(-1.53)	(1.28)	(-0.37)	(-0.98)	(0.04)	(-1.95)	(1.90)	(5.38)	(5.24)
$D3$	0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0002	0.0001	-0.0001	0.0013	0.0046	**0.0045**
	(0.50)	(-0.05)	(-0.17)	(-0.17)	(-0.30)	(0.31)	(0.17)	(-0.11)	(2.10)	(4.97)	(4.77)
Value Weighted Portfolios formed on pre-ranking D1 measure using only data from past . . .											
1-Year	0.0008	0.0001	0.0001	-0.0001	-0.0002	-0.0002	0.0002	-0.0005	0.0011	0.0044	**0.0036**
	(1.83)	(0.30)	(0.15)	(-0.09)	(-0.46)	(-0.49)	(0.40)	(-1.05)	(1.79)	(4.96)	(3.78)
5-Year	0.0001	0.0002	-0.0003	-0.0003	-0.0008	-0.0017	-0.0023	-0.0023	-0.0005	0.0040	**0.0039**
	(0.29)	(0.50)	(-1.05)	(-0.98)	(-1.68)	(-3.67)	(-4.57)	(-4.79)	(-0.91)	(4.89)	(4.44)
All	-0.0001	0.0006	-0.0004	0.0001	-0.0001	0.0001	-0.0009	0.0009	0.0019	0.0092	**0.0093**
	(-0.89)	(1.74)	(-0.93)	(0.31)	(-0.07)	(0.08)	(-2.16)	(1.57)	(2.26)	(6.82)	(6.87)
Value Weighted Portfolios formed on change in delay measure $\Delta D1$											
$\Delta D1$	-0.0020	-0.0005	0.0002	0.0005	-0.0001	0.0002	0.0002	0.0009	0.0003	0.0032	**0.0052**
	(-2.02)	(-0.84)	(0.37)	(1.17)	(-0.41)	(0.87)	(0.31)	(1.65)	(0.70)	(3.76)	(3.96)

Panel B: Robustness of the $10-1$ Value-Weighted Spread in Characteristic-Adjusted Returns

	3-Factor α		4-Factor α		5-Factor α		6-Factor α	
	$D1$	$\Delta D1$	$D1$	$\Delta D1$	$D1$	$\Delta D1$	$D1$	$\Delta D1$
$10-1$	0.0138	0.0075	0.0124	0.0084	0.0124	0.0086	0.0126	0.0086
	(7.26)	(4.05)	(6.41)	(4.50)	(6.40)	(4.56)	(6.43)	(4.50)

$10-1$ *characteristic-adjusted spread in D1 sorted portfolio*

Feb.-Dec.	7/64-6/83	7/83-12/01	NYAM	NASD
0.0070	0.0075	0.0125	0.0044	0.0107
(5.54)	(4.20)	(6.16)	(3.83)	(4.88)
Size > \$5mm	\$Volume > 200	Price > \$3	BE/ME ≤ 2	BE/ME > 2
0.0041	0.0033	0.0030	0.0089	0.0068
(3.70)	(3.01)	(2.89)	(6.86)	(2.36)

Table II:
Interaction of Delay with Other Firm Characteristics

Reported are average monthly characteristic adjusted returns (and t-statistics) on value-weighted portfolios first sorted on each of the firm characteristics (of size, BE/ME, momentum, and idiosyncratic risk) into quintiles and then sorted within each quintile into quintiles based on the delay measure $D1$. The difference in returns between quintiles 5 and 1 is also reported. The adjusted returns employ a characteristic-based benchmark return adjustment which accounts for return premia associated with size, BE/ME, and momentum. Momentum is the cumulative past 12-month return of the stock skipping the most recent month. Idiosyncratic risk (σ_ϵ^2) is the variance of residual firm returns from a market model regression using weekly returns over the prior year from July to June. Returns from all portfolios cover the period July, 1964 to December, 2001.

	1	3	5	**5-1**		1	3	5	**5-1**
	Size and Delay					*Book-to-Market Equity and Delay*			
	low $\longrightarrow$ Delay $\longrightarrow$ *high*					*low* $\longrightarrow$ Delay $\longrightarrow$ *high*			
Size1	0.0040	0.0064	0.0119	**0.0080**	BE/ME1	-0.0002	-0.0016	0.0031	**0.0033**
	(3.96)	(5.02)	(7.02)	(5.74)		(-0.78)	(-2.86)	(2.08)	(2.17)
2	0.0001	0.0012	0.0009	**0.0008**	2	0.0001	0.0004	0.0036	**0.0035**
	(0.02)	(1.83)	(1.08)	(0.83)		(0.25)	(0.82)	(3.37)	(3.18)
3	-0.0003	-0.0007	-0.0012	**-0.0009**	3	0.0001	0.0009	0.0028	**0.0027**
	(-0.57)	(-1.55)	(-2.42)	(-1.13)		(0.06)	(2.10)	(2.76)	(2.67)
4	0.0002	0.0003	-0.0008	**-0.0010**	4	0.0004	-0.0005	0.0041	**0.0038**
	(0.42)	(0.87)	(-2.00)	(-1.56)		(1.37)	(-1.37)	(4.08)	(3.52)
Size5	0.0001	-0.0001	-0.0005	**-0.0006**	BE/ME5	0.0004	-0.0008	0.0083	**0.0079**
	(0.27)	(-0.41)	(-1.57)	(-1.27)		(0.81)	(-1.50)	(5.52)	(5.10)
	Momentum and Delay					*Idiosyncratic Risk,* σ_ϵ^2*, and Delay*			
	low $\longrightarrow$ Delay $\longrightarrow$ *high*					*low* $\longrightarrow$ Delay $\longrightarrow$ *high*			
Mom1	-0.0018	-0.0015	0.0163	**0.0182**	$\sigma_\epsilon^2 1$	0.0002	0.0003	-0.0022	**-0.0024**
	(-2.52)	(-2.11)	(9.03)	(9.14)		(0.75)	(0.61)	(-2.30)	(-2.60)
2	0.0003	-0.0002	0.0035	**0.0033**	2	0.0003	0.0009	-0.0003	**-0.0006**
	(0.84)	(-0.38)	(3.49)	(3.06)		(0.40)	(1.79)	(-0.31)	(-0.40)
3	-0.0001	-0.0004	0.0013	**0.0014**	3	0.0003	0.0010	0.0011	**0.0008**
	(-0.46)	(-1.23)	(1.57)	(1.62)		(0.45)	(2.09)	(1.34)	(0.57)
4	0.0004	0.0014	0.0020	**0.0016**	4	-0.0021	0.0002	0.0050	**0.0070**
	(0.71)	(2.32)	(2.12)	(1.42)		(-1.56)	(0.25)	(4.92)	(3.78)
Mom5	-0.0003	-0.0001	0.0027	**0.0030**	$\sigma_\epsilon^2 5$	-0.0046	0.0029	0.0154	**0.0200**
	(-0.58)	(-0.11)	(2.87)	(3.03)		(-3.26)	(1.92)	(7.30)	(9.91)

Table III:
Price Delay and the Size and Value Effects

At the end of June of each year, stocks are ranked by their market capitalization (Panel A) or book-to-market equity ratio (Panel B) and sorted into deciles using NYSE breakpoints. The equal-weighted and value-weighted monthly returns on these decile portfolios are computed over the following year from July to June. Raw and adjusted average monthly returns and t-statistics (in parentheses) on these portfolio returns, as well as the difference in returns between decile portfolios 10 (highest ranked) and 1 (lowest ranked) are reported over the period July, 1964 to December, 2001 for deciles 1, 5, and 10. The adjusted returns are calculated using a characteristic-based benchmark return adjustment, where the benchmark portfolios are decile sorted portfolios of stocks based on their post ranking delay measure ($D1$). Value weighted benchmarks are used for value weighted portfolios and equal weighted benchmarks are used for equal weighted portfolios. Average returns are also reported for the two subperiods of the sample (July, 1964 to June, 1983 and July, 1983 to December, 2001), for the month of January only, and for portfolios formed on the predicted component of size (or BE/ME) from delay and the unpredicted or orthogonal component of size (or BE/ME) with respect to delay.

	Panel A: Size-Sorted Decile Portfolios							
	Equal-Weighted Portfolios				*Value-Weighted Portfolios*			
	1	5	10	**10-1**	1	5	10	**10-1**
	Raw Returns							
7/64-12/01	0.0157	0.0111	0.0100	**-0.0057**	0.0129	0.0111	0.0101	**-0.0028**
	(4.83)	(4.32)	(4.75)	(-2.17)	(4.10)	(4.32)	(5.01)	(-1.13)
7/64-6/83	0.0200	0.0128	0.0071	**-0.0129**	0.0176	0.0128	0.0072	**-0.0104**
	(3.92)	(3.35)	(2.41)	(-3.35)	(3.56)	(3.34)	(2.62)	(-2.77)
7/83-12/01	0.0110	0.0093	0.0131	**0.0021**	0.0077	0.0093	0.0132	**0.0055**
	(2.82)	(2.73)	(4.39)	(0.61)	(2.08)	(2.73)	(4.49)	(1.77)
January	0.1046	0.0380	0.0160	**-0.0886**	0.0896	0.0380	0.0164	**-0.0733**
	(7.54)	(3.25)	(1.82)	(-7.90)	(6.53)	(3.24)	(1.96)	(-6.66)
	Returns Adjusted for Delay Premium							
7/64-12/01	0.0001	-0.0001	-0.0007	**-0.0008**	0.0002	-0.0002	-0.0001	**-0.0003**
	(0.94)	(-0.43)	(-1.50)	(-1.54)	(1.29)	(-0.44)	(-0.12)	(-0.72)
7/64-6/83	0.0002	-0.0001	-0.0017	**-0.0019**	0.0003	0.0005	-0.0003	**-0.0006**
	(1.95)	(-0.20)	(-2.57)	(-2.66)	(1.45)	(1.16)	(-1.18)	(-0.60)
7/83-12/01	-0.0001	-0.0002	0.0003	**0.0004**	0.0000	-0.0009	0.0003	**0.0003**
	(-1.28)	(-0.45)	(0.43)	(0.54)	(0.25)	(-1.58)	(0.94)	(0.65)
January	0.0014	-0.0032	-0.0057	**-0.0071**	0.0026	0.0005	-0.0015	**-0.0041**
	(4.71)	(-2.42)	(-2.52)	(-2.88)	(4.52)	(0.36)	(-1.50)	(-2.99)
	Portfolios Sorted on $\widehat{Size}(Delay)$, Raw Returns							
7/64-12/01	0.0157	0.0117	0.0106	**-0.0051**	0.0127	0.0115	0.0102	**-0.0025**
	(4.85)	(4.57)	(4.81)	(-2.08)	(4.12)	(4.69)	(4.94)	(-1.05)
	Portfolios Sorted on $\widehat{Size}(Residual)$, Raw Returns							
7/64-12/01	0.0129	0.0132	0.0120	**-0.0009**	0.0116	0.0114	0.0101	**-0.0015**
	(4.13)	(4.82)	(5.54)	(-0.51)	(3.79)	(4.40)	(5.01)	(-0.70)

Panel B: BE/ME-Sorted Decile Portfolios

	Equal-Weighted Portfolios				*Value-Weighted Portfolios*			
	1	5	10	**10-1**	1	5	10	**10-1**
				Raw Returns				
7/64-12/01	0.0078	0.0122	0.0179	**0.0101**	0.0091	0.0097	0.0141	**0.0050**
	(2.33)	(4.75)	(6.12)	(5.30)	(3.67)	(4.57)	(5.63)	(2.54)
7/64-6/83	0.0109	0.0135	0.0207	**0.0098**	0.0073	0.0079	0.0154	**0.0081**
	(2.32)	(3.43)	(4.45)	(3.52)	(2.10)	(2.65)	(3.98)	(2.71)
7/83-12/01	0.0043	0.0107	0.0149	**0.0105**	0.0110	0.0117	0.0127	**0.0017**
	(0.92)	(3.33)	(4.36)	(4.01)	(3.13)	(3.85)	(4.08)	(0.66)
January	0.0543	0.0568	0.0943	**0.0400**	0.0141	0.0180	0.0553	**0.0412**
	(4.36)	(4.90)	(6.15)	(4.21)	(1.40)	(1.89)	(4.35)	(4.27)
				Returns Adjusted for Delay Premium				
7/64-12/01	-0.0032	0.0007	0.0034	**0.0066**	-0.0009	-0.0004	0.0020	**0.0029**
	(-2.43)	(1.53)	(4.08)	(3.53)	(-0.99)	(-0.49)	(1.80)	(1.70)
7/64-6/83	-0.0015	0.0004	0.0028	**0.0044**	-0.0004	-0.0001	0.0033	**0.0038**
	(-0.94)	(0.69)	(2.52)	(1.85)	(-0.32)	(-0.05)	(2.18)	(1.56)
7/83-12/01	-0.0050	0.0010	0.0039	**0.0090**	-0.0015	-0.0007	0.0005	**0.0020**
	(-2.39)	(1.43)	(3.26)	(3.07)	(-1.17)	(-0.72)	(0.32)	(0.81)
January	0.0039	0.0010	0.0083	**0.0044**	-0.0057	-0.0036	0.0205	**0.0262**
	(0.89)	(0.51)	(1.70)	(0.57)	(-1.67)	(-1.21)	(3.81)	(3.59)
				Portfolios Sorted on $\widehat{BE/ME}(Delay)$, Raw Returns				
7/64-12/01	0.0105	0.0110	0.0156	**0.0051**	0.0101	0.0111	0.0126	**0.0025**
	(4.70)	(4.29)	(4.84)	(2.10)	(4.86)	(4.54)	(4.12)	(1.06)
				Portfolios Sorted on $\widehat{BE/ME}(Residual)$, Raw Returns				
7/64-12/01	0.0095	0.0128	0.0156	**0.0061**	0.0095	0.0101	0.0133	**0.0038**
	(2.80)	(4.99)	(5.52)	(3.29)	(3.81)	(4.68)	(5.54)	(2.02)

Table IV:
Fama-MacBeth Regressions

Results from Fama-MacBeth monthly cross-sectional regressions of stock returns on firm size (log of market capitalization), log of the ratio of book-to-market equity, previous month's return, previous year's return (from month $t-12$ to $t-2$), previous three year's return (from month $t-36$ to $t-13$), market β, and idiosyncratic risk are reported over the period July, 1964 to December, 2001. Idiosyncratic risk (σ_ϵ^2) is calculated as the variance of residual returns from a market model regression of each stock's weekly return over the past year from July to June. Market β is the sum of slope coefficients from a regression of each stock's return on the contemporaneous return of the market, plus four lags, estimated weekly over the prior year from July to June. Both idiosyncratic risk and β are the post-ranking portfolio measures, where stocks are first sorted into size deciles and pre-ranking measure deciles, and the post-ranking measures of these portfolios are estimated over the entire sample period and assigned to each stock at each date. Regressions are run for the whole sample of firms, excluding the highest decile of delay firms (Delay 10), and for the highest delay firms only. In addition, the total delay measure and the components of delay predicted by liquidity and attention variables, as well as the residual are employed as regressors. Results are reported over the period July, 1981 to December, 2001. The time-series average of the coefficient estimates and their associated time-series t-statistics (in parentheses) are reported in the style of Fama and MacBeth (1973).

	Dependent Variable = Cross-Section of Monthly Stock Returns						
			Only Firms in Delay				
	7/64-12/01		Deciles 1-9	Decile 10	*7/81-12/01*		
ln(Size)	-0.0009	0.0007	-0.0007	-0.0092	-0.0007	0.0015	0.0008
	(-2.58)	(1.93)	(-1.88)	(-5.82)	(-1.21)	(2.67)	(0.58)
ln(BE/ME)	0.0016	0.0015	0.0016	-0.0009	0.0020	0.0019	0.0011
	(3.72)	(3.41)	(3.48)	(-1.14)	(2.66)	(2.57)	(0.88)
$ret_{-1:-1}$	-0.0735	-0.0739	-0.0699	-0.0987	-0.0570	-0.0574	-0.0546
	(-17.93)	(-18.09)	(-16.92)	(-14.52)	(-12.08)	(-12.25)	(-7.96)
$ret_{-12:-2}$	0.0047	0.0049	0.0070	-0.0077	0.0048	0.0049	0.0100
	(2.94)	(3.07)	(4.30)	(-2.92)	(3.44)	(3.52)	(4.50)
$ret_{-36:-13}$	-0.0027	-0.0026	-0.0023	-0.0076	-0.0021	-0.0018	-0.0022
	(-4.83)	(-4.60)	(-4.19)	(-4.09)	(-3.75)	(-3.34)	(-3.23)
β	-0.0066	0.0031	-0.0001	0.0246			
	(-1.59)	(0.95)	(-0.02)	(2.31)			
σ_ϵ^2	0.0847	0.0117	-0.1384	0.7347			
	(0.53)	(0.07)	(-0.84)	(4.04)			
Total Delay		0.0373				0.0462	
		(5.56)				(5.45)	
$\widehat{Delay}$(Attention)							0.0385
							(2.18)
$\widehat{Delay}$(Liquidity)							-0.0452
							(-0.57)
Residual Delay							0.0282
							(1.29)

Table V:
Decomposing the Impact of Delay on Returns

Reported are the characteristic-adjusted returns of the lowest and highest decile portfolios, as well as the difference between them, sorted by the total delay measure, $D1$, over the period July, 1981 to December, 2001. Also reported are the returns on portfolios formed from only those firms with analyst and institutional coverage ("somewhat-neglected"), the component of $D1$ predicted by the traditional liquidity ($\widehat{Delay}$(Liquidity)) and attention ($\widehat{Delay}$(Attention)) variables, the residual component of delay, and only those stocks that did not have any analyst coverage or institutional ownership ("truly neglected" firms). All portfolios are value-weighted.

	1	10	**10-1**
$\widehat{Delay}$(Attention), all firms	-0.0001	0.0061	**0.0062**
	(-0.13)	(2.96)	(2.91)
$\widehat{Delay}$(Liquidity), all firms	-0.0013	0.0013	**0.0026**
	(-1.12)	(0.70)	(1.22)
Residual Delay	0.0003	0.0004	**-0.0009**
	(1.04)	(0.39)	(-0.60)
Total Delay, all firms	0.0002	0.0131	**0.0129**
	(1.36)	(6.87)	(6.73)
Total Delay, somewhat-neglected firms	-0.0002	0.0050	**0.0053**
	(-0.28)	(2.48)	(2.52)
Total Delay, truly neglected firms	-0.0053	0.0143	**0.0195**
	(-2.67)	(5.00)	(5.99)

Table VI:
Characteristics of Delay Sorted Portfolios and Neglected Firms

At the end of June of each year, stocks are ranked by their total post-ranking delay measure ($D1$) and sorted into deciles. The value-weighted average characteristics of these decile portfolios are computed over the following year from July to June. Average characteristics of the portfolios are reported for the delay measure, size (market capitalization in \$thousands), book-to-market equity ratio (BE/ME), percentage institutional ownership, average weekly dollar volume (in \$thousands), idiosyncratic risk, σ^2_ϵ, which is the variance of residual firm returns from a market model regression using weekly returns over the prior year from July to June, market β, which is the sum of slope coefficients from a regression of each stock's return on the contemporaneous return of the market, plus four lags, estimated weekly over the prior year from July to June, number of analysts, average share price, number of shareholders (thousands), cumulative average return over the past year (skipping a month) and past three years (skipping a year), $ret_{-12:-2}$ and $ret_{-36:-13}$, respectively, and average number of stocks per portfolio. Also reported are F-statistics on whether the characteristics differ across deciles 1 through 10 as well as 1 through 9. Panel A reports characteristics on the decile portfolios formed from all stocks over the period July, 1966 to December, 2001. Panel B reports characteristics across decile portfolios formed only from firms with at least some analyst and institutional coverage over the period July, 1981 to December, 2001, and Panel C reports characteristics from firms with no coverage (e.g., "truly neglected" firms).

	Delay Sorted Decile Portfolios, 07/1964 - 12/2001										F-stat	F-stat
	1	2	3	4	5	6	7	8	9	10	(1-10)	(1-9)
	Panel A: All Firms											
Delay	0.0008	0.0095	0.0219	0.0411	0.0628	0.0942	0.1325	0.1812	0.2474	0.3709	129,652*	83034.6*
Size	19,340,581	9,079,537	356,784	165,464	90,863	51,313	32,331	18,903	10,239	5,480	274.60*	270.99*
BE/ME	0.6	0.981	1.086	1.251	1.583	1.911	1.851	2.141	3.262	8.973	251.73*	140.70*
Inst. Own. (%)	51.62	42.64	33.97	27.68	22.89	19.09	15.70	12.75	9.17	6.32	1,897.47*	1,620.95*
\$Volume	1,027,964	224,483	24,501	11,451	6,313	3,443	2,035	1,129	564	314	76.80*	76.20*
σ^2_ϵ	0.009	0.011	0.013	0.014	0.016	0.018	0.019	0.021	0.024	0.027	71,493.5*	52,998.4*
β	0.993	0.977	1.022	1.025	1.038	1.016	1.001	0.986	0.971	0.930	3,842.43*	1,893.94*
#Analysts	22.18	13.49	6.01	3.88	2.85	2.22	1.85	1.55	1.37	1.40	3,262.51*	3,154.04*
Avg. Price	129.09	43.05	27.53	23.62	19.14	15.17	12.20	9.36	6.79	4.74	308.03*	295.30*
#Shareholders	248.61	124.21	10.69	6.18	4.82	7.70	2.90	2.80	2.33	2.03	873.91*	859.91*
$ret_{-12:-2}$	0.163	0.154	0.174	0.178	0.177	0.163	0.164	0.146	0.113	0.089	6.52*	3.33*
$ret_{-36:-13}$	0.479	0.447	0.478	0.474	0.443	0.419	0.358	0.267	0.172	0.013	74.93*	35.61*
#Trading Days	250.71	247.81	242.45	235.84	229.15	219.47	207.98	192.26	172.76	150.18	338.67*	274.75*
Avg. #Stocks	401.59	420.82	423.26	424.31	422.86	421.23	427.01	417.88	422.86	439.31		

	Delay Sorted Decile Portfolios, 07/1981 - 12/2001										F-stat	F-stat
	1	2	3	4	5	6	7	8	9	10	(1-10)	(1-9)
Panel B: Somewhat-Neglected Firms												
Delay	0.0005	0.0012	0.0092	0.0162	0.0257	0.0383	0.0550	0.0767	0.1104	0.1764	2,325*	1,798*
Size	19,121,318	28,802,009	7,512,278	951,800	344,135	190,407	143,955	82,481	49,667	25,912	169.85*	165.27*
BE/ME	0.583	0.572	0.738	0.973	1.147	1.498	1.881	1.998	3.315	4.577	163.46*	99.84*
Inst. Own. (%)	51.99	51.80	44.29	40.30	35.37	32.00	28.38	24.90	21.44	16.70	1258.06*	1005.79*
$Volume	1,398,980	1,783,060	419,738	66,761	29,413	16,893	11,256	6,587	4,048	1,859	79.75*	77.58*
σ^2_ϵ	0.009	0.009	0.011	0.013	0.014	0.015	0.016	0.017	0.019	0.020	2,212.67*	1,884.11*
β	0.992	0.998	0.982	1.011	1.025	1.042	1.028	1.035	1.015	0.996	273.71*	269.37*
#Analysts	23.60	23.82	15.09	9.12	6.19	4.52	3.83	2.93	2.34	1.80	3,653.67*	3,346.10*
Avg. Price	213.89	60.05	37.76	28.46	23.48	20.02	18.20	14.65	11.56	8.76	75.21*	73.13*
#Shareholders	151.81	183.50	94.48	15.11	7.59	6.01	10.54	3.55	3.68	3.50	518.63*	498.40*
$ret_{-12:-2}$	0.205	0.208	0.175	0.202	0.194	0.179	0.172	0.148	0.123	0.059	11.61*	4.50
$ret_{-36:-13}$	0.613	0.620	0.589	0.536	0.546	0.515	0.451	0.376	0.291	0.121	77.78*	37.23*
#Trading Days	251.66	251.74	248.36	246.83	243.07	238.93	233.79	230.53	224.17	209.72	92.54*	59.07*
Avg. #Stocks	226.08	247.52	250.79	243.79	251.10	247.28	248.41	248.29	248.89	255.23		
Panel C: Truly Neglected Firms Only												
Delay	0.0222	0.0926	0.1332	0.1687	0.2085	0.2422	0.2788	0.3268	0.3684	0.4335	9,907.70*	6931.68*
Size	6,766,649	65,180	36,243	24,265	16,911	12,482	9,287	6,507	4,832	4,733	66.74*	66.70*
BE/ME	1.214	0.895	1.201	0.873	1.437	1.761	1.585	4.451	7.571	2.819	59.47*	62.84*
$Volume	63,650	4,769	2,729	1,686	1,100	851	625	432	376	275	191.14*	190.20*
σ^2_ϵ	0.012	0.018	0.021	0.022	0.023	0.024	0.025	0.026	0.028	0.028	3,188.32*	2,996.56*
β	1.000	1.011	0.991	0.985	0.977	0.969	0.958	0.939	0.919	0.916	1,764.23*	1307.01*
Avg. Price	30.76	13.09	9.63	7.20	6.05	4.77	4.27	3.56	2.69	2.66	1,070.78*	1027.05*
#Shareholders	40.42	5.45	2.78	1.98	1.93	1.68	1.56	1.44	1.46	1.46	88.31*	87.87*
$ret_{-12:-2}$	0.244	0.249	0.362	0.210	0.166	0.105	0.116	0.074	0.064	0.096	8.21*	8.20*
$ret_{-36:-13}$	0.654	0.694	0.495	0.377	0.271	0.194	0.118	0.012	-0.074	-0.103	164.25*	137.54*
#Trading Days	210.71	166.74	152.92	141.05	134.96	121.31	111.08	105.63	91.82	90.80	68.88*	67.20*
Avg. #Stocks	120.12	122.45	122.77	124.43	122.40	120.43	123.23	120.86	125.81	140.95		

*Indicates significance at the 1% level.

Figure 1

Earnings Announcement and Extreme Market Movement Event Returns for Delay Firms

Adjusted returns following both earnings surprises and extreme market movement events are reported and plotted. Earnings news is measured by standardized unexpected earnings (SUE), which is the difference between current quarter's earnings and earnings four quarters prior divided by the standard deviation of unexpected earnings over the past eight quarters. Extreme market movements are the 5th (R_m^{95-}) and 95th (R_m^{95+}) percentile monthly return events on the CRSP value-weighted index. Firms are sorted independently into quintiles based on their post-formation delay rankings and on SUE. The cumulative adjusted return (CAR) on the portfolio of event firms that intersect in the top and bottom quintiles of both delay and SUE are plotted monthly from six months before the event to 12 months after. Extreme market movement events are handled similarly. Abnormal returns are estimated by benchmarking against a value-weighted portfolio of firms matched by size, BE/ME, and past one year returns. The average monthly adjusted return over the six months following each event is reported along with its t-statistic (in parentheses) using the event study approach of Jaffe(1974) and Mandelker(1974). For each calendar month t, we calculate the abnormal return on each firm that had an earnings announcement in calendar month $t+k$, for $k = [-6, 12]$. The value-weighted average of these abnormal returns across firms in each category are computed for each calendar month t and averaged across time.

Average Monthly Adjusted Returns Over the 6 Months Following the Event					
Earnings Surprise (SUE)			**Market Movements**		
High Delay, SUE+	0.0069	(6.82)	High Delay, R_m^{95+}	0.0122	(5.43)
Low Delay, SUE+	0.0007	(1.20)	Low Delay, R_m^{95+}	0.0001	(0.72)
High Delay, SUE−	-0.0042	(-3.30)	High Delay, R_m^{95-}	0.0019	(0.89)
Low Delay, SUE−	0.0001	(0.14)	Low Delay, R_m^{95-}	0.0001	(0.20)