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

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Abstract

We parsimoniously characterize the severity of market frictions affecting a stock using the average 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 part of 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 traditional liquidity effects (price impact and cost), but appear most consistent with investor recognition. The very small segment of extremely delayed, neglected firms captures substantial variation in cross-sectional 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 on portfolio choice and asset prices, such as incomplete information (Merton (1987), Hirshleifer (1988), Basak and Cuoco (1998), Shapiro (2002)), asymmetric information (Kyle (1985), Jones and Slezak (1999), Coval and Moskowitz (2001), 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)), liquidity (Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2003)), and noise trader or sentiment risk (DeLong, Shleifer, Summers, and Waldmann (1992), Shleifer and Vishny (1997)). How important are these features of the economy for understanding the cross-section of expected returns?

We assess the impact of market frictions for cross-sectional return predictability using a parsimonious measure of the severity of frictions affecting a stock: the average delay with which its share price responds to information. The link between the speed of information diffusion and market frictions is consistent with 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)) which argue institutional forces and transactions costs can delay the process of information incorporation for less visible, segmented firms. In addition, Hong and Stein (1999) develop a model of gradual information diffusion and Peng (2002) shows that information capacity constraints can cause a delay in asset price responses to news. Price delay may also result from lack of liquidity of an asset's shares, which can potentially arise from many sources. Our measure of price delay parsimoniously captures the impact of these potential frictions on the price process of a stock.

Delayed firms are small, volatile, less visible, and neglected by many market participants. On a value-weighted basis, the most severely delayed firms (top decile) comprise less than 0.02% of the market, yet capture a great deal of cross-sectional return predictability. First, we find delayed firms 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 traditional liquidity effects associated with price impact and cost measures. Second, the premium for delay subsumes entirely the effect of firm size on the cross-section of returns and a portion 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. Third, post-earnings announcement drift is monotonically increasing in delay and is non-existent among non-delayed firms. Fourth, we find that idiosyncratic risk is priced only among the most severely delayed firms.

We then examine what drives the cross-sectional return predictability associated with the small segment of delayed firms. We find that investor recognition rather than traditional liquidity price impact and cost measures best explain the data. Traditional liquidity proxies, such as volume, turnover, inverse of price, number of trading days, bid-ask spread, and the price impact and trading measures of Amihud (2002) and Chordia, Subrahmanyam, and Anshuman (2001) do not subsume the delay effect nor capture significant cross-sectional return predictability in the presence of delay. There is also little relation between the delay premium and the aggregate liquidity risk factor of Pastor and Stambaugh (2003). Rather, proxies for investor recognition such as analyst coverage, regional exchange membership, number of shareholders and employees, institutional ownership, advertising expense, and remoteness (e.g., average airfare and distance from all airports to firm headquarters) seem to drive the explanatory power of delay, even when controlling for traditional liquidity proxies. We interpret this evidence as suggesting that the premium associated with delay is related to firm recognition or neglect and not liquidity. On the other hand, since liquidity is arbitrarily defined and measured, an alternative interpretation of these findings is that delay identifies the priced component of firm liquidity, which appears related to investor recognition rather than price impact and cost measures. Both views provide a similar interpretation of cross-sectional return predictability. For example, small, value firms seem to carry a premium because they respond slowly to information. Such sluggishness arises because these stocks are less visible and neglected.

Finally, the fact that idiosyncratic risk is priced only among the most delayed firms is also consistent with the investor recognition hypothesis. 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 or momentum stocks and the delay premium, 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)).

We conclude with a brief discussion of the impediments to exploiting the price delay premium and why it may persist in markets. Since the delay premium resides among small, value stocks, recent losers, and stocks with low institutional ownership and high idiosyncratic risk, the ability to exploit this phenomenon may be limited.

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 some of the value effect. We also show that post-announcement drift is monotonically positively related to delay. Section III tests various hypotheses for what drives delay's return predictability. We find that investor recognition as opposed to traditional liquidity effects seem to explain the relation between delay and the cross-section of returns. Section IV then examines the interaction of delay with other firm characteristics for determining cross-sectional returns. We find idiosyncratic risk is priced only among the most severely delayed firms and that the delay effect is stronger among small, value, risky firms with poor recent performance. Section V briefly discusses the tradeability of delayed firms and Section VI 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.[1] Book value

[1]Prior to 1978, COMPUSTAT often back-filled their data for up to two years. We require at least a year of prior return history from CRSP (which does not backfill) and confirm that results are unaltered requiring a two year history (as in Fama and French (1992) and Kothari, Shanken, and Sloan (1995)) and are robust to using only data post-1978. In addition, for analysis using institutional ownership and analyst data, which is only available beginning

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. Moreover, we focus on stocks with the most severe delay (frictions), whose lagged response often takes several weeks. Weekly returns are sufficient for identifying such firms while avoiding issues of higher frequency data. We define weekly returns to be the compounded daily returns from Wednesday to the following Wednesday using closing prices or, when closing prices are not available, the bid-ask midpoint (plus dividends) as in Moskowitz (2003) and Hou (2003).[2] Results are robust to only using closing prices to calculate returns. Measures of price delay require a year of prior weekly return history, so the trading strategy returns begin in July, 1964. Firm-week observations are excluded when weekly returns are missing. In addition, a minimum of one month is skipped between our measures and returns when forming portfolios. Thus, our measure and returns should not be biased by non-trading issues. To be sure, we also control for the number of trading days of a stock in subsequent analysis.

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, mostly small, firms and hence may introduce a bias toward large stocks. We also employ 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. This likely understates our results.

in 1981, this is not an issue.

[2]We compute weekly returns between adjacent Wednesdays since Chordia and Swaminathan (2000), Hou (2003), and others document high autocorrelations using Friday to Friday prices and low autocorrelations using Monday to Monday prices. Wednesday seems like an appropriate compromise.

A. Measuring price delay

We employ several measures to capture the average delay with which a firm's stock price responds to information. The market return is employed as the relevant news to which stocks respond. At the end of June of each calendar year, we run a regression of each stock's weekly returns on contemporaneous and 4 weeks of lagged returns on the market portfolio over the prior year.

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

where $r_{j,t}$ is the return on stock j and $R_{m,t}$ is the return on the CRSP value-weighted market index in week 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. This regression identifies the delay with which a stock responds to market-wide news if expected returns are relatively constant over weekly horizons. Mech (1993), Boudoukh, Richardson, and Whitelaw (1994), McQueen, Pinegar, and Thorley (1996), Chordia and Swaminathan (2000), and Hou (2003) 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 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 individual stock returns explained by the lagged market returns. This is simply one minus the ratio of the R^2 from regression (1) restricting $\delta_j^{(-n)} = 0$, $\forall n \in [1,4]$, over the R^2 from regression (1) with no restrictions.

$$D1 = 1 - \frac{R^2_{\delta_j^{(-n)}=0, \forall n \in [1,4]}}{R^2}. \tag{2}$$

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.

Since $D1$ does not distinguish between shorter and longer lags or the precision of the estimates, the following two measures are also employed (j subscripts suppressed for notational ease):

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

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

where $se(\cdot)$ is the standard error of the coefficient estimate. Variants of these measures 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.

A.1 Alternative delay measures

We also compute the delay measures above adding leading market returns to equation (1) (e.g., $\sum_{n=1}^{4} \delta_j^{(+n)} R_{m,t+n}$). The cross-sectional rank correlation between $D1$ from equation (2) and $D1$ including leading market returns is 0.91.

In equation (1), we employ 4 weekly lags only since autocorrelation coefficients at 5 lags or higher are negligible and highly volatile. Also, 4 weeks seems like a fair amount of time for a stock to respond to news. However, we have run robustness tests using higher order lags and found nearly identical results.[3] Most of the significance on the lagged regressors occurs at 1 or 2 week lags. We have also included lagged regressors on the stock's own return as well in equation (1) and found nearly identical results.

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.

For brevity, therefore, we report results from the simplest specification using only lags in equation (1) and the measures in equations (2)–(4). Results in the paper are robust to adding leads, longer lags, or alternative weighting schemes and are available upon request.

Firms we classify as having "high delay" by our measures do indeed have larger and more 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 (1.02 on average) and lower lagged market coefficients

[3]For instance, at the suggestion of an anonymous referee we included up to 7 lags and employed the weighting scheme $max[m-|m-n|, 0]$ for $m = 4$ for the coefficients in our delay measures $D2$ and $D3$ to capture the notion that higher order lags are more informative about delay and less precise. The cross-sectional rank correlations between $D2$ and $D3$ from equations (3) and (4) and $D2$ and $D3$ using this alternative weighting mechanism are 0.90 and 0.89, respectively. The returns generated from portfolios based on these measures are equally highly correlated.

(0.04, 0.006, and 0.008). These differences are statistically significant.

A.2 Pre-ranking portfolio 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 one month to as much as one year old, ensuring their availability before portfolio formation, as well as rendering microstructure issues immaterial. We then estimate equation (1) using the entire past sample of weekly returns for each of the 100 portfolios and use the estimated coefficients to compute delay measures for each portfolio, which are then assigned to each stock within the portfolio. Pre-ranking portfolio measures are also computed using the most recent past year of returns data, the past five years of data, and the past ten years of data. The noise from smaller sample pre-ranking measures reduces the information content of the sort. However, results are robust to the use of these measures.

Note that because only the response to market return shocks is employed for our delay measures, we avoid problems of interpreting portfolio delay and individual stock delay that would occur if own stock return lags were included. For instance, Lo and MacKinlay (1990) and others find positive portfolio return autocorrelation, but negative individual stock return autocorrelation due to strong cross-autocorrelations among stocks. Using only responses to market returns simplifies interpretation of our portfolio delay measures.

[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.

B. Characteristics of delay sorted portfolios

Before proceeding to the returns associated with delay, it is useful to examine the types of firms experiencing significant price delay. Table I reports the value-weighted average characteristics of portfolios sorted into deciles based on their pre-ranking delay measure $D1$ over the July, 1964 to December, 2001 period. Of particular interest are firms in decile 10, the portfolio of highest delay. Characteristics on the delay measure $D1$, firm size (market capitalization), ratio of book value-to-market value of equity (BE/ME), residual variance σ_ϵ^2 (defined as the variance of the residual from a market model regression (with four lags) of the firm's weekly returns over the prior year), market β (the sum of the slope coefficients from the market model regression), and cumulative returns over the past year (skipping the most recent month, $ret_{-12:-2}$) and past three years (skipping the most recent year, $ret_{-36:-13}$) are reported. F-statistics on the difference in average characteristics across all decile portfolios as well as the first 9 deciles are reported as well as the time-series average of the cross-sectional Pearson and rank correlations between each characteristic and delay.

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. Delayed firms are smaller, value, more volatile firms, with poor recent performance. It will be important to take this into account when we examine returns.

Table I also reports characteristics of firms across variables proxying for a firm's recognition/attention by investors and its liquidity. We employ institutional ownership, number of analysts, shareholders, and employees, and advertising expense as measures of firm recognition. Analyst and institutional coverage are associated with more recognizable firms and improve the speed with which a stock's price responds to information (Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), Hong, Lim, and Stein (2000)). The number of shareholders and employees measures the breadth of ownership. Advertising expense provides another measure of recognizability and has been shown to affect investor's portfolio choices (Cronqvist (2003)) and a firm's liquidity and breadth of ownership (Grullon, Kanatas, and Weston (2003) and Freider and Subrahmanyam (2003)). We employ monthly dollar trading volume, share turnover (monthly number of shares traded divided by shares outstanding), average monthly closing price, number of trading days, and Amihud's (2002) illiquidity measure (average daily absolute return divided by daily dollar volume) over the prior year as measures of liquidity. Hasbrouk (2003) compares a host of effective cost and price impact measures estimated from daily data relative to those from high frequency trading data and finds that Amihud's (2002) measure is the most highly correlated with trade-based measures, exhibiting a correlation of 0.90 for portfolios.

Table I indicates that delay is strongly inversely related to the attention and liquidity proxies. Focusing on decile 10, it is not surprising that the highest delay firms are very small and neglected, with an average market capitalization of only $6 million (nominal dollars from 1964 to 2001), dollar trading volume of $370,000 per month, average share price of $4.89, little analyst or institutional following, and low ownership breadth. Later, we will attempt to decompose delay into components related to attention and liquidity, using these and other proxies, and examine their relation to returns.

II. Delay and the Cross-Section of Stock Returns

Table II reports the average returns of portfolios sorted on various pre-ranking delay measures. 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 Table I shows delay is 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 (past returns). 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 (Grinblatt and

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

Moskowitz (2003)).

Average raw and 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 Table II for equal- (Panel A) and value-weighted (Panel B) portfolios. For delay measure $D1$, the average raw spread between the highest and lowest portfolio of delay firms is a striking 134 basis points per month when equal weighted and 99 basis points when value weighted. Since the characteristics of firms in deciles 1 and 10 are very different, the characteristic-adjusted returns in the next two rows are more informative about delay's relation to average returns. As Table II indicates, the adjusted average returns of the deciles are considerably lower, however, the average spread between deciles 10 and 1 remains largely the same. The 133 (95) basis point spread in equal (value) weighted portfolios after adjusting for size, BE/ME, and momentum premia suggests a strong relation between a firm's price delay and its expected return. Since size, BE/ME, and momentum capture substantial variation in returns (Fama and French (1996)), the volatility of the adjusted spread is considerably lower, resulting in larger statistical significance.

Interestingly, the $10 - 1$ spread derives primarily 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. This asymmetry, consistent with models of market frictions, where only the most constrained or inefficient assets carry a premium, can only exist if the most constrained firms comprise a small fraction of the market. Decile 10 comprises less than 0.02% of the total market capitalization of publicly traded equity on U.S. exchanges.

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 Change in delay

The next two rows of Table II report the equal and 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 $\Delta D1$ is a highly significant 72 basis points per month when equal weighted and 49 basis points when value weighted.

A.2 Alternative measures of delay

The next six rows report characteristic-adjusted returns of portfolios sorted on the delay measure $D1$ using only the most recent one, five, and ten years of past return data to measure portfolio delay. Results are robust to these shorter sample pre-ranking portfolio measures, though profits decrease as the size of the pre-ranking window shrinks. This is likely due to the greater noise induced in the delay measures from using smaller samples. Returns are also reported for portfolios sorted on delay measures $D2$, $D3$, and $D1$ adding leading market returns to equation (1). The cross-sectional rank correlation between these alternative delay measures and $D1$ (without leads) is about 0.90 as indicated in the last column of Table II. Not surprisingly, therefore, the returns generated from these measures are similar in magnitude and significance to our main $D1$ measure.

A.3 Further return adjustment

To ensure our characteristic adjustment procedure is robust and not contributing to the profitability of the strategies, Panel C of Table II reports the α or intercept (along with its t-statistic) from time-series regressions of the raw and characteristic-adjusted returns of the value-weighted spread in $D1$ sorted portfolios on various factor models. We employ 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 Carhart (1997) four factor model, which adds a momentum factor-mimicking portfolio $PR1YR$ to the Fama-French factors, a five-factor model that adds the aggregate liquidity risk factor-mimicking portfolio of Pastor and Stambaugh (2003) to the Carhart model, and a six-factor model that adds a factor-mimicking portfolio for the informed trader risk identified by Easley, Hvidkjaer, and O'Hara (2002) to these factors.[6] In addition to providing further return adjustment, these last two factors indicate whether liquidity risk or asymmetric information drives the delay premium.

[6]Details on the construction of these factor portfolios can be found in Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003), and Easley, Hvidkjaer, and O'Hara (2002). Pastor and Stambaugh (2003) define liquidity risk as the covariance (regression coefficient) between a firm's return and innovations in the equally-weighted aggregate lagged order flow or dollar trading volume signed by the contemporaneous return on the stock in excess of the market. Stocks are ranked by their "liquidity β's" and formed into value-weighted decile portfolios. The $10 - 1$ spread in returns is used as the liquidity risk factor-mimicking portfolio. The informed trading factor is formed at each year-end using independent sorts of stocks into three size and three "probability of informed-trading" (PIN) groups. Easley, Hvidkjaer, and O'Hara (2002) measure the probability of information-based trading using a structural microstructure model and high frequency trading data on order flow and trade sequence from the NYSE. 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. We thank Lubos Pastor and Soeren Hvidkjaer for providing the aggregate liquidity risk and informed trading factors, respectively.

The intercepts from these time-series regressions are large and highly significant, even after adjusting returns using both the characteristic benchmarks and the factor models. Thus, potentially inadequate risk adjustment from the characteristic benchmarks does not seem to be driving the profitability of these strategies. Moreover, the loading of the delay spread on the information-based factor is only -0.05 with a statistically insignificant t-statistic of -0.38. This suggests that the premium associated with delay is not related to information asymmetry.

A.4 Subperiods and subsamples

The value weighted characteristic-adjusted spread in $D1$ sorted portfolios is also reported across various subperiods and subsamples for robustness. Profits excluding the month of January are a little lower, but still highly significant. Profits are significant in both subperiods of the sample, though higher in the second half of the sample. Profits are significant for both NASDAQ and NYAM firms. The higher profits for NASDAQ seem to be due to the smaller firms traded there and the greater dispersion of delay among smaller firms.[7] Subperiod profits on NYAM stocks only (not reported) also revealed higher profits in the second half of the sample as well. Hence, the higher profits in the latter half of the sample cannot entirely be attributed to the introduction of smaller 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 size and liquidity premia have diminished over time. We will show more formally that delay is not driven by size or traditional liquidity effects.

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, firm-weeks with missing return observations over the prior year are dropped. 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 a minimum of one month to 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

[7] We confirm this by subdividing each exchange into five size groups using NYSE/AMEX quintile breakpoints for both exchanges. This generates roughly equal market capitalizations of each group across exchanges. Within each size group on each exchange, we then form decile portfolios based on delay. The spread in delay within a size group across the two exchanges are roughly equal as well. This suggests smaller firms have greater dispersion in delay and that there is no exchange-specific effect on delay itself. Finally, the return premium for delay across the two exchanges are nearly identical within each size group. Hence, controlling for size and delay differences across exchanges generates identical delay premia, suggesting there is no exchange effect on return premia either. Fama-MacBeth regressions of returns on size, delay, and exchange indicators confirm these results as well.

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 itself by buying long delay firms with predicted price increases and shorting those with predicted price decreases. Rather, our strategy buys (shorts) firms with high (low) average delay measured in the past, and ignores the sign of the information trend or any short horizon effects. Thus, stale prices are not an issue for our strategy. For all of the above reasons, non-trading issues (e.g., bid-ask bounce and non-synchronous trading) do not have any impact on our results. In addition, we control for the number of trading days of a stock (and a host of other liquidity measures) in the next section and find our results are robust.

Finally, if we restrict the sample to stocks with market capitalization greater than \$5 million, monthly dollar trading volume of at least \$200,000, and share prices above \$5, the trading strategy profits remain highly significant. In addition, if we exclude firms with extreme value (BE/ME greater than one) profits remain large and significant. This suggests the most extreme value firms or an interactive effect between small, extreme value firms are not driving delay profits.

B. Post-earnings announcement drift

As an additional test of the impact of delay on stock returns we analyze the price response of firms' equity to earnings announcements. This highlights how our delay measure captures the speed of information diffusion. 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. The top quintile of SUE firms represent the "positive earnings surprises" and the bottom quintile the "negative earnings surprises" firms. For each delay quintile we compute adjusted returns (benchmarking against a value-weighted portfolio of firms matched by size, BE/ME, and past one year returns) on the portfolio of firms experiencing positive and negative earnings surprises at each event date (e.g., the intersection of the top and bottom quintiles of SUE rankings and each delay quintile). Returns are computed monthly from six months before the event to 12 months after using the event study approach of Jaffe (1974) and Mandelker (1974), recommended by Fama (1998). For each calendar month t, we calculate the value-weighted average abnormal return on all firms that had an earnings announcement in calendar month $t - k$, for $k = [-6, 12]$, and average these across time.[8] This approach has the added advantage of accounting for the correlation of returns across event firms, providing robust standard errors (Fama (1998)).

The average monthly adjusted return over the six months following positive and negative earnings surprises is reported in Figure 1 across delay quintiles along with t-statistics on their difference from zero and an F-statistic on the joint equality of means across delay quintiles. Post-announcement drift is positively monotonically related to delay for both positive and negative shocks. The F-statistic rejects the equality of means across delay quintiles. Low delay firms exhibit no evidence of post-announcement drift. Figure 1 plots the cumulative adjusted abnormal returns (CAR's) on the earnings surprise portfolios across delay quintiles from six months before the event to 12 months after in event time. The monotonic relation between delay and post-earnings announcement drift is evident from the figure, particularly for positive earnings surprises.

C. 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 and value. Table II shows 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 the decile portfolios as well as the difference between deciles 10 (largest) and 1 (smallest) are reported. Confirming previous evidence, the relation between average returns and size is weakly negative

[8] 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, for each delay quintile event portfolio.

over the whole sample (June, 1964 to December, 2001), strongly negative in the first half of the sample (June, 1964 to June, 1983), absent in the second half of the sample (July, 1983 to December, 2001), and most strongly negative in January. These results are also stronger for equal than value weighted portfolios.

To examine the impact of delay on the size-average return relation, we adjust the size-sorted portfolio 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 5 basis points when equal weighted and from 28 to 1 basis point when value weighted. 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 just 14 (3) after adjusting for delay. This is despite the fact that delay is a stronger economic effect in the latter half of the sample (Table II) as opposed to size. Likewise, the equal (value) weighted size premium in January drops dramatically from 8.9% (7.3%) to only 0.57% (0.39%) after adjusting for delay.

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, each year we run a cross-sectional regression of each firm's size on its delay measure,

$$\text{Market Cap}_j \quad = \quad a + b(\text{delay}_j) + e_j. \tag{5}$$

The predicted component of size related to delay is then $\widehat{size}(delay) = b(\text{delay}_j)$ and the orthogonal component of size with respect to delay is $\widehat{size}(residual) = a+e_j$. As the bottom of Panel A of Table III indicates, only the component of size related to delay captures significant variation in average returns. The component of size unrelated to delay has little cross-sectional return predictability. Taken together, these results suggest that 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 subsamples and January. When returns are adjusted for delay, the next four rows show that the value premium is reduced somewhat. Over the entire sample period the equal (value) weighted value premium declines from 102 (50) basis points to 63 (32) basis points when netting out the delay premium. Similar sized reductions are shown for the first half of the sample period and for January. However, there is a minimal effect of delay on value in the second half of the sample (although the value-weighted value premium is small in this period anyway). The last two rows of Panel B sort stocks into portfolios based on the components of BE/ME related and unrelated to delay, using a decomposition similar to equation (5) with a firm's BE/ME as the dependent variable. The component of BE/ME associated with delay captures about half of the value effect in the data. Overall, these results suggest that the delay premium seems to have at least some impact on the value effect, though value still retains predictive power for returns.

D. 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 (including liquidity measures), and provide an alternative weighting scheme for portfolios.[9]

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 $t-13$ ($ret_{-36:-13}$), and measures of delay. The size, book-to-market, and delay variables are from the previous return year. The first column of Table IV Panel A 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 related to BE/ME and past one 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 previous results. Note, too, that the coefficient on log of size changes from negative and statistically significant to positive and insignificant when including delay in the regression. This is consistent with Merton (1987), who argues that controlling for firm recognition, size should be positively related to expected returns. Both economically and statistically, delay appears to subsume the explanatory power of size. However, the coefficient on log of BE/ME is unaltered, indicating delay

[9]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 (Fama (1976)). The weights are tilted toward stocks with the most extreme (volatile) returns.

has a weaker effect on the value premium under this alternative specification.

The next three columns of Panel A of Table IV report Fama-MacBeth regression results adding various measures of a stock's liquidity. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), and Amihud (2002) document a positive return premium for a share's illiquidity. Since liquidity is arbitrarily defined, these studies employ a variety of liquidity proxies. We control for these as well as other liquidity measures to ensure the delay premium is not simply a manifestation of previously discovered measures. We employ three sets of liquidity variables commonly used in the literature: the average monthly share turnover, average monthly dollar trading volume, and Amihud's (2002) measure of illiquidity (average daily absolute return divided by dollar volume) of the stock estimated over the prior year. Since reported volumes on NASDAQ include inter-dealer trades (which NYSE-AMEX do not), we measure these variables separately for NASDAQ and NYAM traded firms and include a NASDAQ trading dummy in the regression. In addition to the levels of these liquidity variables, we also include the coefficient of variation (standard deviation divided by mean over the prior year) of these variables following Chordia, Subrahmanyam, and Anshuman (2001). Due to multicollinearity problems arising from including all liquidity measures simultaneously, we run three separate regressions for the turnover, dollar volume, and Amihud illiquidity measures. Finally, we also include the number of trading days of the stock and the inverse of its average daily closing share price over the prior year in all regressions. (Note, too, that size is a control in all regressions.)

As Table IV Panel A demonstrates, the premium from delay is robust to the inclusion of these liquidity measures. The point estimate and statistical significance of the delay coefficient declines, which is not surprising given the correlation between delay and these liquidity variables (see Table I), but remains economically and statistically significant. The negative coefficients on turnover and volume are consistent with Amihud and Mendelson (1986) and Brennan, Chordia, and Subrahmanyam (1998), the positive coefficient on Amihud's illiquidity measure is consistent with Amihud (2002), and the negative coefficients on the coefficient of variation of these variables is consistent with Chordia, Subrahmanyam, and Anshuman (2001). Thus, although delay and commonly used proxies for liquidity have some overlap in explaining returns, there appears to be independent variation in their ability to capture returns.

III. What Drives the Delay Premium?

In this section we consider several hypotheses for what drives delay and its associated premium. In particular, we distinguish between the investor recognition hypothesis and traditional liquidity effects arising from trading and price impact costs. The previous section showed that delay has predictive power for returns independent of traditional liquidity proxies. We investigate the source of this additional predictability.

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 proxying for investor attention/recognition in the style of Fama and MacBeth (1973). The regression is estimated as follows,

$$D1_j \quad = \quad a + \sum_{k=1}^{K} b_k Att_{k,j} + \sum_{q=1}^{Q} c_q Liq_{q,j} + \epsilon_j, \tag{6}$$

where Att_k and Liq_q are a set of attention/recognition and traditional liquidity variables, respectively. The investor attention/recognition variables are the log of institutional ownership, log of number of analysts, shareholders, and employees, log of advertising expense, and a regional exchange dummy (obtained from each U.S. regional stock exchange to capture regional visibility given the local portfolio biases documented by Coval and Moskowitz (1999)). We also employ measures of remoteness to characterize investor recognition using the average distance between each stock's headquarters and all U.S. airports as well as the nearest airport, and the average airfare between the nearest airport and all U.S. airports, weighted by the number of air routes (market share) each airport comprises. Stock headquarters location is 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.* Distances are computed using the arclength formula in Coval and Moskowitz (1999) between each headquarters location and every U.S. airport in order to identify the nearest airport distance, average air route distance, and average airfare (average cost per flight for a round-trip standard coach seat across all airlines offering flights between any two airports, weighted by total number of flights between all 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. Firms that are more difficult/costly to visit or gain access to likely deter institutions and other investors from investing.

The liquidity variables are those used previously and are run separately for the turnover, dollar volume, and Amihud illiquidity measures (due to multicollinearity). All firms in the sample must have available data on each of these variables. This requirement tilts the sample toward larger more liquid firms. The regressions are estimated over the period July, 1981 to December, 2001 since some of the variables are only available post-1981.[10]

The time-series averages and t-statistics of the regression coefficients are

$$
\begin{aligned}
\sum_{k=1}^{K} \hat{b}_k Att_{k,j} = \; & \underset{(-1.15)}{-0.0017 \text{ log(Institutional Ownership)}} + \underset{(-6.87)}{-0.0067 \text{ log(\#Analysts)}} \\
& + \underset{(-4.78)}{-0.0057 \text{ Regional Exchange}} + \underset{(-0.94)}{-0.0005 \text{ log(\#Shareholders)}} \\
& + \underset{(-5.75)}{-0.0038 \text{ log(\#Employees)}} + \underset{(0.31)}{0.0002 \text{ log(Advertising)}} \\
& + \underset{(-0.44)}{-0.0054 \text{ Nearest Airport}} + \underset{(-1.46)}{-0.0021 \text{ Air Distance}} \\
& + \underset{(1.99)}{0.0271 \text{ Airfare}}
\end{aligned} \tag{7}
$$

and

$$
\begin{aligned}
\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j} = \; & \underset{(-1.49)}{-0.0078 \text{ NASD}} + \underset{(-0.10)}{-0.0001 \text{ log(Turnover}_{NYAM})} \\
& + \underset{(-1.95)}{-0.0031 \text{ log(Turnover}_{NASD})} + \underset{(-4.98)}{-0.0005 \text{ \#Trading Days}} \\
& + \underset{(14.42).}{0.3282 \text{ (1/Price)}}
\end{aligned} \tag{8}
$$

If dollar volume and Amihud's illiquidity measure are employed instead of turnover,

$$
\begin{aligned}
\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j}^{volume} &= \ldots + \underset{(-13.97)}{-0.0052 \text{ log(Volume}_{NYAM})} + \underset{(-8.56)}{-0.0111 \text{ log(Volume}_{NASD})} \\
\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j}^{illiquidity} &= \ldots + \underset{(13.25)}{0.0052 \text{ Illiquidity}_{NYAM}} + \underset{(7.70)}{0.0094 \text{ Illiquidity}_{NASD}}
\end{aligned}
$$

[10] We have also tried other attention/recognition variables with similar results. For example, as an exogenous 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. In addition, we have also employed other measures of liquidity such as the average monthly bid-ask spread, number of dealers in a stock, and number of trades executed per day, which are available on a limited basis for primarily NASDAQ firms. Including these other measures does not alter any of the results in the paper, but limits the number of firms in our sample, due to missing data for many firms.

where coefficients on the other liquidity and attention variables are similar. We employ all three specifications in our subsequent analysis. In addition, results are similar including firm size as a regressor.

The regressions confirm the negative relation between delay and investor recognition and liquidity suggested by the univariate correlations in Table I. Moreover, equation (7) identifies the component of delay related to investor recognition and orthogonal to traditional liquidity ($\widehat{delay}(attention)$), and equation (8) identifies the component of delay related to traditional liquidity and orthogonal to investor recognition ($\widehat{delay}(liquidity)$). The average adjusted R^2's from these regressions are around 70%, 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 roughly 43% for the liquidity variables alone and 56% for the attention variables alone. Although we call the first set of variables "attention" and the second set "liquidity", because liquidity is arbitrarily defined, one might view all of these variables as potential measures of stock liquidity. Indeed, Chordia, Huh, and Subrahmanyam (2003) find that ownership structure and analyst coverage explain a sizeable fraction of cross-sectional variation in stock trading volume, though they also interpret this as consistent with stock visibility. If one views all of these measures as liquidity proxies (including delay), then the decomposition in equations (7) and (8) can be interpreted as the components of total firm liquidity attributed to proxies for investor recognition and those more traditionally used as price impact and cost measures of liquidity.

B. Decomposing the impact of delay

Using equations (7) and (8), we instrument delay with the attention and traditional liquidity proxies and examine their relation to the cross-section of average returns. Panel B of Table IV reports Fama-MacBeth regression results with the components of delay related to liquidity and attention, as well as the residual, as independent variables. Data availability limits the sample period to July, 1981 to December, 2001. For reference, the first column of Panel B reports results for the total delay measure over this period, where it has a slightly stronger economic effect.

The last three columns of Panel B report results for liquidity and attention components of delay using the three measures of liquidity: turnover, volume, and Amihud's illiquidity. Under all three specifications, the attention/recognition variables primarily drive the explanatory power of delay for average returns. The liquidity-instrumented component of delay is statistically insignificant and in two of three specifications has a negative effect on returns. The residual has a positive but insignificant return effect. Thus, the explanatory power of delay derives mainly from the attention proxies, suggesting that the friction most likely associated with the delay premium is related to investor recognition or firm neglect.

Table V reports results for a similar analysis using portfolio returns instead of Fama-MacBeth regressions. Stocks are ranked by their attention, liquidity, and residual delay components and sorted into decile portfolios. The value-weighted average monthly characteristic adjusted returns on these portfolios as well as the difference between decile 10 (highest delay) and 1 (lowest delay) are reported. The component of delay attributed to the attention variables (and orthogonal to traditional liquidity measures) generates substantial profits of 62 to 93 basis points per month, whereas the component of delay attributed to traditional liquidity variables exhibits little relation to returns. The residual component also generates an insignificant return spread. The weakness of residual delay suggests a substantial portion of the explanatory power of delay is captured by our variables (this is also indicated by the high adjusted R^2's from the first-stage regressions). These results support the hypothesis that investor recognition drives the premium associated with price delay.

C. Completely neglected firms

Finally, since we drop firms with missing attention variable data, which for some of our variables are only available on a limited sample of firms (such as analyst coverage and institutional ownership data), we may be missing the truly neglected firms in our analysis. This will tend to understate our findings. For instance, if we employ log(1+#analysts) and log(1+institutional ownership) and include zero coverage firms, the predictability of $\widehat{delay}(attention)$ increases significantly. To test this more directly, we report results for delay sorted portfolios on two samples of stocks: those that have at least some analyst and institutional ownership coverage, and those that seem to have no analyst or institutional following (i.e., "completely neglected" firms).[11] Firms with at least some analyst coverage and institutional ownership tend to be larger, more liquid, and by definition are more recognized. The delay profits from such firms are still an impressive 54 basis points per month (t-statistic of 3.79). However, consistent with the investor recognition hypothesis, the premium for

[11] 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. However, because of this uncertainty we chose to drop such firms from the main analysis when using analyst or institutional ownership data to be conservative.

delay more than triples for the "completely neglected" firms, which generate a striking 177 basis points per month, after adjusting for size, BE/ME, and momentum premia.

IV. Interaction of Delay with Other Firm Characteristics

One of the implications of the investor recognition hypothesis is that idiosyncratic risk will carry a premium among firms with limited investor participation. Prior research examining the pricing role of residual/idiosyncratic volatility has yielded mixed results.[12] 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 be widely held and recognized, and therefore should not be expected to have priced idiosyncratic risk.

We examine the relation between idiosyncratic risk and returns across firms with different average price delay, as a proxy for how segmented or neglected the firm is. Specifically, we rank stocks on their average delay into quintiles and then within each delay quintile sort stocks into quintiles based on their residual variance. The value-weighted characteristic-adjusted returns of these 25 portfolios as well as the spread in returns between the highest and lowest idiosyncratic risk quintiles within each delay category are shown in Figure 2. As the figure shows, idiosyncratic risk is positively related to average returns only among the most delayed firms. The quintile of firms with the most idiosyncratic risk outperforms those with the least by 116 basis points per month (t-statistic of 4.22) among high delay firms. There is little or a slight negative relation between idiosyncratic volatility and average returns among the other four delay quintiles. This highlights the fact that idiosyncratic risk is only priced among the most constrained (as measured by price delay) firms, consistent with the investor recognition hypothesis.

We also examine how the delay premium varies within idiosyncratic risk quintiles by first sorting on residual variance and then sorting stocks into delay quintiles within each idiosyncratic risk quintile. The value-weighted average adjusted return spread between the highest and lowest delay quintiles within each idiosyncratic risk group are shown in Figure 3. The delay premium increases monotonically with idiosyncratic risk, rising to 162 basis points per month among stocks with the highest residual volatility.

[12] 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.

In addition, we examine delay profits within size, BE/ME, and momentum quintiles. This provides another control for these firm characteristics in addition to highlighting their interaction with delay. As Figure 3 shows, the delay premium is prevalent only among the smallest stocks, is slightly increasing in BE/ME, and is most pronounced among the worst past year performing stocks (e.g., losers). Consistent with this, the variation in delay itself is also greater among small, value, and recent poor performing stocks.[13] The stronger delay among losers is consistent with evidence of slower information diffusion regarding negative news found in Hong, Lim, and Stein (2000) and Hou (2003). 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.

V. Trading Costs Associated with Delay

Finally, as noted by Merton (1987), if neglected firms or 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 its associated premium. In equilibrium, therefore, either this premium will be priced away or impediments to trading must prevent exploitation.

An investor trying to take advantage of delay would need to account for trading costs. Since our delay strategies are only updated once a year and there is persistence in delay rankings from year to year, there is relatively little turnover (about 35 percent per year) in our strategies. However, firms with significant delay tend to be small, low priced, and less liquid, making trading costs potentially high. Since the profitability of our delay strategies comes mostly from the long side, short-selling constraints and costs may not be prohibitive. On the other hand, going long high delay firms exposes an investor to market risk. Shorting the benchmark portfolio to hedge this risk entails shorting small, value, recent losing stocks, which may be difficult and costly.

An investor could downweight stocks with particularly high trading costs by focusing on stocks with at least some analyst and institutional coverage, which still generates 54 basis points per month and avoids extremely low priced and tiny firms. The average market capitalization for the top decile of delayed stocks among such firms is $35 million, with an average share price of $9.28 and $2.4 million in monthly 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

[13]The spread in the average delay characteristic between the top and bottom quintiles is 0.26 (0.30, 0.26) for the smallest (highest BE/ME, lowest past year returns) stocks versus 0.03 (0.17, 0.21) for the largest (lowest BE/ME, highest past year returns) stocks.

of going long decile 10 firms (with at least some analyst and institutional coverage) and shorting either decile 1 or decile 10's characteristic-matched benchmark would require a round-trip trading cost of roughly 4.5 percent per year to wipe out the 54 basis point per month (6.4 percent per year) profit (assuming turnover of 35 percent per year on the long and short side).

Whether actual trading costs would exceed this estimate is difficult to say. Keim and Madhavan (1997) estimate that average one-way trading costs for buys (sells) in the smallest size quintile of stocks for trade sizes larger than 0.0556% (0.0775%) of outstanding shares are approximately 2.35% (2.68%) on the NYSE/AMEX and 3.34% (4.08%) on NASDAQ. These costs would not entirely eliminate profits from delay. On the other hand, Keim and Madhavan (1997) did not estimate costs for trading in the smallest, neglected firms with severe price delay, which could be higher. However, even if returns net of costs from a delay strategy were significant, the potential dollar profits may be small due to price impact. For firms with at least some analyst coverage and institutional ownership, going long the most delayed firms (about 255 firms) and allowing ownership of as much as 5 percent of outstanding market capitalization of a firm, would generate only a $332 million dollar investment. With a return of 6.4 percent per year, even absent trading costs, this is only $21.25 million in profits, which seems too small to peak the interests of large institutions.

VI. Conclusion

As a parsimonious measure of the severity of market frictions affecting a firm, price delay is a powerful predictor of cross-sectional average returns. Delay subsumes the size effect and some of the value effect. Idiosyncratic risk is shown to be priced only among the most severely delayed firms and post-earnings announcement drift is monotonically increasing in delay. These results cannot be explained by microstructure, liquidity effects, market risk, or other known determinants of average returns, but appear most consistent with Merton's (1987) investor recognition hypothesis.

These findings support a growing body of evidence of non-news events such as advertising increasing visibility and investor attention (Grullon, Kanatas, and Weston (2003), Freider and Subrahmanyam (2003), Cronqvist (2003)). Our results are also consistent with recent evidence that investor recognition and ownership breadth affect trading activity (Chordia, Huh, and Subrahmanyam (2003)). They may also help explain why corporate managers concern themselves with visibility, public relations, press releases, dual exchange listing (Kadlec and McConnell (1994), Foerster and Karolyi (1999), and Chaplinsky and Ramchand (2002)), and media coverage. Further investigating the broader implications of investor recognition is an interesting area of future study.

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Table I:
Characteristics of Delay Sorted Portfolios

At the end of June of each year, stocks are ranked by their pre-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 from 1964 to 2001. Average characteristics of the portfolios are reported for the delay measure $D1$, size (market capitalization in \$millions), book-to-market equity ratio (BE/ME), percentage institutional ownership, average monthly dollar trading volume (\$millions), monthly turnover (monthly number of shares traded divided by number of shares outstanding), Amihud's (2002) illiquidity measure (average daily absolute return over daily dollar trading volume) $\times 10^5$, idiosyncratic risk σ^2_ϵ (the variance of residual firm returns from a market model regression using weekly returns over the prior year), market β (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), number of analysts, average share price, number of shareholders (thousands), number of employees (thousands), advertising expense (\$millions), 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, average number of trading days per year, and average number of stocks per portfolio. Also reported are F-statistics for testing the equality of characteristics across deciles 1 through 10 and 1 through 9. The final two columns report the time-series average of the cross-sectional Pearson and rank correlations of each firm characteristic with the delay measure $D1$.

	Delay-sorted ($D1$) decile portfolios, July, 1964 to Dec., 2001										F-stat	F-stat	Correlation with Delay	
	1	2	3	4	5	6	7	8	9	10	(1-10)	(1-9)	Pearson	Rank
Firm characteristics														
Delay	0.002	0.011	0.022	0.037	0.053	0.074	0.103	0.144	0.196	0.341	868.82*	820.52*		
Size($)	18,444	9,003	3,030	1,188	690	101	515	33.2	12.9	6.0	185.60*	180.91*	-0.45	-0.94
BE/ME	0.635	0.691	0.756	0.794	0.819	0.892	0.937	1.028	1.164	1.375	149.22*	97.95*	0.86	0.85
σ^2_ϵ	0.008	0.010	0.011	0.012	0.014	0.016	0.017	0.020	0.023	0.027	1987.07*	1992.85*	0.94	0.95
β	1.07	1.11	1.13	1.16	1.22	1.24	1.24	1.29	1.28	1.26	117.28*	167.05*	0.31	0.49
$ret_{-12:-2}$(%)	16.42	17.72	17.05	17.20	17.17	17.06	16.71	15.88	11.45	8.92	6.47*	2.90*	-0.33	-0.25
$ret_{-36:-13}$(%)	47.85	51.04	45.08	44.96	45.25	42.83	37.43	29.83	17.24	3.01	73.33*	35.80*	-0.64	-0.55
Investor attention variables														
Inst. own(%)	52.7	47.9	40.5	34.8	27.6	23.0	18.1	13.8	9.7	6.3	1762.58*	1428.92*	-0.88	-0.99
#Analysts	22.4	13.8	10.6	6.7	3.4	2.7	2.1	1.5	1.3	1.3	1459.24*	1386.87*	-0.65	-0.97
#Shareholders	265.7	79.4	65.7	35.4	4.0	7.8	2.6	2.3	1.5	1.4	648.01*	631.70*	-0.47	-0.95
#Employees	115.7	51.7	30.8	22.3	13.1	4.0	12.4	1.8	1.0	0.5	419.97*	399.81*	-0.48	-0.94
Advertising($)	357.5	227.8	81.0	26.2	8.7	6.7	3.5	2.3	1.4	0.7	233.03*	226.12*	-0.50	-0.92
Liquidity variables														
Volume($)	913	382	99.4	27.6	11.3	5.3	4.4	1.5	0.75	0.37	75.70*	74.38*	-0.48	-0.94
Turnover	0.043	0.050	0.055	0.056	0.053	0.052	0.048	0.045	0.041	0.040	14.48*	11.66*	-0.37	-0.28
Illiquidity	0.012	0.011	0.021	0.036	0.086	0.158	0.319	1.047	1.534	3.756	344.63*	160.74*	0.91	0.96
Avg. price($)	126.87	78.13	37.67	29.88	27.17	19.10	17.20	11.44	7.54	4.89	113.24*	105.33*	-0.63	-0.95
#Trading Days	250.6	248.8	245.7	242.0	231.5	221.2	209.4	194.5	171.9	150.8	329.82*	276.28*	-0.96	-0.96
Avg. #Stocks	369.0	386.9	388.4	388.0	387.5	388.3	385.3	389.3	384.2	406.0				

*Indicates significance at the 1% level.

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

The equal- (Panel A) and value- (Panel B) 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. Raw and characteristic-adjusted returns of the delay-sorted decile portfolios are reported using characteristic-based benchmarks to account for return premia associated with size, BE/ME, and momentum. Pre-ranking $D1$ delay measures from equation (2) using all past return data, the most recent year, five years, and ten years of data are employed. In addition, delay measures $D2$ and $D3$ from equations (3) and (4), respectively, and $D1$ including leading returns are employed. Panel C reports the intercepts, α, from time-series regressions of the value-weighted spread in raw and characteristic-adjusted average returns between decile portfolios 10 and 1 for $D1$ delay-sorted portfolios on the Fama-French 3-factor model, the Carhart (1997) 4-factor model (which adds a momentum factor to the Fama-French factors), a 5-factor model which adds the Pastor and Stambaugh (2003) aggregate liquidity risk factor-mimicking portfolio to the Carhart model, and a 6-factor model which adds Easley, Hvidkjaer, and O'Hara's (2002) probability of informed trading (PIN) factor-mimicking portfolio (available from July, 1984) to the other factors. The characteristic-adjusted spread in returns between $D1$ delay decile portfolios 10 and 1 is also reported excluding 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 and greater than or equal to 1, for firms with average share prices above \$5, for firms with monthly dollar trading volume above \$200,000, and for firms with at least \$5 million in market capitalization.

	Delay-sorted decile portfolios										
	Panel A: Equal-weighted					**Panel B: Value-weighted**					
	1	2	9	10	**10-1**	1	2	9	10	**10-1**	
Raw returns (% per month)											
$D1$	1.13	1.15	1.42	2.47	**1.34**	1.07	1.19	1.28	2.06	**0.99**	
	(4.69)	(4.42)	(4.27)	(6.61)	**(4.27)**	(4.89)	(5.05)	(4.02)	(5.69)	**(3.17)**	
Characteristic-adjusted returns (% per month)											
$D1$	-0.01	0.03	0.29	1.32	**1.33**	-0.03	0.06	0.21	0.93	**0.95**	
	(-0.37)	(0.94)	(3.39)	(8.30)	**(7.97)**	(-1.50)	(1.72)	(2.49)	(6.63)	**(6.69)**	
$\Delta D1$	0.18	0.11	0.21	0.89	**0.72**	-0.13	-0.03	0.05	0.35	**0.49**	
	(2.32)	(2.33)	(3.60)	(7.73)	**(6.44)**	(-1.47)	(-0.45)	(0.89)	(4.30)	**(4.18)**	
Characteristic-adjusted returns (% per month), $D1$ measure using only data from past . . .											
1 Year	0.16	-0.01	0.40	0.87	**0.71**	0.08	0.01	0.11	0.44	**0.36**	
	(2.88)	(-0.03)	(5.32)	(7.60)	**(6.53)**	(1.83)	(0.30)	(1.79)	(4.96)	**(3.78)**	
5 Years	-0.01	0.02	0.07	0.77	**0.77**	0.01	0.02	-0.05	0.40	**0.39**	
	(-0.11)	(1.05)	(1.16)	(7.94)	**(7.61)**	(0.29)	(0.50)	(-0.92)	(4.89)	**(4.44)**	
10 Years	-0.01	0.01	0.28	1.25	**1.25**	0.00	-0.01	0.16	0.88	**0.87**	Rank
	(-0.08)	(0.37)	(3.19)	(8.47)	**(8.10)**	(0.27)	(-0.29)	(1.94)	(6.79)	**(6.72)**	correlation
Alternative delay measures, characteristic-adjusted returns (% per month)											with $D1$
$D2$	0.02	0.02	0.44	1.23	**1.21**	0.01	-0.01	0.33	0.79	**0.78**	0.906
	(0.56)	(0.57)	(4.69)	(8.27)	**(7.70)**	(0.69)	(-0.33)	(3.74)	(6.38)	**(6.12)**	
$D3$	0.01	0.02	0.48	1.11	**1.10**	0.01	0.01	0.25	0.65	**0.64**	0.885
	(0.19)	(0.72)	(4.97)	(7.89)	**(7.39)**	(0.41)	(0.29)	(2.96)	(5.52)	**(5.22)**	
$D1$	-0.01	0.02	0.38	1.32	**1.34**	-0.01	-0.01	0.27	0.93	**0.94**	0.899
w/leads	(-0.37)	(0.73)	(4.31)	(8.56)	**(8.15)**	(-0.44)	(-0.33)	(3.25)	(6.89)	**(6.73)**	

Panel C: Value-weighted 10 − 1 spread in returns (% per month)

Fama-French 3-Factor α		Carhart 4-Factor α		Pastor-Stambaugh 5-Factor α		+PIN 6-Factor α	
Raw	Adj.	Raw	Adj.	Raw	Adj.	Raw	Adj.
0.96	1.41	0.98	1.28	0.99	1.30	1.00	1.31
(3.13)	(6.76)	(3.09)	(6.02)	(3.07)	(6.03)	(3.06)	(6.04)

	Feb.-Dec.	7/64-6/83	7/83-12/01	NYAM	NASD
$D1$, adj.	0.65	0.58	1.34	0.35	1.04
	(4.96)	(3.31)	(5.98)	(2.96)	(4.77)
	Size > \$5mill.	Volume > \$200	Price > \$5	BE/ME < 1	BE/ME ≥ 1
$D1$, adj.	0.47	0.31	0.24	0.80	0.99
	(4.32)	(2.88)	(2.55)	(5.44)	(5.43)

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. Average monthly returns and t-statistics (in parentheses) on these portfolios, as well as the difference between decile portfolios 10 (highest ranked) and 1 (lowest ranked) are reported over the period July, 1964 to December, 2001. Returns are also adjusted for delay by subtracting the return of a characteristic-based delay ($D1$) benchmark portfolio. 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 orthogonal/residual component of size (or BE/ME) with respect to delay.

Panel A: Size-sorted decile portfolios

	Equal-weighted portfolios					Value-weighted portfolios				
	1	2	9	10	**10-1**	1	2	9	10	**10-1**
Raw returns (% per month)										
07/64-12/01	1.57	1.12	1.06	1.00	**-0.57**	1.29	1.12	1.05	1.01	**-0.28**
	(4.83)	(3.88)	(4.73)	(4.75)	**(-2.17)**	(4.10)	(3.87)	(4.71)	(5.01)	**(-1.13)**
07/64-07/83	2.00	1.43	0.84	0.71	**-1.29**	1.76	1.42	0.82	0.72	**-1.04**
	(3.92)	(3.18)	(2.69)	(2.41)	**(-3.35)**	(3.56)	(3.15)	(2.63)	(2.62)	**(-2.77)**
07/83-12/01	1.10	0.78	1.30	1.31	**0.21**	0.77	0.79	1.30	1.32	**0.55**
	(2.82)	(2.22)	(4.04)	(4.39)	**(0.61)**	(2.08)	(2.24)	(4.08)	(4.49)	**(1.77)**
January	10.46	6.49	2.29	1.60	**-8.86**	8.96	6.45	2.25	1.64	**-7.33**
	(7.54)	(4.97)	(2.41)	(1.82)	**(-7.90)**	(6.53)	(4.91)	(2.38)	(1.96)	**(-6.66)**
Returns adjusted for the delay premium (% per month)										
07/64-12/01	0.01	-0.01	-0.01	-0.04	**-0.05**	0.01	-0.01	-0.03	0.01	**-0.01**
	(1.08)	(-0.16)	(-0.13)	(-0.87)	**(-0.96)**	(0.97)	(-0.18)	(-0.54)	(0.30)	**(-0.21)**
07/64-07/83	0.01	0.03	-0.04	-0.13	**-0.14**	0.02	0.04	-0.01	-0.02	**-0.03**
	(0.98)	(0.78)	(-0.99)	(-2.11)	**(-2.12)**	(0.76)	(0.96)	(-0.01)	(-0.57)	**(-0.79)**
07/83-12/01	0.01	-0.04	0.04	0.05	**0.05**	0.01	-0.06	-0.07	0.04	**0.02**
	(0.48)	(-1.20)	(0.88)	(0.73)	**(0.66)**	(0.60)	(-1.51)	(-0.82)	(1.00)	**(0.55)**
January	0.10	0.03	0.12	-0.48	**-0.57**	0.24	0.29	0.26	-0.15	**-0.39**
	(4.24)	(0.36)	(0.86)	(-2.00)	**(-2.30)**	(3.98)	(2.12)	(0.86)	(-1.28)	**(-2.52)**
Portfolios sorted on $\widehat{size}(delay)$, raw returns (% per month)										
07/64-12/01	1.61	1.16	1.07	1.06	**-0.55**	1.33	1.13	1.01	1.03	**-0.30**
	(4.85)	(3.93)	(4.48)	(4.69)	**(-2.28)**	(4.18)	(3.91)	(4.60)	(4.87)	**(-1.28)**
Portfolios sorted on $\widehat{size}(residual)$, raw returns (% per month)										
07/64-12/01	1.16	1.22	1.89	1.17	**0.01**	1.18	1.19	1.06	1.00	**-0.17**
	(3.82)	(4.15)	(6.33)	(4.96)	**(0.04)**	(3.91)	(4.15)	(4.62)	(4.91)	**(-0.93)**

Panel B: BE/ME-sorted decile portfolios

	Equal-weighted portfolios					Value-weighted portfolios				
	1	2	9	10	**10-1**	1	2	9	10	**10-1**
Raw returns (% per month)										
07/64-12/01	0.78	1.01	1.64	1.79	**1.02**	0.91	1.08	1.33	1.41	**0.50**
	(2.33)	(3.44)	(6.10)	(6.12)	**(5.30)**	(3.67)	(4.64)	(5.87)	(5.63)	**(2.54)**
07/64-07/83	1.09	1.21	1.84	2.07	**0.98**	0.73	0.80	1.30	1.54	**0.81**
	(2.32)	(2.79)	(4.31)	(4.45)	**(3.52)**	(2.10)	(2.39)	(3.73)	(3.98)	**(2.71)**
07/83-12/01	0.43	0.79	1.41	1.49	**1.05**	1.10	1.39	1.37	1.27	**0.17**
	(0.92)	(2.02)	(4.51)	(4.36)	**(4.01)**	(3.13)	(4.29)	(4.79)	(4.08)	**(0.66)**
January	5.43	5.27	7.85	9.43	**4.00**	1.41	1.97	4.68	5.53	**4.12**
	(4.36)	(4.70)	(6.17)	(6.15)	**(4.21)**	(1.40)	(2.15)	(4.03)	(4.35)	**(4.27)**
Returns adjusted for the delay premium (% per month)										
07/64-12/01	-0.38	-0.15	0.26	0.25	**0.63**	-0.08	0.01	0.17	0.24	**0.32**
	(-2.91)	(-2.09)	(3.93)	(3.04)	**(3.34)**	(-0.84)	(0.14)	(1.79)	(2.11)	**(1.82)**
07/64-07/83	-0.23	-0.09	0.20	0.24	**0.47**	-0.09	-0.07	0.35	0.37	**0.46**
	(-1.42)	(-0.92)	(2.20)	(2.05)	**(1.92)**	(-0.63)	(-0.73)	(2.44)	(2.19)	**(1.75)**
07/83-12/01	-0.53	-0.21	0.32	0.27	**0.80**	-0.07	0.09	0.01	0.11	**0.18**
	(-2.60)	(-2.01)	(3.36)	(2.24)	**(2.75)**	(-0.56)	(1.11)	(0.03)	(0.75)	**(0.78)**
January	0.01	-0.12	0.01	0.53	**0.53**	-0.68	-0.18	1.47	2.06	**2.73**
	(0.01)	(-0.46)	(0.03)	(1.09)	**(0.65)**	(-2.02)	(-1.07)	(3.43)	(3.73)	**(3.70)**
Portfolios sorted on $\widehat{BE/ME}(delay)$, raw returns (% per month)										
07/64-12/01	1.04	1.08	1.17	1.60	**0.56**	1.01	1.03	1.14	1.32	**0.31**
	(4.57)	(4.65)	(3.95)	(4.84)	**(2.31)**	(4.77)	(4.74)	(3.96)	(4.17)	**(1.32)**
Portfolios sorted on $\widehat{BE/ME}(residual)$, raw returns (% per month)										
07/64-12/01	1.52	1.07	1.26	1.32	**-0.20**	1.07	0.82	1.14	1.25	**0.18**
	(4.53)	(3.58)	(5.27)	(5.13)	**(-1.01)**	(3.34)	(2.78)	(5.24)	(5.71)	**(0.80)**

Table IV:
Fama-MacBeth Regressions

Results from Fama-MacBeth monthly cross-sectional regressions of stock returns on log of firm size (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 $t-13$), pre-ranking delay measure $D1$, and a host of liquidity variables are reported in Panel A over the period July, 1966 to December, 2001. Liquidity variables include the number of trading days of the stock over the prior year, the reciprocal of the average daily share price, a Nasdaq trading dummy, and the log of the level and coefficient of variation (CV, standard deviation divided by mean) of three sets of liquidity measures: turnover (average monthly number of shares traded divided by shares outstanding over the past year), volume (average monthly dollar trade volume over the past year), and Amihud's (2002) measure (average daily absolute return divided by dollar trading volume over the past year), defined separately for NYAM and NASD traded firms. Panel B reports Fama-MacBeth regression results of returns on the total delay measure ($D1$) and the components of delay predicted by liquidity and attention variables over the period July, 1981 to December, 2001. The components of delay predicted by attention and liquidity variables are estimated in a first stage cross-sectional regression of the delay measure on the liquidity measures above plus measures of investor attention: log of institutional ownership, log of number of analysts, regional exchange membership, log of number of shareholders, log of number of employees, log of advertising expense, nearest airport distance, average air distance, and average airfare from firm headquarters to all U.S. airports (weighted by number of flights). The predicted components of delay due to liquidity and attention, as well as the residual, are employed in the second stage return regressions. 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								
	Panel A: July, 1966 to Dec., 2001					**Panel B: July, 1981 to Dec., 2001**			
			Liquidity measures =				Liquidity measures =		
			Turnover	Volume	Illiquidity		Turnover	Volume	Illiquidity
log(size)	-0.0010	0.0003	0.0001	0.0017	0.0017	0.0012	0.0031	0.0052	0.0046
	(-2.39)	(0.82)	(0.02)	(2.03)	(2.59)	(2.37)	(2.30)	(2.88)	(2.87)
log(BE/ME)	0.0018	0.0016	0.0019	0.0018	0.0020	0.0019	0.0017	0.0019	0.0019
	(3.92)	(3.65)	(3.95)	(3.92)	(4.02)	(2.84)	(1.62)	(1.80)	(1.77)
$ret_{-1:-1}$	-0.0714	-0.0719	-0.0771	-0.0774	-0.0764	-0.0613	-0.0523	-0.0528	-0.0528
	(-17.50)	(-17.72)	(-18.49)	(-18.60)	(-18.14)	(-14.35)	(-8.71)	(-8.71)	(-8.72)
$ret_{-12:-2}$	0.0047	0.0049	0.0056	0.0056	0.0051	0.0050	0.0110	0.0107	0.0107
	(2.98)	(3.14)	(3.40)	(3.48)	(3.04)	(3.46)	(5.55)	(5.37)	(5.42)
$ret_{-36:-13}$	-0.0027	-0.0026	-0.0018	-0.0018	-0.0018	-0.0016	0.0001	0.0000	-0.0001
	(-4.50)	(-4.48)	(-2.73)	(-2.79)	(-2.82)	(-2.88)	(0.08)	(-0.06)	(-0.13)
Delay $D1$		0.0406	0.0215	0.0208	0.0226	0.0535			
		(4.49)	(3.04)	(2.96)	(3.24)	(5.89)			
#Trading days			0.0001	0.0001	0.0001				
			(2.39)	(2.15)	(1.29)				
1/price			0.0088	0.0091	0.0066				
			(1.31)	(1.35)	(0.96)				
NASD dummy			-0.0362	-0.3245	-0.0592				
			(-0.25)	(-1.15)	(-0.96)				
log(liquidity)			-0.0021	-0.0017	0.0014				
NYAM			(-3.11)	(-2.64)	(3.08)				
log(liquidity)			-0.0046	0.0224	-0.0039				
NASD			(-0.14)	(1.06)	(-0.93)				
CV(liquidity)			-0.0015	-0.0016	-0.0025				
NYAM			(-3.05)	(-2.87)	(-2.72)				
CV(liquidity)			-0.0163	-0.0676	-0.0226				
NASD			(-1.44)	(-1.34)	(-1.91)				
$\widehat{Delay}$(liquidity)							0.2638	-0.0145	-0.2277
							(0.78)	(-0.05)	(-0.90)
$\widehat{Delay}$(attention)							0.1592	0.2043	0.1931
							(2.21)	(2.46)	(2.43)
Residual Delay							0.0378	0.0510	0.0476
							(1.27)	(1.51)	(1.44)

Table V:
Decomposing the Impact of Delay on Returns

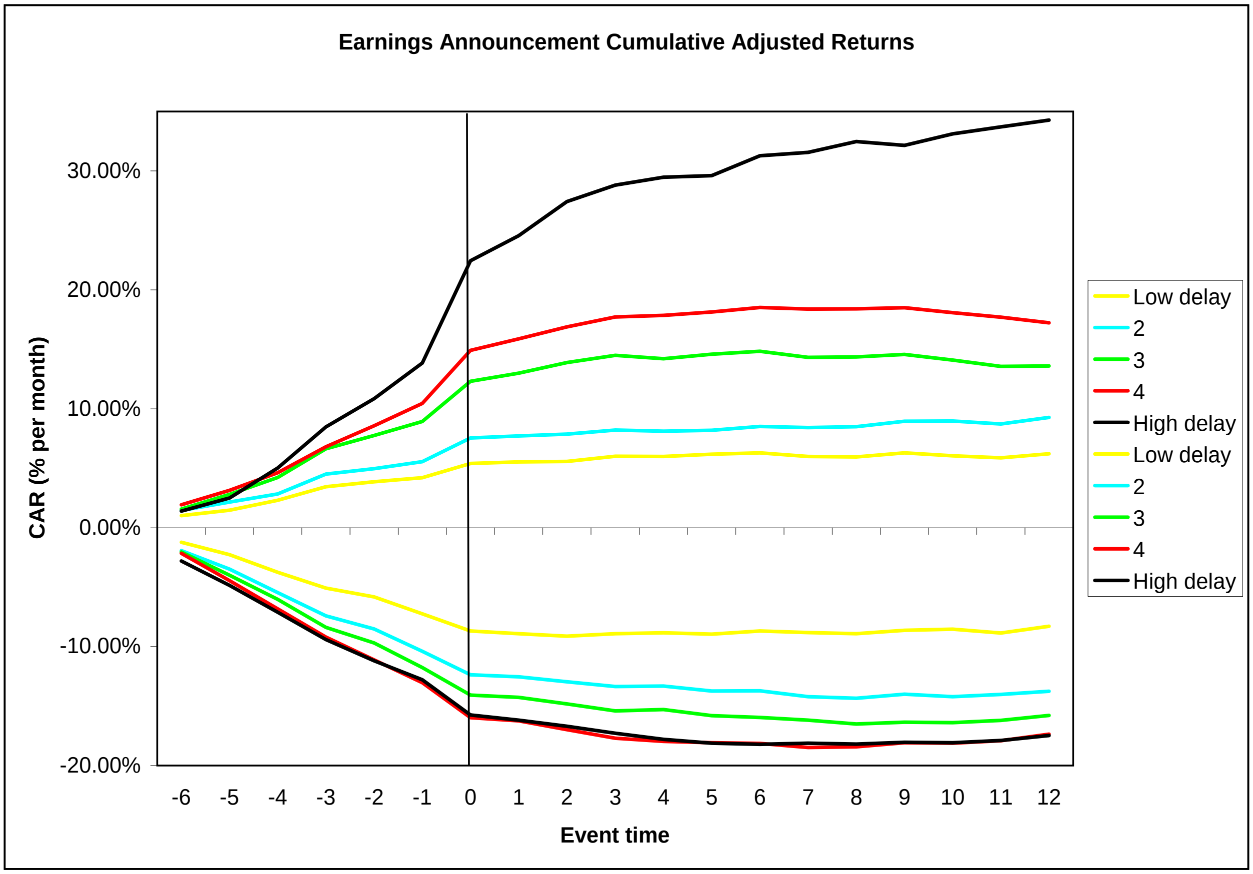
Reported are the characteristic-adjusted returns of decile portfolios, as well as the difference between the lowest and highest deciles, sorted by the total delay measure, $D1$, and the components of $D1$ predicted by traditional liquidity measures ($\widehat{Delay}$(liquidity)) and investor attention measures ($\widehat{Delay}$(attention)). Liquidity variables include the number of trading days of the stock over the prior year, the reciprocal of the average daily share price, a Nasdaq trading dummy, and the log of the level and coefficient of variation (standard deviation divided by mean, σ/μ) of three sets of liquidity measures: turnover (average monthly number of shares traded divided by shares outstanding over the past year), volume (average monthly dollar trade volume over the past year), and Amihud's (2002) measure (average daily absolute return divided by dollar trading volume over the past year), defined separately for NYAM and NASD traded firms. Attention variables include the log of institutional ownership, log of number of analysts, regional exchange membership, log of number of shareholders, log of number of employees, log of advertising expense, nearest airport distance, average air distance, and average airfare from firm headquarters to all U.S. airports (weighted by number of flights). The components of delay predicted by attention and liquidity variables are estimated in a first stage cross-sectional regression with delay as the dependent variable. The residual from this regression is also used to form portfolios. Also reported are the returns on portfolios formed from only those firms with analyst and institutional coverage and those with no analyst coverage or institutional ownership. Portfolios are value-weighted and returns are characteristically adjusted for size, BE/ME, and momentum premia over the period July, 1981 to December, 2001.

Delay-sorted decile portfolios, characteristic-adjusted returns (% per month)					
	1	2	9	10	**10-1**
$\widehat{Delay}$(attention), all firms					
Turnover	0.01	-0.01	0.38	0.63	**0.62**
	(0.09)	(-0.10)	(2.34)	(2.96)	**(2.76)**
Volume	0.01	0.08	0.43	0.66	**0.66**
	(0.01)	(0.56)	(2.21)	(2.62)	**(2.50)**
Illiquidity	-0.03	0.08	0.33	0.90	**0.93**
	(-0.24)	(0.46)	(1.44)	(3.03)	**(2.93)**
$\widehat{Delay}$(liquidity), all firms					
Turnover	0.17	-0.06	0.03	0.05	**-0.11**
	(2.10)	(-1.14)	(0.17)	(0.25)	**(-0.50)**
Volume	0.30	-0.10	-0.06	0.14	**-0.16**
	(2.83)	(-1.69)	(-0.38)	(0.63)	**(-0.64)**
Illiquidity	0.27	0.00	-0.09	0.31	**0.04**
	(2.37)	(-0.01)	(-0.62)	(1.27)	**(0.14)**
Residual delay, all firms					
Turnover	0.45	0.46	0.11	0.06	**-0.39**
	(2.42)	(3.15)	(1.07)	(0.55)	**(-1.81)**
Volume	0.44	0.26	0.04	0.34	**-0.09**
	(1.34)	(1.07)	(0.22)	(1.25)	**(-0.21)**
Illiquidity	0.16	0.57	0.12	0.36	**0.20**
	(0.50)	(2.48)	(0.64)	(1.17)	**(0.42)**
Delay, all firms	-0.02	0.11	0.26	1.35	**1.38**
	(-1.30)	(2.14)	(2.05)	(6.48)	**(6.51)**
Delay, (#analysts> 0 & %inst. own> 0)	-0.05	0.12	0.20	0.49	**0.54**
	(-1.86)	(2.51)	(2.44)	(3.53)	**(3.79)**
Delay, (#analysts= 0 & %inst. own= 0)	-0.44	-0.80	1.52	1.34	**1.77**
	(-1.80)	(-4.70)	(4.41)	(4.51)	**(5.08)**

Figure 1

Post-Earnings Announcement Drift Across Delay Quintiles

Adjusted returns (benchmarking against a value-weighted portfolio of firms matched by size, BE/ME, and past one year returns) following earnings surprises 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. Firms are sorted independently into quintiles based on their delay measure ($D1$) and on SUE. The cumulative adjusted return (CAR) on the portfolio of firms in the top and bottom quintiles of SUE intersected with each delay quintile are plotted monthly from six months before the event to 12 months after for each delay quintile group. In addition, 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) as suggested by Fama (1998). For each calendar month t, the value-weighted average abnormal return on all firms having an earnings announcement in calendar month $t-k$, for $k=[-6,12]$ are computed for each calendar month t and averaged across time. An F-statistic on the joint equality of means across delay quintiles is also reported (p-value in parentheses).



Calendar time portfolio returns

Average adjusted returns (% per month) over the 6 months following the event

Earnings surprise	Low delay	2	3	4	High delay	F-statistic of equal mean (p-value)
Positive	0.07	0.22	0.38	0.54	1.10	9.41
	(1.15)	(1.67)	(4.34)	(5.22)	(6.34)	(0.0001)
Negative	0.04	-0.23	-0.40	-0.41	-0.48	3.60
	(0.57)	(-2.51)	(-4.41)	(-4.18)	(-5.01)	(0.0062)

Figure 2
Is Idiosyncratic Risk Related to Average Returns?

The average monthly characteristic-adjusted returns of idiosyncratic risk-sorted portfolios within quintiles of stocks sorted on the delay measure ($D1$) are plotted. Portfolios are formed by first sorting firms into quintiles based on delay and then within each delay quintile into quintiles based on idiosyncratic variance, defined as the variance of residual firm returns from a market model regression using weekly returns over the prior year from July to June. The characteristic-adjusted spread in returns between idiosyncratic risk quintiles 5 and 1 is also plotted across delay quintiles. Adjusted returns employ a characteristic-based benchmark return adjustment which accounts for return premia associated with size, BE/ME, and momentum. Returns cover the period July, 1964 to December, 2001.

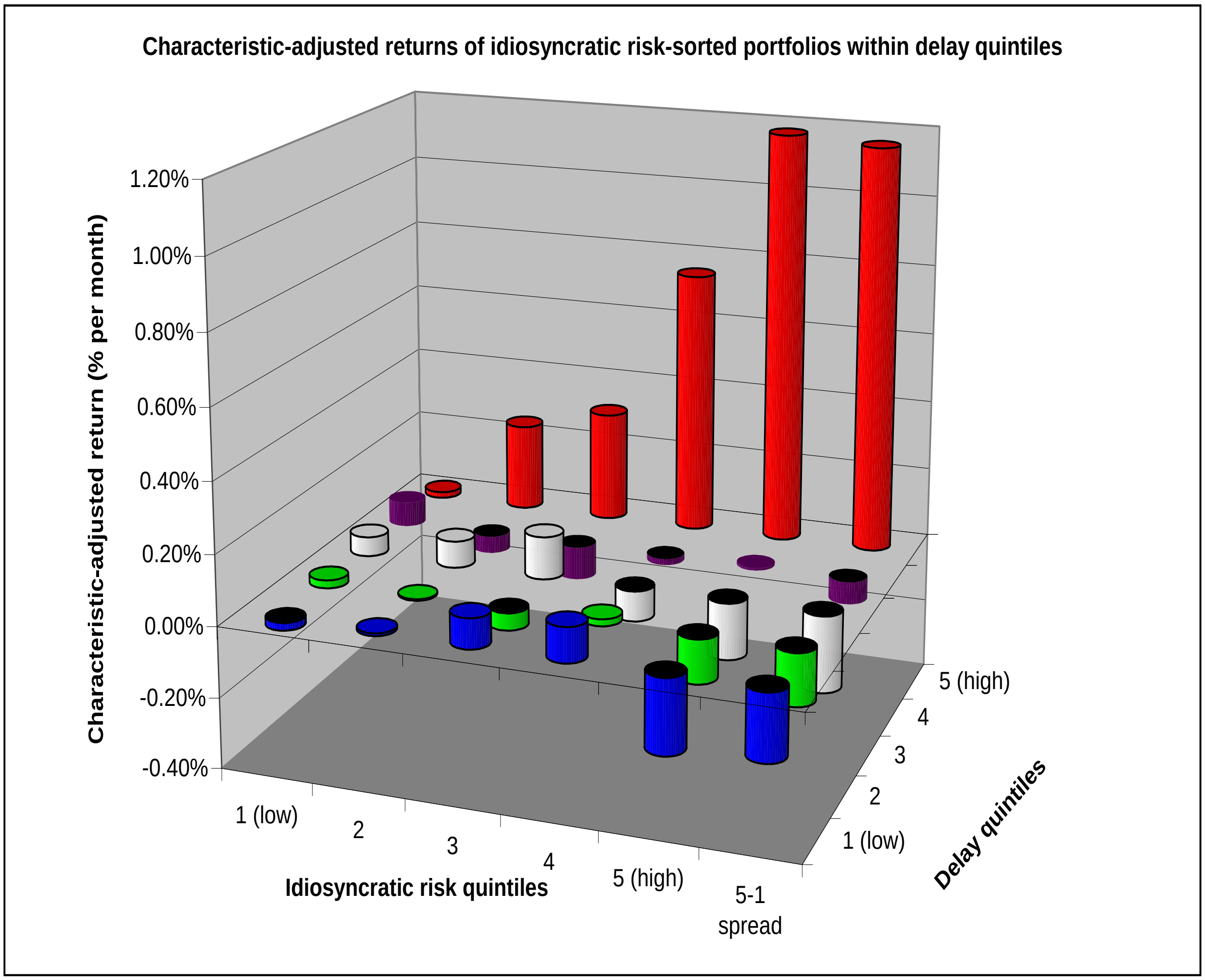


Figure 3
Interaction of Delay with Other Firm Characteristics

The average monthly characteristic-adjusted delay premium is plotted within quintiles of stocks sorted on each of the firm characteristics of size, BE/ME, momentum, and idiosyncratic risk, respectively. Portfolios are formed by first sorting firms into quintiles based on each of the firm characteristics (of size, BE/ME, momentum, and idiosyncratic risk) and then within each firm characteristic quintile into quintiles based on the delay measure $D1$. The characteristic-adjusted spread in returns between delay quintiles 5 and 1 is plotted across each firm characteristic quintile. 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.