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

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We parsimoniously characterize the severity of market frictions affecting a stock using the delay with which its price responds to information. The most delayed firms command a large return premium not explained by size, liquidity, or microstructure effects. Moreover, delay captures part of the size effect, idiosyncratic risk is priced only among the most delayed firms, and earnings drift is monotonically increasing in delay. Frictions associated with investor recognition appear most responsible for the delay effect. The very small segment of delayed firms, comprising only 0.02% of the market, generates substantial variation in average returns, highlighting the importance of frictions.

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

Theoretically and empirically, much research focuses on the importance of a variety of market frictions on portfolio choice and asset prices, such as incomplete information [Merton (1987), Hirshleifer (1988), Basak and Cuoco (1998), and Shapiro (2002)], asymmetric information [Jones

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and Slezak (1999), Coval and Moskowitz (2001), and Easley, Hvidkjaer, and O'Hara (2002)], short-sale constraints [Miller (1977) and Jones and Lamont (2002)], taxes [Brennan (1970) and Constantinides (1984)], liquidity [Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Pastor and Stambaugh (2003)], and noise trader or sentiment risk [DeLong et al. (1990) and Barberis, Shleifer, and Vishny (1998)]. 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), and Shapiro (2002)] or of neglected firms [Arbel and Strebel (1982), Arbel, Carvell, and Strebel (1983), and Arbel (1985)] that argue institutional forces and transactions costs can delay the process of information incorporation for less visible, segmented firms. Hong and Stein (1999) develop a model of gradual information diffusion, and Peng (2004) 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 arise from many sources. Our measure of price delay aims to parsimoniously capture the impact of all these potential frictions on the price process of a stock.

Using a share's price delay, we assess whether market frictions have a significant influence on the cross-section of expected returns. We find that 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 variation in returns. Delayed firms command a return premium as large as 12% per year, after accounting for other return premiums, 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 trading costs. Furthermore, the premium for delay captures part of the effect of firm size on the cross-section of returns. These results are confirmed for both halves of the sample period, for the month of January, and for a number of specifications, return adjustments, and subsamples. We also find that idiosyncratic risk is priced only among the most severely delayed firms. Likewise, the premium associated with trading volume is largely contained among delayed stocks. Post-earnings announcement drift is monotonically increasing in delay and is nonexistent among non-delayed firms. The value premium is also stronger among delayed firms. However, delayed firms do not exhibit intermediate-term price momentum.

Given the significant impact this small segment of firms has on cross-sectional return predictability, we then examine what drives the relation between delay and average returns. We find that frictions associated with investor recognition [Merton (1987)] rather than traditional liquidity price impact and cost measures are most consistent with the data. Traditional liquidity proxies, such as volume, turnover, price, number of trading days, bid-ask spread, and the price impact and trading cost 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). Conversely, proxies for investor recognition such as analyst coverage, institutional ownership, number of shareholders and employees, regional exchange membership, 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 a battery of liquidity and size proxies.

We interpret this evidence as suggesting that the premium associated with delay is related to firm recognition or neglect and not traditional 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. Both views provide a similar interpretation of cross-sectional return predictability. For example, part of the premium associated with small firms may arise because they respond slowly to information as a result of these stocks being less visible or neglected.

The delay premium is strongest among small, value, illiquid, volatile, and poorly performing stocks, which are more likely to be neglected, and is weak or negligible among large, glamour, liquid, and winning stocks, which receive a lot of attention. In addition, the fact that idiosyncratic risk is priced only among the most delayed firms is consistent with the investor recognition hypothesis. Since the most delayed firms are segmented from the rest of the market, residual volatility, as opposed to covariance with the market, 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)].

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)].

Finally, since the delay premium resides among small, illiquid, value stocks, recent losers, and stocks with low institutional ownership and high idiosyncratic risk, the ability to exploit these effects may be severely limited. As Merton (1987) and Shleifer and Vishny (1997) note, significant impediments to exploiting such phenomena may allow them to persist in markets.

The rest of the article is organized as follows. Section I describes the data and presents measures of price delay designed to capture the severity of market frictions affecting a stock. Section II examines how price delay predicts the cross-section of expected stock returns. Section III examines the interaction of delay with firm size and other firm characteristics for determining cross-sectional returns. Section IV tests various hypotheses for what drives the return predictability associated with delay, comparing investor recognition versus traditional liquidity explanations. Section V concludes with a brief discussion of the potential tradeability of delayed firms.

1. 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 from July, 1963, to December, 2001. From 1963 to 1973, the CRSP sample includes NYSE and AMEX firms only, and post-1973 NASDAQ 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 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 for the majority of our price delay measures. At monthly frequencies, there is little dispersion in delay measures since most stocks respond to information within a month's time. Also, lower frequencies generate more estimation error. Although higher frequencies, such as daily or intradaily data, provide more precision and perhaps more dispersion in delay, they may also introduce more confounding microstructure influences such as bid-ask bounce and nonsynchronous trading. We employ daily

[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, using only data after 1978.

data for some of our tests for robustness. Since we focus on stocks with the most severe delay (frictions), whose lagged response often takes several weeks, weekly returns are generally sufficient for identifying delayed firms. 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 (2005).[2] Results are robust to using only 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. We also control for a stock's number of trading days, most recent month's return, and a host of liquidity measures 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 to December, 2001 from Standard & Poors (S&P) and analyst coverage data available from January, 1976 to December, 2001 from Institutional Brokers Estimate System (I/B/E/S). Analyst coverage is defined as the number of analysts providing current fiscal year annual earning 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, which likely understates our results.

1.1 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 four weeks of lagged returns on the market portfolio over the prior year.

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

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

[2] We compute weekly returns between adjacent Wednesdays since Chordia and Swaminathan (2000), Hou (2005), and others document high autocorrelations using Friday to Friday prices and low autocorrelations using Monday to Monday prices. Wednesday seems like an appropriate compromise.

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 (2005) 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 lagged market returns. This measure 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.

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

Equation (2) 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):

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

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

where se(·) 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.

1.1.1 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 (Spearman) correlation between $D1$ from Equation (2) and $D1$ including leading market returns is 0.90.

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

All of these measures ignore the sign of the lagged coefficients 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) through (4). Results 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 positively 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 of 1.02 on average and lower lagged market coefficients of 0.04, 0.006, and 0.008. These differences are statistically significant.

1.1.2 Individual stock and portfolio delay measures. We estimate Equation (1) and compute delay measures in Equations (2) through (4) for each individual stock, as described above. We refer to these as the "first-stage individual stock delay" measures. However, due to the volatility of weekly individual stock returns, the coefficients from Equation (1) are estimated imprecisely. To mitigate an errors-in-variables problem, we also sort

[3] For instance, at the suggestion of an anonymous referee we included up to seven 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.

firms into portfolios based on their market capitalization and individual delay measure, compute delay measures for the portfolio, and assign the portfolio delay measure to each firm in the portfolio. We refer to these as the "second-stage portfolio delay" measures. Specifically, 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 first-stage 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. The equal-weighted weekly returns of the 100 size-delay portfolios are computed over the following year from July to June, and Equation (1) is reestimated using the entire past sample of weekly returns for each of the 100 portfolios in the second stage. The computed-delay measures for each portfolio are then assigned to each stock within the portfolio. This procedure essentially shrinks each stock's individual delay measure to the average for stocks of similar size and individual "first-stage" delay.[5] We also sort stocks independently on size and individual delay in assigning second-stage portfolio measures and obtain similar results.

However, one concern with this two-stage procedure is that it may increase the correlation between size and delay. Since we wish to examine variation in delay unrelated to size, and whether delay captures part of the size effect, we also employ just the first-stage individual delay measures and orthogonalize them with respect to size. To reduce estimation error, we use up to five years of weekly return data to estimate individual delay and use daily data over the past one and five years to improve precision further in estimating individual stock delay. Results are slightly stronger using daily versus weekly data in estimating individual delay, but in either case individual delay produces weaker results than those produced from the second-stage portfolio delay measure.

1.2 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 1

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

[5] Because only the response to market return shocks is employed for our delay measures, we avoid potential 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 because of strong serial cross-correlations among stocks. Using only responses to market returns simplifies interpretation of the delay measures.

Table 1
Characteristics of portfolio delay-sorted portfolios

	Delay-sorted ($D1$) decile portfolios, July 1964 to December 2001										F-statistics	F-statistics	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	51.5	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														
Institutional ownership (%)[1]	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
Number of analysts[1]	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
Number of 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
Number of 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
Average 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
Number of 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
Average number of stocks	369.0	386.9	388.4	388.0	387.5	388.3	385.3	389.3	384.2	406.0				

At the end of June of each year, stocks are ranked by their 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 $D1$.

[1]Averages include only those firms with analyst and institutional data availability over the period 1976 to 2001 and 1981 to 2001, respectively.

*Significance at the 1% level.

reports the value-weighted average characteristics of portfolios sorted into deciles based on their second-stage portfolio 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), BE/ME, residual variance, $\sigma_{\in}^2$, 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, defined as 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 nine deciles are reported as well as the time-series average of the cross-sectional Pearson and Spearman rank correlations between each characteristic and delay.

As Table 1 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 small, value, volatile firms, with poor recent performance. It will be important to take this into account when we examine returns.

Table 1 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), and Hou (2005)]. Since analyst and institutional ownership data are only available for a limited sample of firms beginning in 1976 and 1981, respectively, the averages in Table 1 reflect only those firms with analyst and institutional coverage and hence are not directly comparable with the other averages. 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)] as well as a firm's liquidity and breadth of ownership [Frieder and Subrahmanyam (2005) and Grullon, Kanatas, and Weston (2004)].

We employ monthly dollar trading volume, share turnover, defined as the monthly number of shares traded divided by shares outstanding, average monthly closing price, number of trading days, and Amihud's (2002) illiquidity measure, which is the 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 1 indicates that delay is strongly inversely related to attention and liquidity proxies. Not surprisingly, 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. We attempt to decompose delay into components related to attention and liquidity, using these and other proxies, and examine their relation to returns.

2. Price Delay and the Cross-Section of Expected Returns

Table 2 reports the average returns of portfolios sorted on various delay measures. At the end of June of each year, stocks are ranked by a measure of 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 1 shows delay is correlated with other

Table 2
Price delay and the cross-section of expected stock returns

	Equal weighted					Value weighted					
Decile portfolio	1	2	9	10	10−1	1	2	9	10	10−1	Rank correlation with $D1$
Panel A: Portfolio delay measures assigned to individual stocks											
$D1$, raw	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)	
$D1$,	−0.01	0.03	0.29	1.32	1.33	−0.03	0.06	0.21	0.93	0.95	
adjusted	(−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	
adjusted	(2.32)	(2.33)	(3.60)	(7.73)	(6.44)	(−1.47)	(−0.45)	(0.89)	(4.30)	(4.18)	
$D1$,	−0.01	0.02	0.38	1.32	1.34	−0.01	−0.01	0.27	0.93	0.94	0.90
adjusted w/leads	(−0.37)	(0.73)	(4.31)	(8.56)	(8.15)	(−0.44)	(−0.33)	(3.25)	(6.89)	(6.73)	
$D2$,	0.02	0.02	0.44	1.23	1.21	0.01	−0.01	0.33	0.79	0.78	0.91
adjusted	(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	0.89
adjusted	(0.19)	(0.72)	(4.97)	(7.89)	(7.39)	(0.41)	(0.29)	(2.96)	(5.52)	(5.22)	
Panel B: Individual stock $D1$ delay measures (characteristic-adjusted returns)											
Five	−0.05	−0.04	0.13	0.15	0.20	−0.06	−0.03	0.11	0.11	0.16	
years weekly	(−1.16)	(−1.05)	(2.47)	(1.99)	(2.23)	(−1.36)	(−0.69)	(2.11)	(1.46)	(1.90)	
One	−0.10	−0.07	0.21	0.21	0.31	−0.09	−0.06	0.20	0.17	0.27	
year daily	(−2.52)	(−1.60)	(3.48)	(2.72)	(3.40)	(−2.43)	(−1.35)	(3.23)	(2.29)	(3.05)	
Five	−0.13	0.01	0.13	0.21	0.33	−0.12	0.02	0.11	0.18	0.30	
years daily	(−2.93)	(0.35)	(2.27)	(2.35)	(3.09)	(−2.95)	(0.56)	(1.89)	(2.02)	(2.79)	

Table 2
(continued)

Panel C: Robustness of $D1$ portfolio delay, value-weighted 10–1 spread

	Fama–French Three-factor α		Carhart Four-factor α		Pastor–Stambaugh Five-factor α		… + PIN Six-factor α	
	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
$D1$, α	0.60 (2.98)	1.00 (7.35)	0.77 (3.63)	0.95 (6.67)	0.78 (3.84)	0.93 (6.76)	1.01 (3.08)	1.32 (6.08)

	February–December	7/64–6/83	7/83–12/01	NYSE/AMEX	NASDAQ
$D1$, adjusted	0.65 (4.96)	0.58 (3.31)	1.34 (5.98)	0.35 (2.96)	1.04 (4.77)

	Size > \$5 million	Volume > \$0.2 million	Price > \$5	BE/ME < 1	BE/ME $\geq$ 1
$D1$, adjusted	0.47 (4.32)	0.31 (2.88)	0.24 (2.55)	0.80 (5.44)	0.99 (5.43)

The equal- and value-weighted monthly returns (in %) 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 premiums associated with size, book-to-market equity (BE/ME), and momentum. Panel A reports results for decile portfolios sorted on portfolio delay measures assigned to individual stocks. Stocks are assigned to one of ten size deciles and then one of ten individual delay deciles within each size category. The delay measure for the portfolio of stocks to which each stock belongs is then assigned to the stock and used to rank and form portfolios to compute returns out of sample. Returns across portfolio delay-sorted deciles are reported for delay measures $D1$, from Equation (2), the annual change in $D1$, $D1$ including leading returns in Equation (2), and $D2$ and $D3$ from Equations (3) and (4). Panel B reports returns from decile portfolios formed solely from ranking stocks on their *individual* delay measures (e.g., no portfolio shrinkage). Results are reported for individual delay calculated from weekly returns over the past five years, daily returns over the past one year, and daily returns over the past five years. 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 portfolio $D1$ delay-sorted deciles on the Fama–French three-factor model, the Carhart (1997) four-factor model (which adds a momentum factor to the Fama–French factors), a five-factor model which adds the Pastor and Stambaugh (2003) aggregate liquidity risk factor-mimicking portfolio to the Carhart model, and a six-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 portfolio delay $D1$ decile portfolios 10 and 1 is also reported excluding the month of January, for the two subperiods of the sample, for NYSE/AMEX and NASDAQ stocks separately, for firms with BE/ME ratios 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.

known determinants of average returns, due to risk or other sources, we adjust returns using a characteristic-based benchmark to account for return premiums associated with size, BE/ME, and momentum (past one-year returns). The benchmark portfolio is based on an extension and variation of the matching procedure used in Daniel et al. (1997) and is motivated by Daniel and Titman's (1997) finding that characteristics, rather than estimated covariances, seem to better capture the cross-section of returns in the post-1963 period. 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 month $t-12$ to $t-2$) to capture the momentum effect of Jegadeesh and Titman (1993). 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.[6] 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. Although there is no direct hedging of beta risk, these hedged returns are close to having zero beta exposure [Grinblatt and Moskowitz (2004)].[7]

2.1 Portfolio delay measure $D1$

We focus mainly on the second-stage portfolio delay measure $D1$, but report results for a variety of alternative delay measures in the next subsection. As the first row of panel A of Table 2 shows, 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 row are more informative about delay's relation to average returns. The adjusted average returns of each of the deciles are considerably lower, but 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 premiums suggests a strong relation between a firm's price delay and its expected return.

Interestingly, the 10−1 spread derives primarily from the astounding performance of decile 10. However, average return differences between deciles 9 and 1 and deciles 9 and 2 are also significant, though substantially

[6] We do not exclude the stock itself from the benchmark portfolios, which understates our results.

[7] At the request of a referee, we also adjusted returns using a similar $5 \times 5 \times 5$ benchmark portfolio sort using betas/factor sensitivities with respect to the Fama and French (1993) three-factor model rather than characteristics. The results are significantly strengthened with this less stringent adjustment, consistent with the results of Daniel and Titman (1997) and the poor precision of factor loading estimates [e.g., Berk (2000)].

weaker. In all cases, the spread in returns comes mainly from the long side or high delay firms. This result is in contrast with most long–short strategies where profits from the short side typically comprise the bulk of the strategy's profitability [e.g., momentum, see Grinblatt and Moskowitz (2004)]. Stocks with high price delay command large abnormal returns, whereas 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 on average less than 0.02% of the total market capitalization of publicly traded equity on US exchanges.

2.2 Robustness

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

2.2.1 Change in portfolio delay. The third row of Table 2 reports the equal- and value-weighted characteristic-adjusted returns of decile portfolios formed from sorting on the *change* in portfolio 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.

2.2.2 Alternative measures of portfolio delay. The next three rows report characteristic-adjusted returns of portfolios sorted on the portfolio delay measure $D1$ adding leading market returns to Equation (1) as well as portfolio delay measures $D2$ and $D3$. 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 2. Not surprisingly, therefore, the returns generated from these measures are similar in magnitude and significance to our main $D1$ measure.

2.2.3 Individual stock delay. Panel B of Table 2 reports adjusted returns of portfolios sorted on the first-stage individual stock delay measure. At the individual stock level, these measures are highly noisy, which is why we use the second-stage portfolio measures for the majority of our analysis. However, it is useful to gauge the profitability of individual stock delay for robustness and to ensure that size, used to form portfolios for the second stage, is not driving our results. To improve precision, we estimate individual stock delay over the past five years using weekly returns, where stocks must have at least two years of past return data.

As the first row of panel B of Table 2 indicates, individual delay produces much weaker, but still economically and statistically significant profits even after adjusting for size, BE/ME, and momentum premiums. To improve precision further, we also employ daily returns to estimate individual delay over the past one and five years. The profits increase by about 50 percent. Thus, although individual delay produces substantially smaller profits than portfolio delay measures, the profits are still economically and statistically significant despite the fact that individual delay measures are very noisy. Equal- and value-weighted portfolios generate similar results.

2.2.4 Further return adjustment. To ensure our characteristic adjustment procedure is robust, panel C of Table 2 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 portfolio $D1$-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.[8] In addition to providing further return adjustment, the coefficients on these last two factors indicate whether aggregate liquidity risk or asymmetric information are related to the delay premium.

The intercepts from these time-series regressions are large and highly significant, even after essentially adjusting returns twice using both the characteristic benchmarks and the factor models. Thus, potential

[8] 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 three-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.

inadequate risk adjustment from the characteristic benchmarks does not seem to be driving the profitability of these strategies. Moreover, the loadings of the delay spread on the aggregate liquidity risk factor and the information-based factor are only -0.01 (t-statistic = -0.25) and -0.06 (t-statistic = -0.26), respectively. The insignificance of these loadings suggests that the premium associated with delay is not related to either aggregate liquidity risk or information asymmetry.

2.2.5 Subperiods and subsamples. The value-weighted characteristic-adjusted spread in $D1$-sorted portfolios is also reported across various subperiods and subsamples. 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 NYSE/AMEX firms. The higher profits for NASDAQ seem to be because of the smaller firms traded there and the greater dispersion of delay among smaller firms.[9] Subperiod profits on NYSE/AMEX stocks only (not reported) also reveal higher profits in the second half of the sample. 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 premiums have diminished over time. We show more formally in the next section that delay is not driven by size or traditional liquidity effects.

2.2.6 Microstructure and liquidity issues. The returns of the delay portfolios do not seem to be tainted by microstructure effects such as bid-ask bounce or nonsynchronous 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 most likely be affected

[9] We subdivide each exchange into five size groups using NYSE/AMEX quintile breakpoints for both exchanges, generating 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, suggesting that 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 premiums, suggesting there is no exchange effect on return premiums. Fama-MacBeth regressions of returns on size, delay, and exchange indicators confirm these results.

by potential microstructure effects. Skipping a month (e.g., excluding July) produces nearly identical results.

The trading strategy does not attempt to take advantage of delay itself by buying high 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 nonsynchronous trading) do not have any impact on our results. In addition, results are robust to controlling for the number of trading days of a stock, its most recent month's return, which may reflect bid-ask bounce, and a host of other liquidity measures.

Finally, if we restrict the sample to stocks with market capitalizations greater than \$5 million, monthly dollar trading volume of at least \$200,000, and share prices above \$5, the trading strategy profits are reduced considerably, but remain significant. Removing firms with less than \$5 million market capitalizations (\$200,000 monthly trading volume, less than \$5 share prices) reduces profits by approximately one half (two thirds, three fourths). This reduction is consistent, however, with market frictions' predicted effect on the cross-section of returns. The most severely constrained firms, least recognized, facing the most significant frictions, will be the least liquid and smallest firms by definition. Such firms should have the largest impact on returns, consistent with these results. In addition, if we exclude firms with extreme value, BE/ME greater than one, profits remain large and significant. This result suggests that the most extreme value firms or an interactive effect between small and extreme value firms are not driving delay profits.

2.3 Fama–MacBeth cross-sectional regressions

Table 3 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 returns, including liquidity measures, and provide an alternative weighting scheme for portfolios.[10]

The cross-section of stock returns in excess of the one-month T-bill rate each month is regressed on the firm characteristics of log of size (market capitalization), log of BE/ME, the previous year's return on the stock

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

Table 3
Fama–MacBeth cross-sectional regressions

Dependent variable = cross-section of monthly stock returns

	Panel A: July, 1966, to December, 2001					Panel B: July, 1981, to December, 2001			
			Liquidity measures				Liquidity measures		
			Turnover	Volume	Illiquidity		Turnover	Volume	Illiquidity
log(size)	−0.0013	0.0003	0.0004	0.0021	0.0022	0.0015	−0.0004	0.0017	0.0015
	(−2.57)	(0.55)	(1.08)	(2.87)	(3.66)	(2.98)	(−0.78)	(1.58)	(1.84)
log(BE/ME)	0.0016	0.0015	0.0018	0.0018	0.0020	0.0021	0.0019	0.0018	0.0020
	(2.77)	(2.69)	(3.96)	(3.93)	(4.09)	(3.26)	(3.26)	(3.16)	(3.25)
$ret_{-36:-13}$	−0.0027	−0.0025	−0.0019	−0.0019	−0.0020	−0.0014	−0.0006	−0.0006	−0.0006
	(−3.80)	(−3.56)	(−3.26)	(−3.31)	(−3.35)	(−2.46)	(−1.06)	(−1.12)	(−1.21)
$ret_{-12:-2}$	0.0051	0.0052	0.0054	0.0054	0.0048	0.0048	0.0055	0.0052	0.0048
	(3.10)	(3.15)	(3.28)	(3.36)	(2.87)	(3.18)	(3.74)	(3.64)	(3.24)
$ret_{-1:-1}$	−0.0687	−0.0691	−0.0771	−0.0774	−0.0765	−0.0639	−0.0668	−0.0670	−0.0662
	(−15.91)	(−16.10)	(−18.55)	(−18.68)	(−18.24)	(−14.59)	(−16.04)	(−16.20)	(−15.82)
Delay $D1$		0.0399	0.0328	0.0309	0.0331	0.0596	0.0405	0.0402	0.0416
		(4.86)	(4.37)	(4.15)	(4.46)	(5.75)	(4.60)	(4.57)	(4.85)
Number of			0.0001	0.0001	0.0001		0.0001	0.0001	−0.0001
trading days			(2.76)	(2.55)	(2.03)		(0.76)	(0.30)	(−0.34)
log(price)			−0.0013	−0.0014	−0.0008		−0.0012	−0.0013	−0.0005
			(−1.40)	(−1.47)	(−0.88)		(−2.03)	(−2.05)	(−1.67)
NASDAQ			−0.0351	−0.3238	−0.0561		0.0011	−0.0016	0.0202
			(−0.25)	(−1.15)	(−0.92)		(0.04)	(−0.02)	(0.59)

log(liquidity)	−0.0021	−0.0018	0.0016	−0.0027	−0.0021	0.0016
NYSE/AMEX	(−3.14)	(−2.65)	(3.39)	(−3.46)	(−2.53)	(3.55)
log(liquidity)	−0.0045	0.0225	−0.0036	−0.0024	−0.0014	0.0030
NASDAQ	(−0.14)	(1.06)	(−0.86)	(−0.33)	(−0.24)	(1.18)
CV(liquidity)	−0.0017	−0.0016	−0.0026	−0.0005	−0.0006	−0.0025
NYSE/AMEX	(−3.27)	(−2.96)	(−2.89)	(−0.69)	(−0.77)	(−2.39)
CV(liquidity)	−0.0156	−0.0656	−0.0227	−0.0031	0.0078	−0.0015
NASDAQ	(−1.37)	(−1.31)	(−1.93)	(−0.24)	(0.35)	(−0.19)
log(number of				0.0009	0.0009	0.0009
analysts)				(4.61)	(4.65)	(4.68)
log(institutional				0.0035	0.0032	0.0033
ownership %)				(6.87)	(6.36)	(5.91)

Results from Fama–MacBeth monthly cross-sectional regressions of stock returns in excess of the one-month T-bill rate on log of firm size (market capitalization), log of the ratio of book-to-market equity (BE/ME), previous year's return (from month $t-12$ to $t-2$), previous three year's return (from month $t-36$ to $t-13$), previous month's return, portfolio 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 log of the average daily share price, a NASDAQ trading dummy, and the log of the level and coefficient of variation (CV, standard deviation of liquidity measures over the past year divided by their 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 trading volume over the past year), and Amihud's (2002) illiquidity measure (average daily absolute return divided by dollar trading volume over the past year), each defined separately for NYSE/AMEX and NASDAQ traded firms. Panel B reports Fama–MacBeth regression results including the log of one plus the number of analysts covering the stock and log of one plus the percentage of shares held by institutional investors as regressors. These data are available only over the period July, 1981, to December, 2001. The time-series average of the coefficient estimates and their associated time-series t-statistics (in parentheses) are reported in the style of Fama and MacBeth (1973).

skipping the most recent month, from month $t-12$ to $t-2$ ($ret_{-12:-2}$), the previous three year's return on the stock skipping the most recent year, from month $t-36$ to $t-13$ ($ret_{-36:-13}$), and measures of delay. We include the previous month's return on the stock $ret_{-1:-1}$ as an additional control for the one-month reversal effect of Jegadeesh (1990). If this effect is largely driven by bid-ask bounce and illiquidity, then this regressor can be viewed as another liquidity control. The coefficient on delay is slightly stronger excluding this variable. The size, book-to-market, and delay variables are from the previous year. The first column of Table 3 panel A confirms the standard results found in the literature that average returns are negatively related to size, past one month, and past three-year returns, and positively related to BE/ME and past one-year returns. The second column adds the portfolio delay measure $D1$ to the cross-sectional regression. Delay is strongly positively associated with average returns, consistent with the previous decile portfolio results. The economic significance of the delay coefficient is also in line with our previous results. Moving from the lowest decile of delay, which has a delay measure of 0.002, to the highest decile, which has a measure of 0.341 (Table 1), the coefficient on delay in Table 3 implies a difference in returns between the two deciles of 135 basis points per month. This return difference is almost identical to our equal-weighted results in Table 2, which is not surprising since Fama–MacBeth regressions minimize least squares which tends to put more weight on smaller, volatile stocks.

The next three columns of panel A of Table 3 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, which we control for as well as other liquidity measures to ensure the delay premium is not simply a manifestation of previously discovered variables. 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 interdealer trades (which NYSE/AMEX do not), we measure these variables separately for NASDAQ and NYSE/AMEX traded firms and include a NASDAQ exchange dummy in the regression. In addition to the levels of these liquidity variables, we also include the coefficient of variation, defined as the standard deviation of each liquidity measure divided by its mean estimated over the prior year, 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 log of its average daily closing share price over the prior year in all regressions, as well as size and the most recent past month's return, which may also be related to a stock's liquidity.

As Table 3 shows, the premium from delay is robust to the inclusion of these liquidity measures. The point estimate and statistical significance of the delay coefficient declines slightly, which is not surprising given the correlation between delay and these liquidity variables from Table 1, but remains economically important. 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 are consistent with Chordia, Subrahmanyam, and Anshuman (2001). Thus, delay and commonly used proxies for liquidity have independent variation in their ability to capture returns.

Panel B of Table 3 adds two measures of stock visibility to the regression: the log of one plus the number of analysts covering the stock and the log of one plus the percentage of institutional ownership of the stock. Since institutional ownership is only available after July, 1981, we restrict the sample period from July, 1981, to December, 2001. The first column of Table 3 panel B reports Fama–MacBeth regression coefficients excluding the liquidity and attention variables over the post-1981 period for reference. Consistent with Table 2, delay is a stronger phenomenon in the latter half of the sample. As the last three columns of Table 3 panel B show, adding the various sets of liquidity variables plus the two attention variables, analyst coverage and institutional ownership, decreases the coefficient on delay, but does not completely capture its effect on the cross-section of returns. Since delay is correlated with these variables, it is not surprising that they pick up some of the same effects. However, delay continues to explain a significant portion of returns beyond these measures. Since price delay can be estimated from return data alone, and therefore is not constrained by the availability of analyst or institutional ownership data, delay may be used to capture liquidity or recognition effects over a longer sample period. We investigate the success of delay in capturing liquidity and recognition effects in Section IV.

3. Interaction of Delay with Size and Other Firm Characteristics

Although delay does not appear to be subsumed by a variety of characteristics known to explain average returns, it is interesting to examine the interaction between delay and these characteristics for determining the cross-section of returns.

3.1 Delay and the size effect

Since size is highly negatively correlated with delay and is used to form our second-stage portfolio delay measures, we begin by examining the interaction between size and delay. Since the early work of Banz (1981) and Keim (1983) researchers have attempted to understand why small firms earn higher returns on average than large firms. We examine how much of the size premium is captured by delay as well as the interaction between them.

Panel A of Table 4 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 the decile portfolios are computed over the following year from July to June, and average returns and t-statistics, 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 over the entire sample period (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-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 second-stage portfolio 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 portfolio 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. In the first half of the sample, the equal- (value-) weighted size premium drops from 129 (104) basis points to just 14 (3) after adjusting for portfolio delay, despite the fact that delay is a stronger economic effect in the latter half of the sample (Table 2) while the size effect is stronger in the first half of the sample. Even the enormous size effect in January drops dramatically from 8.9 (7.3)% to only 0.57 (0.39)% for equal- (value-) weighted portfolios after adjusting for portfolio delay.

Since the portfolio delay measure is formed from size-individual delay sorts, the impact of delay on the size effect may be overstated here if size is partly confounded with the second-stage portfolio delay measure. For robustness, we repeat the above exercise using only first-stage individual stock delay measures, which is conservative since individual stock

Table 4
Price delay and the size effect

	Equal-weighted portfolios					Value-weighted portfolios				
	1	2	9	10	10−1	1	2	9	10	10−1
					Panel A: Market capitalization (size)-sorted decile portfolios					
Raw returns										
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 using portfolio delay										
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)
Returns adjusted for the delay premium using individual delay										
07/64–12/01	0.16	−0.13	−0.10	−0.12	−0.28	−0.04	−0.10	−0.09	−0.11	−0.08
	(2.12)	(−2.57)	(−0.77)	(−0.81)	(−1.34)	(−0.49)	(−1.94)	(−0.79)	(−0.77)	(−0.38)
07/64–07/83	0.33	−0.11	−0.49	−0.58	−0.90	0.19	−0.06	−0.45	−0.55	−0.74
	(2.78)	(−1.93)	(−2.62)	(−2.55)	(−2.74)	(1.70)	(−0.94)	(−2.65)	(−2.34)	(−2.23)
07/83–12/01	−0.01	−0.16	0.33	0.38	0.39	−0.28	−0.15	0.30	0.36	0.63
	(−0.12)	(−1.77)	(2.14)	(2.09)	(1.54)	(−3.24)	(−1.73)	(2.08)	(2.00)	(2.66)
January	2.64	−0.73	−2.93	−3.16	−5.80	1.83	−0.32	−2.56	−2.57	−4.40
	(8.32)	(−3.82)	(−5.53)	(−4.74)	(−6.40)	(6.17)	(−1.52)	(−5.27)	(−3.82)	(−4.82)

Table 4
(continued)

	Equal-weighted portfolios					Value-weighted portfolios				
	1	2	9	10	10−1	1	2	9	10	10−1
Raw returns of portfolios sorted on residual size orthogonal to portfolio delay										
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)
Raw returns of portfolios sorted on residual size orthogonal to individual delay										
07/64–12/01	1.45	1.14	1.05	1.00	−0.45	1.20	1.13	1.04	0.98	−0.22
	(4.45)	(3.77)	(4.64)	(4.64)	(−1.75)	(3.80)	(3.73)	(4.63)	(4.80)	(−0.90)
Panel B: Delay-sorted decile portfolios										
Adjusted returns of portfolios sorted on residual portfolio delay orthogonal to										
Size	0.02	−0.01	0.03	0.91	0.89	0.03	0.00	0.07	0.80	0.77
	(0.77)	(−0.03)	(0.50)	(8.24)	(7.43)	(0.81)	(−0.08)	(1.10)	(7.18)	(6.30)
Size rank	−0.15	−0.06	0.04	0.92	1.06	−0.01	0.06	0.04	0.83	0.84
	(−2.41)	(−1.31)	(0.94)	(8.21)	(6.86)	(−0.16)	(1.56)	(1.33)	(5.89)	(5.23)
Size deciles	−0.23	−0.28	−0.02	0.92	1.15	0.01	−0.09	0.04	0.80	0.79
	(−3.39)	(−6.21)	(−0.45)	(8.60)	(7.18)	(0.26)	(−2.24)	(0.59)	(6.18)	(5.30)
Adjusted returns of portfolios sorted on residual individual delay orthogonal to										
Size	−0.09	−0.10	0.22	0.20	0.30	−0.08	−0.08	0.20	0.17	0.25
	(−2.24)	(−2.10)	(3.50)	(2.64)	(3.21)	(−2.10)	(−1.77)	(3.27)	(2.22)	(2.85)
Size rank	−0.10	−0.10	0.14	0.19	0.29	−0.09	−0.08	0.13	0.15	0.24
	(−2.31)	(−1.84)	(2.49)	(2.55)	(3.06)	(−2.13)	(−1.61)	(2.36)	(2.09)	(2.65)
Size deciles	−0.09	−0.10	0.13	0.12	0.21	−0.08	−0.08	0.11	0.09	0.17
	(−1.96)	(−1.85)	(2.24)	(1.70)	(2.28)	(−1.75)	(−1.57)	(1.93)	(1.35)	(1.92)

	Equal-weighted portfolios					Value-weighted portfolios				
	1	2	3	4	5	1	2	3	4	5
Panel C: Double-sorted quintile portfolios of size and delay										
Size premium within portfolio delay quintiles, raw returns										
Size 5–1	−0.20	−0.19	−0.20	−0.56	−2.15	−0.21	−0.10	−0.16	−0.52	−1.93
	(−1.15)	(−1.12)	(−1.15)	(−3.18)	(−9.57)	(−1.14)	(−0.52)	(−0.88)	(−2.88)	(−8.83)
Size premium within individual delay quintiles, raw returns										
Size 5–1	−0.51	−0.19	−0.53	−1.23	−1.95	−0.39	−0.08	−0.36	−0.92	−1.75
	(−1.94)	(−0.74)	(−1.80)	(−4.01)	(−6.65)	(−1.41)	(−0.29)	(−1.18)	(−2.79)	(−5.22)
Delay (portfolio) premium within size quintiles, adjusted returns										
Delay 5–1	0.89	−0.08	−0.17	−0.07	0.05	0.70	−0.01	−0.09	−0.05	0.05
	(5.67)	(−0.75)	(−1.78)	(−0.89)	(0.86)	(4.83)	(−0.10)	(−1.00)	(−0.56)	(0.84)
Delay (individual) premium within size quintiles, adjusted returns										
Delay 5–1	0.39	0.05	−0.08	0.09	−0.03	0.37	0.05	−0.08	0.09	−0.03
	(2.52)	(0.34)	(−0.79)	(1.04)	(−0.50)	(2.39)	(0.34)	(−0.83)	(1.06)	(−0.50)

Panel A reports raw size-sorted decile portfolio returns in various subperiods. 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 (% per month) 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 (*D*1) benchmark portfolio using both the second-stage portfolio delay measure and the first-stage individual delay measure. 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 residual component of size orthogonal to delay (both portfolio and individual delay), determined by the error term from the regression of the cross-section of firm market capitalizations on delay measures. Panel B reports characteristic-adjusted [for size, book-to-market equity (BE/ME), and momentum] returns for delay-sorted portfolios formed on the residual component of delay (both portfolio and individual delay) orthogonal to size, size rank, and size decile dummies. These are the error terms from the regression of the cross-section of delay measures on size, size rank, and dummies for size decile membership, respectively. Panel C reports returns for double-sorted portfolios on size and delay. The raw size premium, defined as the difference in returns between the largest quintile and smallest quintile of stocks, within each delay quintile is reported for both portfolio and individual delay measures. In addition, the characteristic-adjusted delay premium within each size quintile is reported.

measures are noisy and therefore have a much weaker relation with average returns (Table 2). As panel A of Table 4 shows, individual delay-adjusted size portfolios also experience a reduction in returns, though much less than the portfolio delay-adjusted returns. Equal- (value-) weighted size spreads decline from 57 (28) to 28 (8) basis points when adjusted for individual delay. The effect of individual delay on the size spread is also nontrivial in the first half of the sample (though a bit weaker) and in January. Although the size premium is still large after adjusting for individual delay, it is interesting that even this noisy measure of delay has a significant impact on the size effect.

In addition to adjusting returns for the delay premium, we also form portfolios based on the component of a firm's size unrelated to delay. Specifically, each year we run a cross-sectional regression of each firm's size on its portfolio delay measure,

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

The orthogonal component of size with respect to delay is simply the intercept plus residual from this regression. As the bottom of panel A of Table 4 indicates, the component of size unrelated to portfolio delay has little cross-sectional return predictability. Repeating this exercise using individual stock delay as the regressor in Equation (5), the last row of panel A of Table 4 indicates that residual size still retains predictive power, though it is weaker after accounting for individual delay.

Panel B of Table 4 reverses regression Equation (5) and examines portfolios sorted on delay that are orthogonal to size. Because size exhibits significant skewness, we also employ the size rank as a regressor, and because size may exhibit a nonlinear relation with delay, we also employ size decile dummies as regressors and examine residual delay's predictive power for returns.[11] Under all three specifications, residual delay retains substantial predictive power, though profitability declines. Repeating this exercise for individual stock delay measures, we find that residual delay retains nearly all of its predictive power, suggesting that size has little impact on individual stock delay.

Finally, panel C of Table 4 reports results from double-sorted portfolios of size and delay. The first row of panel C of Table 4 reports the size spread (difference in value-weighted returns between the largest and smallest size quintiles) within quintiles of portfolio delay. The second

[11] Since we are more concerned with the robustness of our delay measure, we employ more stringent tests on delay-sorted portfolios than we do for size-sorted portfolios. For instance, we do not include delay rank or delay decile adjustments for determining residual size. When we do, the impact of residual size on the cross-section of returns is muted further. In addition, we employ raw returns for residual size portfolios rather than adjusted returns as we do for residual delay portfolios. Adjusting the returns to residual size portfolios with delay benchmark returns further weakens their profitability.

row reports size spreads within quintiles of individual delay. Under both measures, delay appears to enhance the size effect. The size premium increases significantly among the most delayed firms. The last two rows reverse the sort order and examine the delay premium within size quintiles. Delay is also enhanced by size, where the delay premium is largely concentrated among the smallest quintile of stocks. The double sorts also provide another control for each of these characteristics, where neither size nor delay appears completely subsumed by the other.

We conclude that although there is some overlap between size and delay, each have significant independent explanatory power for cross-sectional returns. Portfolio delay seems to subsume most of the size effect, but may overstate delay's influence on size due to the sorting procedure. On the other hand, individual stock delay, which may understate delay's effect due to estimation error, still explains part of the size effect. In the next section, we investigate what might be driving the delay premium and, hence, part of the size premium.

3.2 Delay and other firm characteristics

We also examine the interaction between delay and BE/ME, long-term reversals (past three-year returns), momentum (past one-year returns), share turnover, trading volume, and residual volatility. Panel A of Table 5 reports the characteristic-adjusted delay premium, defined as the difference in characteristic-adjusted returns between the highest and lowest quintile of

Table 5
Interaction of delay with other firm characteristics

	Panel A: Delay premium across characteristic quintiles				
	Characteristic				
	1 (low)	2	3	4	5 (high)
Across BE/ME quintiles					
Delay 5–1	0.35	0.30	0.25	0.34	0.71
	(2.05)	(2.54)	(2.26)	(3.01)	(4.47)
Across contrarian $\text{ret}_{-36:-13}$ quintiles					
Delay 5–1	0.93	0.21	0.04	0.04	0.04
	(4.48)	(1.57)	(0.37)	(0.40)	(0.31)
Across momentum $\text{ret}_{-12:-2}$ quintiles					
Delay 5–1	1.94	0.24	0.07	0.01	0.14
	(9.34)	(2.04)	(0.63)	(0.07)	(1.04)
Across share turnover quintiles					
Delay 5–1	0.67	0.50	0.53	0.32	−0.29
	(4.52)	(3.68)	(3.51)	(2.18)	(−1.85)
Across trading volume quintiles					
Delay 5–1	1.18	0.07	0.02	−0.20	0.01
	(5.98)	(0.43)	(0.13)	(−1.58)	(0.07)
Across residual volatility σ^2_ϵ quintiles					
Delay 5–1	0.08	0.20	0.17	0.58	1.63
	(0.99)	(1.32)	(0.92)	(3.05)	(7.83)

Table 5
(continued)

	Panel B: Characteristic premiums across delay quintiles				
	Delay				
	1 (low)	2	3	4	5 (high)
Value premium across delay quintiles					
BE/ME 5–1	0.32	0.39	0.94	0.90	0.87
	(1.67)	(2.07)	(4.76)	(4.05)	(3.88)
Contrarian premium across delay quintiles					
Contrarian 5–1	−0.24	−0.28	−0.66	−0.59	−1.11
	(−1.17)	(−1.47)	(−3.12)	(−2.55)	(−3.83)
Momentum premium across delay quintiles					
Momentum 5–1	0.66	1.28	1.58	1.67	−0.08
	(2.56)	(5.07)	(6.07)	(6.00)	(−0.30)
Turnover premium across delay quintiles					
Turnover 5–1	−0.15	−0.32	−0.50	−0.61	−0.49
	(−0.65)	(−1.27)	(−1.88)	(−2.16)	(−1.74)
Volume premium across delay quintiles					
Volume 5–1	−0.20	−0.25	−0.73	−0.67	−1.30
	(−1.46)	(−1.63)	(−3.92)	(−2.91)	(−4.92)
Volatility premium across delay quintiles					
Volatility 5–1	−0.02	−0.25	−0.37	−0.25	1.07
	(−0.08)	(−0.79)	(−1.17)	(−0.71)	(3.06)

Raw and characteristic-adjusted [for size, book-to-market equity (BE/ME), and momentum premiums] returns for double-sorted portfolios on various firm characteristics and delay are reported. Panel A reports the delay premium, defined as the difference in adjusted returns between the highest and lowest quintile of delayed firms, within quintiles formed by first sorting on the firm characteristics of BE/ME, past three-year return (skipping the most recent year), past one-year return (skipping the most recent month), turnover (average monthly number of shares traded divided by number of shares outstanding over the past year), dollar trading volume (average monthly volume over the past year), and residual volatility (variance of the residual from a market model regression using weekly returns over the prior year), respectively. At the end of June of each year, stocks are ranked by each of these characteristics and sorted into quintiles. Within each characteristic quintile, stocks are then sorted into quintiles based on their portfolio delay measure $D1$. The value-weighted adjusted average monthly return differences between delay quintiles five and one within each characteristic quintile and their t-statistics (in parentheses) are reported. Panel B reports average monthly returns from the reverse sort, where portfolios are first sorted on the portfolio delay measure $D1$ and then on each of the firm characteristics. Raw return differences between the highest and lowest quintiles within each delay quintile are reported for BE/ME, past three-year return, past year return, turnover, volume, and residual volatility. Average returns are in percent per month covering the period July, 1964, to December, 2001.

delayed firms, within quintiles sorted on each of these characteristics.[12] This analysis provides another control for these firm characteristics in addition to highlighting their interaction with delay. As panel A of Table 5 shows, the delay premium doubles among value stocks, resides almost exclusively among the worst past performing stocks, recent and long-term losers, increases with lower turnover and trading volume, and is predominant among high idiosyncratic volatility stocks. The variation in delay itself is

[12] Breakpoints for NYSE/AMEX and NASDAQ stocks are determined separately for turnover and volume due to the different conventions of recording volume on these two exchanges.

also greater among such firms.[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 (2005). Although consistent with short-sale constraints that hinder bad news from being incorporated immediately into prices, these results are also consistent with poorly performing firms receiving less investor attention.

Panel B of Table 5 reports results from the reverse sort, where the unadjusted raw premium associated with each of these characteristics is examined across delay quintiles. The value premium is higher among delayed firms, as are long-term contrarian profits. Momentum is increasing in delay across the first four quintiles, but is nonexistent among the highest delayed firms. Turnover premiums are only marginally significant and do not exhibit much relation with delay, but the premium associated with trading volume exists primarily among delayed firms. Finally, idiosyncratic risk exhibits a large positive premium, but only among the most delayed firms. Prior research examining the pricing role of residual volatility has yielded mixed results.[14] One possible reason for the disparity of results 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 may not face significant frictions. Therefore, the average firm should not be expected to have priced idiosyncratic risk, as indicated across the first four quintiles of delay. However, for the highest delay quintile, the premium for residual volatility is 107 basis points per month, highlighting the fact that idiosyncratic risk is only priced among the most constrained firms.

3.3 Post-earnings announcement drift

Finally, as an additional test of the impact of delay on the cross-section of stock returns, we analyze the price response of firms' equity to earnings announcements. This analysis 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) and Bernard and Thomas (1989)], 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

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

[14] 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 (2003) 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.

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 represents 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 6 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.[15] This approach has the added advantage of accounting for the correlation of returns across event firms, providing standard errors robust to cross-correlated residuals.

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 (CARs) on the earnings surprise portfolios across delay quintiles from 6 months before the event to 12 months after the event in event time. The monotonic relation between delay and post-earnings announcement drift is evident from Figure 1, particularly for positive earnings surprises.

4. What Drives the Delay Premium?

In this section, we investigate what drives delay and its associated premium. Delay has predictive power for returns independent of traditional liquidity proxies, size, and other firm attributes. We investigate the source of this additional predictability by distinguishing between the investor recognition hypothesis and traditional liquidity effects arising from trading and price impact costs.

[15] For example, suppose we want to measure the average price response of event firms in month four after the earnings announcement, where month zero 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 four 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.

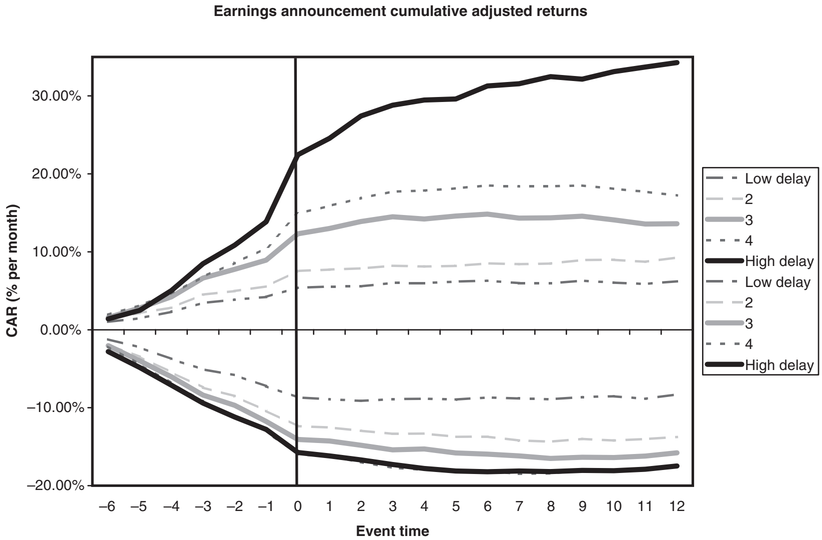

Figure 1

Post-earnings announcement drift across delay quintiles

Adjusted returns [benchmarking against a value-weighted portfolio of firms matched by size, book-to-market equity (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 6 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 $k = [-6,12]$ is 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 (0.0001)
	(1.15)	(1.67)	(4.34)	(5.22)	(6.34)	
Negative	0.04	−0.23	−0.40	−0.41	−0.48	3.60 (0.0062)
	(0.57)	(−2.51)	(−4.41)	(−4.18)	(−5.01)	

4.1 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,

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

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 US regional stock exchange to capture regional visibility given the local portfolio biases documented by Coval and Moskowitz (1999, 2001)]. We also employ measures of remoteness to characterize investor recognition using the average distance between each stock's headquarters and all US airports as well as the nearest airport, and the average airfare between the nearest airport and all US 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 US airport in order to identify the nearest airport distance, average air route distance, and average airfare, which is the 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 or costly to visit may be neglected by institutions and other investors.

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

The time-series averages and t-statistics (in parentheses) of the regression coefficients are

$$\begin{aligned}\sum_{k=1}^{K} \hat{b}_k Att_{k,j} = &\underset{(-1.15)}{-0.0017} \log(\text{Institutional ownership}) + \underset{(-6.87)}{-0.0067} \log(\text{number of analysts}) \\ &+ \underset{(-4.78)}{-0.0057} \text{ Regional exchange} + \underset{(-0.94)}{-0.0005} \log(\text{number of shareholders}) + \underset{(-5.75)}{-0.0038} \log(\text{number of employees}) \\ &+ \underset{(0.31)}{0.0002} \log(\text{Advertising}) + \underset{(-0.44)}{-0.0054} \text{ Airport} + \underset{(-1.46)}{-0.0021} \text{ Distance} + \underset{(1.99)}{0.0271} \text{ Airfare}\end{aligned} \tag{7}$$

$$\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j} = \underset{(-1.49)}{-0.0078}\ \text{NASDAQ} + \underset{(-0.10)}{-0.0001} \log\left(\text{Turnover}_{NYSE/AMEX}\right)$$
$$+ \underset{(-1.95)}{-0.0031} \log\left(\text{Turnover}_{NASDAQ}\right) + \underset{(-4.98)}{-0.0005}\ \text{Number of trading days} + \underset{(14.42)}{0.3282}\ (1/\text{Price}) \quad (8)$$

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

$$\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j}^{volume} = \cdots + \underset{(-13.97)}{-0.0052} \log\left(\text{Volume}_{NYSE/AMEX}\right) + \underset{(-8.56)}{-0.0111} \log\left(\text{Volume}_{NASDAQ}\right)$$

$$\sum_{q=1}^{Q} \hat{c}_q Liq_{q,j}^{illiquidity} = \cdots + \underset{(13.25)}{0.0052}\ \text{Illiquidity}_{NYSE/AMEX} + \underset{(7.70)}{0.0094}\ \text{Illiquidity}_{NASDAQ}$$

where coefficients on the other liquidity and attention variables are similar. We employ all three specifications in our subsequent analysis.[16]

The regressions confirm the negative relation between delay and investor recognition and delay and liquidity suggested by the univariate correlations in Table 1. 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^2s 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^2s 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

[16] 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 article, but limits the number of firms in our sample because of missing data for many firms.

explain a sizeable fraction of cross-sectional variation in stock trading volume, though they also interpret this evidence 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.

4.2 Decomposing the impact of delay on returns

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 A of Table 6 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 from July, 1981, to December, 2001. The three columns of panel A of Table 6 correspond to 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 the wrong sign. 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 may be related to investor recognition or firm neglect.

Table 6
Decomposing the impact of delay on returns

Panel A: Fama–MacBeth cross-sectional regressions

	Liquidity measures		
	Turnover	Volume	Illiquidity
log(size)	0.0031	0.0052	0.0046
	(2.30)	(2.88)	(2.87)
log (BE/ME)	0.0017	0.0019	0.0019
	(1.62)	(1.80)	(1.77)
$ret_{-36:-13}$	0.0001	−0.0001	−0.0001
	(0.08)	(−0.06)	(−0.13)
$ret_{-12:-2}$	0.0110	0.0107	0.0107
	(5.55)	(5.37)	(5.42)
$ret_{-1:-1}$	−0.0523	−0.0528	−0.0528
	(−8.71)	(−8.71)	(−8.72)
Component of delay related to attention,	0.1592	0.2043	0.1931
$\widehat{delay}$ (attention)	(2.21)	(2.46)	(2.43)
Component of delay related to liquidity,	0.2638	−0.0145	−0.2277
$\widehat{delay}$ (liquidity)	(0.78)	(−0.05)	(−0.90)
Component orthogonal to attention and	0.0378	0.0510	0.0476
liquidity, residual delay	(1.27)	(1.51)	(1.44)

Panel B: Delay-sorted decile portfolios, characteristic-adjusted returns

	1	2	9	10	10–1
Component of delay related to attention, $\widehat{delay}$ (attention)					
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)
Component of delay related to liquidity, $\widehat{delay}$ (liquidity)					
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 orthogonal to attention and liquidity					
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)
Total delay-sorted decile portfolios for firms					
All	−0.02	0.11	0.26	1.35	1.38
	(−1.30)	(2.14)	(2.05)	(6.48)	(6.51)
Covered by analysts and institutions	−0.05	0.12	0.20	0.49	0.54
	(−1.86)	(2.51)	(2.44)	(3.53)	(3.79)
Not covered by analysts or institutions	−0.44	−0.80	1.52	1.34	1.77
	(−1.80)	(−4.70)	(4.41)	(4.51)	(5.08)

Panel A reports Fama–MacBeth regression results of returns on the components of delay predicted by liquidity [$\widehat{delay}$ (liquidity)] and attention [$\widehat{delay}$ (attention)] variables. Panel B reports the characteristic-adjusted returns (% per month) of decile portfolios, as well as the difference between the lowest and highest deciles, sorted by the portfolio delay measure $D1$ and the components of delay predicted by traditional liquidity and investor attention measures. The 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) 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) illiquidity measure (average daily absolute return divided by dollar trading volume over the past year), each defined separately for NYSE/AMEX and NASDAQ 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 US 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 predicted components of delay due to liquidity and attention, as well as the residual from the first-stage regression, are used in the second stage Fama–MacBeth regressions in panel A, where the time-series average of the coefficient estimates and their associated time-series t-statistics (in parentheses) are reported, and are used to form portfolios in panel B. Panel B also reports returns on delay-sorted 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, book-to-market equity (BE/ME), and momentum premiums. All results cover the period July, 1981, to December, 2001.

Panel B of Table 6 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 deciles 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 the traditional liquidity variables exhibits little relation to returns. The residual component also generates an insignificant return spread. This result suggests that a substantial portion of the explanatory power of delay is captured by our attention variables and supports the hypothesis that investor recognition drives the premium associated with delay.

4.3 Completely neglected firms

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 excluding the most neglected firms from our analysis, which will tend to understate our findings. For instance, if we employ log(1 + number of analysts) and log(1 + institutional ownership) in order to include zero coverage firms, the predictability of $\widehat{delay}$ (*attention*) increases significantly. To examine this issue 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).[17] 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 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 premiums.

Finally, one of the implications of the investor recognition hypothesis is that idiosyncratic risk will carry a premium among firms with limited investor participation, consistent with the results in Table 5, where only the most delayed firms carry a premium for residual volatility.

[17] 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.

5. 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 is partly related to the size effect and interacts with other known determinants of average returns. 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. The very small segment of delayed and neglected firms captures a great deal of cross-sectional return variation.

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. Since firms with significant delay tend to be small, low priced, and less liquid, trading costs may be exceedingly high. Moreover, the trading float available on such firms may be very small due to concentrated inside/family ownership more typical of small, neglected firms. Price impact costs are also likely to be large for such firms and hence may seriously limit the amount an investor could invest in such a strategy. Consequently, dollar trading profits from such a strategy may be nonexistent or too small to interest institutional traders.

These findings support a growing body of evidence of nonnews events such as advertising increasing visibility and investor attention [Cronqvist (2003), Frieder and Subrahmanyam (2005), and Grullon, Kanatas, and Weston (2004)]. Our results are also consistent with recent evidence that investor recognition and ownership breadth affect trading activity [Chordia, Huh, and Subrahmanyam (2003)], and 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 (2000)], and media coverage. Further investigating the broader implications of investor recognition is an interesting area of future study.

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