

Stock Resiliency and Expected Returns[†]

Nazli Sila Alan¹, Jian Hua², Lin Peng³ and Robert A. Schwartz⁴

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Keywords: stock returns, resiliency, liquidity, price discovery

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¹ Department of Finance, Dolan School of Business, Fairfield University, 1073 North Benson Rd., Fairfield, CT 06824. Phone: (203) 254-4000 x3018, fax: (203) 254-4105, Email: nalan@fairfield.edu.

² Department of Economics and Finance, Zicklin School of Business, Baruch College / CUNY, One Bernard Baruch Way, 10-225, New York, NY 10010. Phone: (646) 312-3487, fax: (646) 312-3451, Email: jian.hua@baruch.cuny.edu.

³ Department of Economics and Finance, Zicklin School of Business, Baruch College / CUNY, One Bernard Baruch Way, 10-225, New York, NY 10010. Phone: (646) 312-3491, fax: (646) 312-3451, Email: lin.peng@baruch.cuny.edu.

⁴ Department of Economics and Finance, Zicklin School of Business, Baruch College / CUNY, One Bernard Baruch Way, 10-225, New York, NY 10010. Phone: (646) 312-3467, fax: (646) 312-3451, Email: robert.schwartz@baruch.cuny.edu.

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Abstract

This paper examines a simple measure of stock resiliency based on the intraday return serial correlations. We argue that stock resiliency is an important aspect of liquidity and that a stock that lacks resiliency should be associated with higher expected returns. We find that long-short portfolios based on resiliency generate a monthly return differential of 37 basis points for the equal weight portfolios and 69 basis points for the value weighted portfolios. The effect of resiliency on future return is robust and cannot be explained by an extensive list of control variables. We further show that the pricing effect of resiliency is particularly important during periods of greater stock specific or market wide uncertainty, and periods during which resiliency is in high demand.

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1. Introduction

While traditional asset pricing theory assumes markets are frictionless, recent studies have recognized that market frictions such as an asset's liquidity and liquidity risk can be very important determinants of expected returns.⁵ The liquidity of an asset refers to the degree to which an appreciable quantity can be traded within a short time frame without incurring a large transaction cost or adverse price impact. Liquidity has several important aspects: immediacy, breadth, depth, and resiliency.⁶

Previous research has confirmed that investors demand an illiquidity premium for stocks with high bid-ask spreads, which captures breadth, and large price impacts, which proxies depth (see, for example, Amihud and Mendelson, 1986 and Acharya and Pedersen, 2005). However, there could be times in which there may appear to be depth and breadth, but the market lacks immediacy and resiliency. The 2007-2009 financial crisis provides a vivid example of such episodes. In this paper, we propose a simple measure of stock resiliency and compare it with the other liquidity measures. We further investigate the importance of resiliency in determining expected returns.

As described by Black (1972) and Kyle (1985), a resilient market is one in which prices recover from liquidity shocks quickly, whereas in a market with low resiliency, order flows result in large price dislocations that take longer to reverse (see also, Coppejans, Domowitz, and Madhavan, 2004 and Large, 2007). These arguments suggest that price reversals can be a natural measure of resiliency: in a market that lacks resiliency, we are more likely to observe negative return autocorrelation that is longer lasting. For instance, Heston, Korajczyk and Sadka (2010) compare intraday return autocorrelation over various horizons to measure resiliency. Furthermore, Vayanos and Wang (2002) show in a theoretical model that price reversal captures a dimension of

⁵ See, among others, Amihud and Mendelson (1986), Constantinides (1986), Amihud and Mendelson (1989), Brennan and Subrahmanyam (1996), Heaton and Lucas (1996), Eleswarapu (1997), Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998), Vayanos (1998), Amihud (2002), Duffie, Gârleanu, and Pedersen (2002), Huang (2003), Pástor and Stambaugh (2003), Gârleanu and Pedersen (2004), Lo, Mamaysky, and Wang (2004), Acharya and Pedersen (2005), Duffie, Gârleanu, and Pedersen (2005), Hasbrouck (2009), Bali, Peng, Shen and Tang (2014).

⁶ Immediacy refers to the speed with which a trade of a given size and cost can be completed. Breadth, often measured by the bid/ask spread, refers to the costs of providing liquidity. Depth refers to the maximum size of a trade for any given bid/ask spread. Resiliency refers to how quickly prices revert to fundamental values after a large transaction.

illiquidity due to transitory price fluctuations and that it impacts the expected returns of risky assets. The focus of the paper is thus to construct a stock resilience measure based on price reversals and investigates how it affects the stocks' expected returns.

Different from the existing liquidity measures (such as the bid-ask spread or the price impact of trades) that take a snap shot of liquidity at a point in time, resiliency captures the time dimension of liquidity -- how quickly the transitory price dislocation caused by an order gets repaired. Trading in a market that lacks resiliency means that the order will incur large price impacts, and that this impact can last for a long time. Thus a lack of resiliency manifests itself as an implicit transaction cost. One can apply models such as Amihud and Mendelson (1991) to show that investors should require a higher return to compensate for the higher trading costs associated with a lack of resiliency.

A market that lacks resiliency is also associated with slower price discovery and, hence, greater price uncertainty. Asset prices serve important information roles. It aggregates investors' information about a firm's future prospects and profitability, which helps investors make more efficient capital allocation decisions. In addition, managers extract information from the firm's stock prices and make real investment decisions based on it. However, price discovery can be a protracted, noisy process. It can vary depending on several factors including the fundamental uncertainty about a company and the macro environment, as well as the microstructure frictions and trading environment of the stock.

The persistent price dislocation caused by orders in a market that lacks resiliency delays price discovery, which reduces the information efficiency of prices and creates an additional source of price uncertainty. In a world in which investors cannot perfectly diversify away this source of uncertainty, they would require higher expected returns to compensate the transaction price uncertainty.⁷ In addition, transaction price uncertainty can be a cause of unfairness across traders. Less sophisticated investors may either end

⁷ There are several mechanisms by which stock specific risk can be priced. For example, in a setting in which there is incomplete risk sharing (Merton 1987), stock specific risk cannot be diversified away. Alternatively, one can view transaction price uncertainty is a source of noise trader risk that, in a world that there are limits to arbitrage (DeLong, Shleifer, Summers and Waldman, 1990, and Shleifer and Vishney, 1997), translate into a higher required rate of return to compensate for the noise trading risk. Furthermore, risk averse market makers who do not hold a diversified portfolio would be more reluctant to provide liquidity, this further increases transaction costs and results in higher required rate of returns.

up with the wrong side of the bargain, or they may suspect that the system is rigged (Lewis, 2014), resulting in higher required rate of returns.⁸

Our paper focuses on stock market resiliency during the opening half-hour period – one of the most crucial periods of the trading. This is a time, following the overnight non-trading period, when uncertainty tends to be particularly high and price discovery is particularly challenged. During the first thirty minutes of trading, markets are particularly challenged with high trading volume and accentuated volatility (Wood, McInish, and Ord (1985), Harris (1986), Jain and Joh (1988), and Pagano, Peng, and Schwartz (2008)). It is natural to focus on resiliency in this opening period.

Our simple and parsimonious measure of resiliency is based on the intraday serial correlation of the opening half-hour stock returns with the returns over the remainder of the trading day. In a resilient market where incoming orders create temporary price dislocations that are quickly repaired within the opening half-hour period, the return serial correlation should be zero. On the other hand, in a market that lacks resiliency, the price dislocation persists beyond the first half hour, and the restoration of prices only takes place between 10:00 and the end of the trading day, resulting in a negative return correlation for our chosen observation intervals.

Existing studies linking liquidity with asset pricing is based on daily bid-ask spread or on Amihud illiquidity measures. However, market quality and trading dynamics are not constant throughout the trading day. Our resiliency measure takes advantage of the intraday information and assesses the time dimension of liquidity by focusing on opening period price resiliency. We show that investors care about opening period stock market resiliency, and that it is an important factor in determining future returns.⁹

Our stock market resiliency measure is not driven by the bid-ask bounce effect studied in Roll (1984), who shows that bid-ask bounce can induce a negative first order

⁸ While the dealer's obligation is to trade at the NBBO, within the window of time immediacy he has an incentive to pick the price that maximizes his own profit. Stoll and Schenzler (2006) show that slower traders' orders provide a free look-back trading option for those traders with lower latency and result in higher transaction costs for slow orders. Higher transaction price uncertainty increases the value of this look back option at the expense of the less sophisticated traders.

⁹ We do not find a significant relationship between future returns and the average bid-ask spread for the opening half hour or the Amihud price impact measured for the opening half hour. This confirms that our resiliency measure captures a dimension of liquidity that is different from those captured by bid-ask spread or price impact.

serial correlation in returns constructed from transaction prices.¹⁰ In the Roll (1984) type models, there should be no serial correlations for returns computed with mid-quotes. Thus our resiliency measure is constructed from mid-quotes, which alleviates the concern that it is merely capturing the bid-ask bounce. Furthermore, we control for spreads throughout our analysis.

Our resiliency measure complements the existing liquidity measures, such as bid-ask spread or Amihud's liquidity measure. The correlations between our resiliency measure and the other liquidity measures are low. We also formally controlled for an extensive list of liquidity variables, as well as other determinants of expected returns, through double sorted portfolios and Fama-MacBeth regressions. We find the effect of stock market resiliency on future returns robust.

The paper's focus on the speed of recovery after price dislocations contributes to a literature that examines reversals in returns or dealer's inventory positions. Chordia, Roll, and Subrahmanyam (2005) examines the intraday return serial correlation for 150 actively traded NYSE stocks during calendar years 1996, 1999, and 2002. They find evidence of negative return serial correlation for intervals longer than five minutes but less than thirty minutes. Heston, Korajczyk and Sadka (2010) examine return serial correlation at various lags and find that the NYSE stocks take, on average, longer than 30 minutes (but less than 60 minutes) to restore shocks to liquidity. Bao, Pan and Wang (2011) use negative return covariances to capture corporate bond illiquidity as a manifestation of transitory price movements that reverses subsequently. They find that this measure of illiquidity contributes significantly to bond prices.

Price dislocations can be driven by a liquidity provider's aversion to inventory risks; thus, examining the speed of reversals in their inventory positions provides another angle to study resiliency. Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993) show that the rate of mean reversion for NYSE specialist inventories varies across stocks; in some cases, they are as long as one or two months. Hendershott and Menkveld (2014) examine daily prices and specialist inventory positions for 697 NYSE stocks for

¹⁰ In the Roll (1984) setting, order flows is not serially correlated, thus bid-ask bounce induces negative first-order serial correlation, but there is no return serial correlation at higher orders. In a more general setting that allows order imbalances to be serially correlated, bid-ask bounce can lead to negative return serial correlation of higher orders.

the period of 1994-2005; they find that the transitory price effect of an order has an average half-life of 0.92 days. Anand, Irvine, Puckett and Venkataraman (2013) show that the lack of resiliency can span months during financial crisis due to the withdrawal of liquidity suppliers. This paper bridges stock resiliency with asset pricing by quantifying the economic importance of stock resiliency in terms of required rate of returns.

The stock resiliency measure that we use in the paper focuses on the half-hour opening period; it is simple and parsimonious. It does not rely on any structural model and does not require any other information such as order flow. All it requires is price and quote data. On the other hand, it is likely to be measured with noise, and is not meant to be a one-size-fit-all measure of stock resiliency. First, the monthly resiliency measure is only computed with about twenty-one daily observations, which means the measure could contain a certain degree of measurement error. Furthermore, factors other than resiliency can influence the return serial correlation. For example, when informed order flows are positively correlated over time, or when investor sentiment exhibits intraday momentum, it can add a positive component to return correlation.

These errors are likely to bias against our finding any results. Thus the resiliency that our measure documents is likely to be a lower bound estimate of resiliency's true economic importance. For future work, one might examine stock resiliency for different intraday periods or even at lower frequencies such as days, weeks or months. Utilizing additional information such as specialist or dealer's inventory positions and institutional investors trading records can also paint a sharper picture of the drivers of resiliency, and resiliency's relation to returns.

Our paper is organized as follows. Section 2 contains data and variable descriptions. Section 3 presents the results of the cross-sectional analysis between our stock resiliency measure and stock returns. Section 4 provides a number of robustness checks. Section 5 concludes.

2. Data

Our analysis is conducted primarily on a monthly level and, correspondingly, most of our variables are calculated at the monthly level. For the variables that are

initially calculated on a daily level, we take a simple average of the daily values across the month for each stock.

Our sample includes all common stocks traded on the NYSE, AMEX, and NASDAQ exchanges, covering the period January 1993 through December 2012. We eliminate stock-months with average daily closing prices of less than \$5. Firm-level daily and monthly return and volume data are from CRSP. Accounting variables are obtained from the Merged CRSP/Compustat database. Analysts' earnings forecasts come from the I/B/E/S dataset and cover the period from 1983 to 2012. Intraday variables are calculated using Trade and Quotes (TAQ) data for the period 1993–2012. Institutional ownership data are from Thompson 13F filings for the period of 1980–2010.

2.1 Variable Description

Our main variable of interest, stock resiliency during the opening period for a given stock in a given month, is measured as the serial correlation of the opening half-hour return and the remaining return of the day:

$$CORR_{i,t} = \rho[R_{9:30-10am}, R_{10am-4pm}]$$

where $CORR_{i,t}$ is a proxy for the resiliency for stock i in month t , $R_{9:30-10am}$ represents the opening half-hour returns for stock i on each trading day in month t , and $R_{10am-4pm}$ represents the returns for the remainder of the day (from 10am to 4pm) for the same stock on each trading day in the month.¹¹ To alleviate the influence of bid-ask bounce, CORR is computed using mid-quote prices. We also conduct robustness checks with CORR measured with trade prices.

In a market without market microstructure frictions and with efficient prices, return processes should be independent over time and thus ρ should be zero. On the other hand, when markets during the opening period lack resilience, temporary deviations from

¹¹ To ensure that the resiliency variable is constructed with reasonable precision, we impose the following data filters for TAQ data: at least one trade must happen during the first half-hour of the trading day; non-missing daily closing price. After we calculate the intraday returns that are used in our main variable constructions, we trim each return at the .5 and 99.5 percentiles. This filter reduces the sample size to 14,861,610. Using these stock/day observations, we calculate our monthly measures, which lead to 892,921 stock/month observations. Finally, imposing at least 15 valid returns per month yields a sample size of 637,320 stock/month observations. The exception is for September 2001, during which the market was closed for several days due to the event of 9/11, we impose at least 10 valid returns for that month.

fundamental prices may not be fully repaired at 10am. This results in a price reversal during the remaining trading day and a negative return serial correlation between opening period returns and the remaining trading day returns. Thus the more negative return serial correlations are, the market is less resilient.

Below we describe the construction of the list of control variables used. First, we control for other measures of the level of illiquidity. Following Amihud (2002), we measure the illiquidity of stock i in month t , denoted $ILLIQ$, as the average daily ratio of the absolute stock return to the dollar trading volume within the month. Bid-ask spreads are calculated as the volume-weighted effective spread ($VRSPR$). More specifically, we first calculate the difference between the price and the corresponding quote midpoint for each trade of the day where the trades and quotes are matched following the Lee and Ready (1995) algorithm; scale it by the trade price; and then compute the trade-size weighted average across the trading day. $VRSPR$ is the monthly average of the daily volume-weighted effective spread. For robustness, we also use other spread measures such as equal-weighted effective spread ($ERSPR$), time-weighted quoted spread ($TSPR$), and equal-weighted quoted spread ($ESPR$); they all yield similar results. A measure that is related to liquidity is the share turnover ($TURN$), defined as number of shares traded divided by the number of shares outstanding (calculated daily, averaged over a month).

We then control for variables that capture an asset's exposure to liquidity risk. Following Pastor and Stambaugh (2003), we estimate the stock's liquidity exposure (PS) to innovations in the aggregate liquidity factor.¹² To capture covariances of a stock's own return and liquidity with the market return and market liquidity, we follow Acharya and Pedersen (2005) and estimate four betas: $AP1$ is the market beta, $AP2$ corresponds to the covariation of a stock's liquidity with the market liquidity, $AP3$ captures the covariation between a stock's return and market liquidity, and $AP4$ captures the covariation between a stock's liquidity and market returns. More specifically, each month, we classify common stocks listed on NYSE, AMEX, and NASDAQ into 25 test portfolios sorted on the average daily Amihud illiquidity over the previous year using NYSE breakpoints. We then normalize the Amihud illiquidity measure as suggested by Acharya and Pedersen (2005) and estimate the monthly innovations of illiquidity for the market and the test

¹² Innovations in aggregate liquidity factor are downloaded from Lubos Pastor's website.

portfolios by extracting the residuals from an AR(2) model using a 60-month rolling window with at least 24 monthly observations. Using these illiquidity innovations and returns, we estimate the liquidity betas for testing portfolios, and assign the betas of the illiquidity portfolio to the stocks that compose it.

We further control for exposure to the illiquidity risk factor of Sadka (2006).¹³ For each month, a stock's illiquidity risk loadings on the fixed and the variable components (denoted FT and VP , respectively) are estimated using monthly return data over the prior 60 months with a minimum of 24 monthly observations available after controlling for the monthly market, size and book-to-market factors.

In addition, we control for a list of variables that have been known to predict returns. Following Fama and French (1992), we estimate the market beta of individual stocks ($BETA$) using monthly returns over the prior 60 months (with a minimum of 24 months). The stock's size ($LNME$) is computed as the natural logarithm of the market capitalization of the stock (in million dollars). The natural logarithm of the book-to-market equity ratio at the end of June of year t ($LNBM$) is computed as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock for the last fiscal year end in $t-1$, scaled by the market value of equity at end of December of $t-1$.

Following Jegadeesh and Titman (1993), momentum returns (MOM) are calculated as the cumulative compounded stock returns over a period of 11 months from $t-12$ to $t-2$. Short-term reversal (REV) is measured as the stock return over the prior month, as defined by Jegadeesh (1990). Following Harvey and Siddique (2000), we construct a stock's monthly co-skewness ($COSKEW$) using the monthly return observations over the prior 60 months (with at least 24 observations). The monthly idiosyncratic volatility of stock ($IVOL$) is computed as in Ang et al. (2006). The stock's extreme positive return (MAX) is defined as its maximum daily return in a month following Bali, Cakici, and Whitelaw (2011). Analyst earnings forecast dispersion, denoted as $DISP$, is measured as the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast, following

¹³ We download the time series of the monthly fixed and variable components of the illiquidity factor from Ronnie Sadka's webpage.

Diether, Malloy, and Scherbina (2002). The fundamental volatility measure (*RET5VOL*) is the monthly return volatility of a stock for the past five years, estimated similarly to the idiosyncratic volatility (*IVOL*) above which is the standard deviation of the residuals from the monthly time-series regression over the prior 60 months with a minimum of 24 monthly observations available.

For our analyses of the determinants of return correlations, we also include a *NASDAQ* dummy variable that takes the value of one if a stock is listed on the NASDAQ and an earnings announcement dummy variable (*EA*) that takes the value of one if there is an earnings announcement for a stock in a given month.

In subsequent robustness analysis, we control for the effect of earnings surprises on stock returns and measure earnings surprise (*ES*) as the difference between expected and actual earnings per share normalized by the share price.

2.2 Summary Statistics

Summary statistics for our variables are reported on Panel A of Table 1. Our key variable of interest, return correlation between the opening half-hour returns and the remaining return of the day (*CORR*) has a mean of -0.013. This negative value suggests that intraday return reversals on average, although the standard deviation is large, at 0.26. The average skewness and excess kurtosis of return correlations are 0.00 and -0.12 respectively. These statistics, along with the average median (-0.014) that is very close to the time-series average of the mean, suggest the return correlations are fairly normally distributed.

As noted earlier, in a frictionless market, *CORR* should be zero, and if the market lacks resilience holding other things constant, *CORR* should be negative. In reality, other factors can also affect return serial correlation. As argued in Bao et al. (2011), return serial covariance not only captures the reversal of temporary component in prices, but also depends on the dynamics of the fundamental price component and the transitory price component themselves. For example, when informed order flows are positively correlated over time, or when investor sentiment exhibits intraday momentum, it can add a positive component to return correlation. Thus it is possible to observe positive *CORR*. In addition, *CORR* is measured with noise. The monthly resiliency measure is only

computed with about twenty-one daily observations, which means the measure could contain a certain degree of measurement error that can also give rise to positive values even when the true parameter may be negative. Therefore it is not the level of *CORR*, but its relative magnitude that matters. Everything else equal, the stocks with lower *CORR* tend to be less resilient.

2.3 Determinants of *CORR*

In this section, we take a closer look at the *CORR* variable and its determinants. In Table 2 we present the Fama-MacBeth regression results of *CORR* regressed on its potential determinants. A stock's resiliency can depend on its size, volatility, other aspects of illiquidity, as well as the exchange that it is listed. In addition, resiliency can also be affected by information events such as earnings announcements. The lagged explanatory variables included in these models are idiosyncratic volatility (*IVOL*), past 5-year monthly return volatility (*RET5VOL*), turnover (*TURN*), market capitalization (*LNME*), an indicator dummy for NASDAQ-listed stocks,¹⁴ Amihud illiquidity (*ILLIQ*), the volume-weighted bid-ask spread (*VRSPR*), and earnings announcement indicator (*EA*).

Panel A presents results using mid-quote-based *CORR* measures. It suggests the *CORR* tends to be high (or stocks are more resilient) for larger firms and firms with high share turnover; and low for firms with wider spreads greater illiquidity. An interesting result is that earnings announcements have a positive effect on the current month *CORR*. This may be related to the post earnings announcement drift phenomenon in which price continuation occurs months following the earnings surprises (Bernard and Thomas, 1989), this drift may give rise to intraday return continuations, thus positive *CORR* values. However, the lagged *EA* variable is insignificant, suggesting the effect of post earnings announcement drift on intraday return correlations are limited to the same month only. In Panel B, when *CORR* is computed with trade prices, similar coefficient on the determinants is obtained.

¹⁴ The indicator dummy is included because there are key microstructural differences between NYSE and NASDAQ.

3. Cross Sectional Analysis

3.1. Univariate Portfolio Analysis

We begin our empirical analysis with univariate portfolio sorts. In each month, we sort all stocks in the sample into decile portfolios based on intraday return correlation (CORR) and report the subsequent month decile portfolio returns. Decile 1 portfolio contains stocks with the lowest correlation and Decile 10 portfolio contains stocks with the highest correlation. In addition to raw returns (RET), we also construct abnormal returns extracted either as the Carhart (1997) 4-factor alphas (AlphaFF), or size and book-to-market characteristics adjusted abnormal returns (AlphaM) following Daniel, et al. (1997).

Table 3 presents the time series average of monthly portfolio returns, as well as CORR and market capitalization (Mkt Share) for the corresponding portfolio. In panels A and B, CORR is measured with mid-quote prices, while in panels C and D, CORR is measured with trade prices. Panel A and C uses CRSP CORR decile breakpoints to form portfolios, while in panels B and D, portfolios are sorted by NYSE CORR break-points to alleviate the concern that the CRSP decile breakpoints may be distorted by the large number of small NASDAQ and AMEX stocks.

Panel A shows that average portfolio raw returns, both for the equal-weighted and the value-weighted, return decreases almost monotonically with CORR: from 1.58% (1.06%) per month for the lowest CORR decile portfolio to 1.21% (0.37%) per month for the highest CORR decile portfolio. As a result, the equal-weighted (value-weighted) raw return difference and the corresponding alphas are, respectively, 0.37% and 0.69% (0.42% and 0.65%) per month between the Low- and High-CORR portfolios that are significant at the 1% (5%) level based on the Newey and West (1987) t-statistics.

The positive return differential between low- and high-CORR portfolios remain robust after controlling for exposures to the Carhart (1997) four factors (market, size, book-to-market, and price momentum) as well as after adjusting for size and book-to-market characteristics based benchmark returns. The equal-weighted (value-weighted) abnormal returns are 0.62% (0.20%) for the lowest CORR portfolio, while it is 0.32% (-0.38%) for the highest CORR portfolio. The Low-High difference of abnormal returns is

very similar to the raw return differences; 0.29% for the equal-weighted, and 0.59% for the value-weighted portfolios. These return differentials are not only statistically significant, but also economically important: it suggests that investors require an additional monthly return premium of 29 to 69 basis points for the stocks with the lowest CORR relative to stocks in the highest CORR decile. The return differentials are even more pronounced for the value-weighted portfolios, indicating that the observe premium for the low CORR stocks is not restricted to the small and illiquid stocks, but rather a general pattern that is important for large stocks.

The NYSE breakpoints sorted portfolio results reported in Panel B has almost identical patterns. The raw month return differential between the low- and high-CORR portfolios are 38 basis points for the equal weighted, and 62 basis points for the value weighted portfolios. The abnormal returns range from 30 to 62 basis points. The similarity between Panel A (CRSP breakpoints) and Panel B (NYSE breakpoints) is consistent with the relative even pattern of *Mkt Share* variable across different CORR deciles, showing that there is no pronounced relation between CORR and the market capitalization of a stock. Panels C and D reports similar results with CORR measured with trade prices. The raw month return differential between the low- and high-CORR portfolios ranges from 49 to 57 basis points per month, with abnormal returns range from 34 to 57 basis points.

Overall, these results indicate that, regardless of how we measure CORR or the portfolio-weighting scheme that we use, a portfolio that goes long stocks in the lowest CORR decile and shorts stocks in the highest CORR decile yield significant raw and risk-adjusted returns for both the equal-weighted and the value-weighted portfolios. Our findings is consistent with the hypothesis that stock market requires a premium for stocks that lack resiliency.

Table 4 reports the average statistics of the variable for the decile portfolios that are formed based on CORR.

3.2. Bivariate Portfolio Analysis

As discussed earlier, CORR can be correlated with many well-known characteristics that forecast cross-sectional stock returns, such as level of illiquidity and liquidity risk, past return characteristics (reversal, momentum), co-skewness,

idiosyncratic volatility, analyst disagreement, and demand for lottery-like stocks. As such, there is some concern that our CORR may capture effects other than resiliency. We control for these other factors with bivariate sorts in this subsection and Fama-MacBeth regressions in Section 3.3.

We consider bivariate sorts on CORR in combination with market beta (BETA), size (LNME), book-to-market ratio (LNBM), momentum (MOM), short-term reversal (REV), Amihud's illiquidity measure (ILLIQ), value-weighted effective bid-ask spreads (VRSPR), Pastor and Stambaugh liquidity beta (PS), monthly co-skewness (COSKEW), monthly idiosyncratic volatility (IVOL), maximum daily return in a month (MAX), turnover in a month (TURN), prior five-year monthly return volatility (RET5VOL), and analyst earnings forecast dispersion (DISP). We show that each control alone fails to subsume the pricing effect of CORR.

Panel A of Table 5 reports the conditional bivariate portfolio sort results. Stocks are first sorted into tercile portfolios based on one control variable, and then into CORR decile within each control variable tercile. We then group together the stocks in the same correlation deciles and report the average decile returns and the low-minus-high CORR decile return differences for the following month. We report the returns of the CORR portfolios, averaged across the three control terciles to produce decile portfolios with dispersion in CORR but with similar levels of the control variable. The predictive power of CORR remains intact in dependent bivariate portfolios. The average raw return differences between the low- and the high-CORR portfolios range from 27 basis points to 45 basis points per month. The corresponding abnormal return differentials range from 19 to 38 basis points. All of the raw return differentials are significant based on the Newey-West t-statistics, as well as most of the abnormal returns.

Panel B of Table 5 presents the same set of results from the independent bivariate sorts. For each month, we conduct two independent sorts of stocks into deciles based on CORR and terciles based on a control variable at the beginning of the month. We then take the intersection of these sorts to form 30 portfolios. We hold these portfolios for one month and then rebalance at the end of the month. This sorting procedure creates a set of liquidity shock portfolios with nearly identical levels of the control variable. The independent sort results are very similar to those obtained from dependent sorts – the raw

and abnormal return differentials are positive and significant, and the corresponding 4-factor alphas are positive and significant; the average raw return differences are in the range of 0.30% to 0.45% per month, with the t-statistics ranging from 1.75 to 2.63. Abnormal return differences range from 0.22% to 0.40%, and the 4-factor alphas are in the range of 0.33% and 0.42% per month.

3.3. Firm-Level Cross-Sectional Regressions

In addition to portfolio analysis, we also analyze our measure while accounting for the possible simultaneous effect of the control variables. Specifically, we check our measure's predictive power after controlling other competing predictors of stock returns by running monthly cross-sectional predictive regressions:

$$R_{i,t+1} = \alpha_{t+1} + \gamma_{t+1}CORR_{i,t} + \varphi_{t+1}X_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, $CORR_{i,t}$ represents our return correlation measure, and $X_{i,t}$ is a vector of control variables for stock i in month t .

We start with the baseline model, where the control variables are the market beta (BETA), the log market capitalization (LNME), and the log book-to-market ratio (LNBM). We then include the momentum (MOM) and the short-term reversal (REV). Next we add a variety of liquidity-based variables including the Amihud's illiquidity measure (ILLIQ), the liquidity exposure (PS) of Pastor and Stambaugh, the volume-weighted effective bid-ask spreads (VRSPR), the four liquidity exposures (AP1 to AP4) of Acharya and Pedersen (2005), the exposures to the fixed (FT) and the variable components (VP) of Sadka's liquidity factors. Furthermore, we add the other variables that have shown to predict returns including the co-skewness (COSKEW), the idiosyncratic volatility (IVOL), the maximum daily return in the previous month (MAX), the shares turnover (TURN), the monthly return volatility for the past five years (RET5VOL), and the analyst forecast dispersions (DISP).

Table 6 presents the time-series average of slope coefficients from monthly predictive regressions that are estimated for each month using Fama and MacBeth (1973) methodology. In Panel A, CORR is measured using mid-quotes. The results show that the average slope coefficients of CORR are between -0.216 (Newey-West t-statistic=2.12)

and -0.274 (Newey-West t-statistic=3.05). These statistically significant coefficients have similar economic significance and interpretation as the long-short portfolio results reported in Table 2. The CORR coefficients suggest that the return differential between stocks in the lowest and the highest CORR deciles range from 19 to 24 basis points per month.

The coefficients of the control variables are mostly consistent with existing findings. For example, size and short term return reversal (REV) are negative and significant, consistent with Fama and French (1992) and Jegadeesh (1990). The level of illiquidity (ILLIQ) is negative and significant for most specifications, consistent with Amihud (2002). Idiosyncratic volatility (IVOL) is negative and generally significant, consistent with Ang. et al (2006).

Panel B presents results where CORR is computed using trade prices. The results are similar with the coefficient on CORR being somewhat larger for all specifications except M5. This suggests that our result is robust to alternative measures of CORR.

The findings thus suggest that the CORR measure of stock resiliency is a new liquidity measure that complements the previously documented liquidity variables, and that investors do demand a return premium for stocks that lack resiliency.

3.4. The Time-Varying Effect of CORR on Returns

Similar to other established liquidity measures, stock resiliency is also time varying, and we expect that investors would assign particular importance to resiliency when it is scarce -- periods with greater stock specific or market wide uncertainty, and periods during which resiliency is in high demand. Thus we further investigate the effect of CORR on future returns by interacting CORR with firms' earnings announcements, and by looking at various sub-periods.

Table 7 presents the Fama and MacBeth regression coefficients of month stock returns regressed on lagged determinants. In addition to the main set of explanatory variables included in Table 6, we include both earning surprises (ES) and an interactive variable of the absolute value of ES and CORR ($|ES|*CORR$).¹⁵ The results show that the coefficient on CORR remains negative and significant. More importantly, $|ES|*CORR$ is

¹⁵ Including all explanatory variables from Table 6 does not qualitatively affect our results.

negative and significant, suggesting that the effect of CORR on future returns are more pronounced during months with large earnings surprises. This indicates that, during periods with large information shocks investors place a greater value on the resiliency of a stock, thus prices for stocks lack of resiliency should fall, leading to higher future returns.

Similarly, one would expect that investors value resiliency during periods of great macroeconomic uncertainty, during recessions and financial crisis. We compare two sets of subsamples: 1) Expansion and Non-Crisis vs. Recession and Crisis; 2) Low VIX and High VIX. The Recession and Crisis period spans March 2001 to November 2001, and July 2007 to June 2009, and the remaining periods in our main sample are the Expansion and Non-Crisis periods. We also split the sample based on VIX, considering high VIX (VIX is greater than 35%, which is the 95 percentile value). These periods correspond to October 1997 to December 1997, August 1998 to February 1999, September 2001 to November 2001, July 2002 to November 2002, September 2008 to May 2009, and August 2011 to November 2011. The low VIX periods are when VIX is less than 20% (which is the median VIX level).

Table 8 presents the results of the subsample Fama-MacBeth regression analysis, with the main set of control variables.¹⁶ The results show a striking difference in the effect of CORR on future returns. While the coefficient of CORR is negative and significant at -0.193 during normal (expansion and non-crisis_ periods, it is -0.695 during recession and crisis periods. The difference is 0.5 and statistically significant. In terms of the economic significant, these coefficients show that the monthly return differential between stocks in the lowest and the highest CORR deciles is 17 basis points during normal periods, it surges to 62 basis points during recession and crisis periods. Subperiods of VIX also paints a similar picture. The coefficient on CORR is negative but insignificant during low VIX periods, but it is highly significant, at 0.505, during high VIX periods. These results suggests that, while the economic impact of stock resilience may be small during normal periods, it has substantiate effects on asset prices during periods of large macroeconomic uncertainty, especially during recessions and financial crisis.

¹⁶ Results are robust to including all control variables from Table 6.

The other period during which stock resiliency may be of great importance is in January, a month during which investors are more likely to balance their portfolios than the other months. It is a time of relatively high trading volume, a period during which stock trading is under pressure due to large order imbalances, and a time stock resiliency should matter more. Thus we examine how the effect of CORR on future returns varies across between January versus the rest of the year. This also serves as a robustness check, since certain anomalies may disappear once January is excluded.

Table 9 reports the Fama-Macbeth regression coefficient of one-month-ahead returns regressed on CORR and other control variables, comparing the results when the explanatory variables are measured as of January versus other months. The results suggest our conjecture: the average coefficient for the January regressions is -0.704, while for the non-January months it is only -0.222, and the differences are statistically significant. In terms of the economic significant, these coefficients show that the monthly return differential between stocks in the lowest and the highest CORR deciles is 63 basis points during January, and 20 basis points during other months.

4. Robustness Checks

Asparouhova, Bessembinder, and Kalcheva (2010) show that market microstructure effects can bias the Fama-MacBeth regression coefficients. To ensure that our results are not driven by this bias, we use their technique and run monthly weighted least squares (WLS) regressions, where each observed return is weighted by the gross return on the same stock in the prior month. The results presented in Table 10 show that CORR remain negative and significant across models with various control variables. In fact, under the WLS specification, the CORR coefficients are actually slightly larger than the counterparts in Table 6, showing that the predictive power of CORR is robust to potential microstructure-related biases.

We also construct an alternative measure of intraday return correlation, using Spearman correlation coefficient. As Spearman correlation assesses the dependence nonparametrically, it is less susceptible to outliers problem. Table 11 Panels A to D present results of the univariate portfolio sorts from the Spearman correlation of our return correlation measure. The findings are very similar to those based on Pearson

correlation (Table 3). This further demonstrates that our results are robust to potential outliers in the measurement of CORR.

5. Conclusion

In this paper, we examine a simple measure of stock resiliency and compare it with the other liquidity measures. Our measure of resiliency is based on the intraday serial correlation of the opening half-hour stock returns with the returns over the remainder of the trading day. We investigate the importance of resiliency in determining expected returns. Long-short portfolios based on CORR generate a monthly return differential of 37 basis points for the equal weight portfolios and 69 basis points for the value weighted portfolios. The effect of CORR on future return is robust and cannot be explained by an extensive list of control variables. We further show that the pricing effect of CORR is particularly important during periods with greater stock specific or market wide uncertainty, and periods during which resiliency is in high demand.

Our findings suggest that the CORR measure of stock resiliency is a new liquidity measure that complements the previously documented liquidity variables. Investors do demand a return premium for stocks that lack resiliency and this premium increases during recessions, financial crisis, and periods of stock specific information uncertainty.

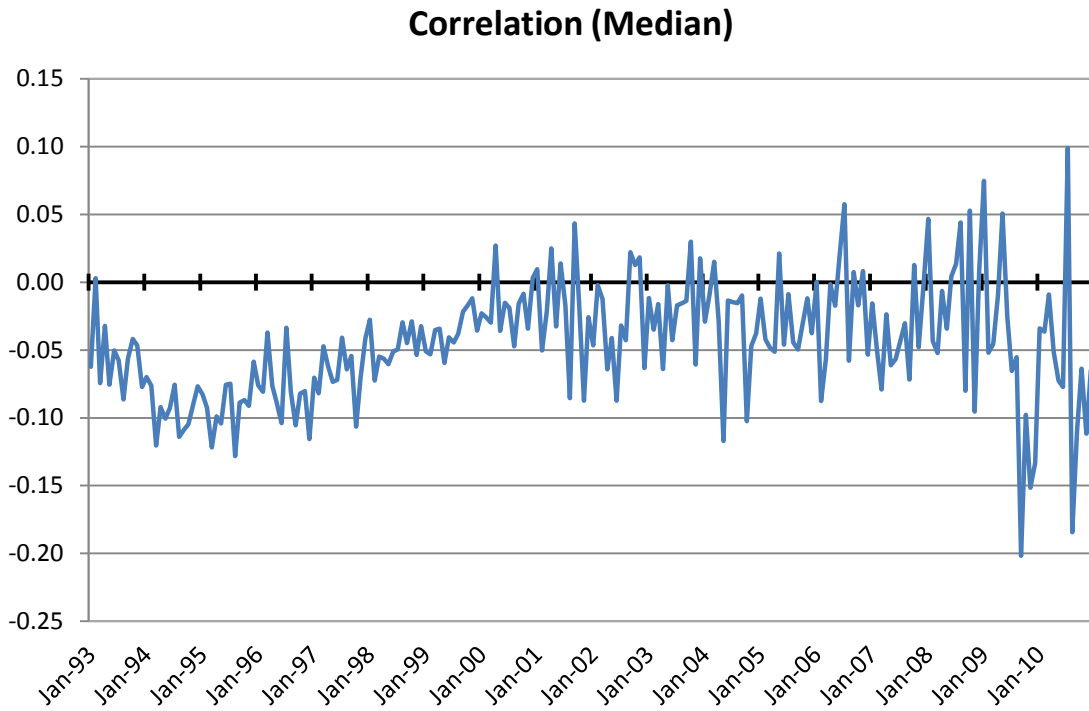
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Figure 1: Monthly Correlations
Panel A: Monthly Median Correlation



Panel B: Average Correlation against 25th and 75th Percentile Correlation

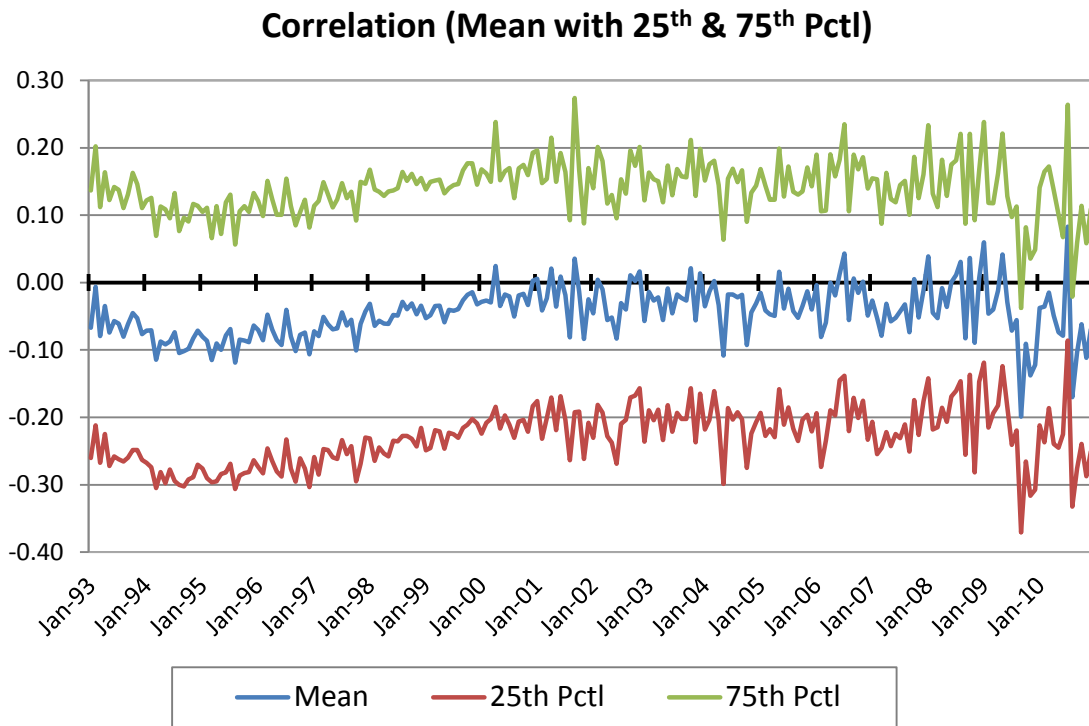


Figure 2: Monthly Average Abnormal Returns of Low-High Return Correlation Portfolios

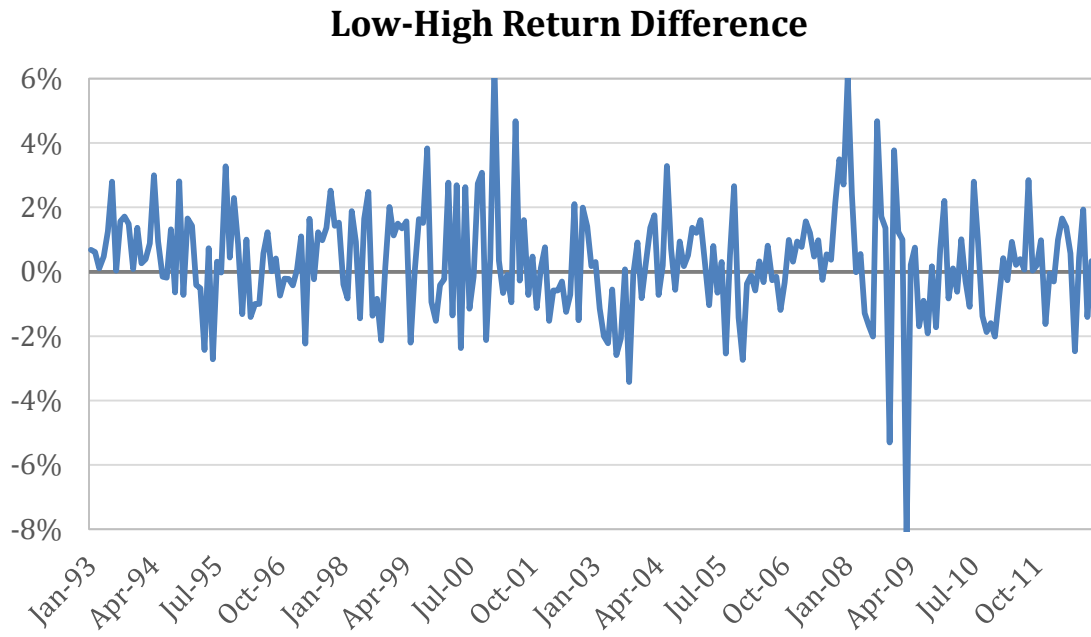


Table 1: Descriptive Statistics

Panel A reports the time-series averages of the cross-sectional mean, median, standard deviation, skewness and kurtosis of the main variables used in this paper. All the variables, except for *RET*, the return in month $t + 1$, are computed for individual firms at the end of the portfolio formation month (month t). *CORR* denotes the monthly correlation between the opening half-hour quote returns and the remaining quote return of the day. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted bid-ask spreads. *FT* and *VP* denote Sadka's illiquidity risk exposure on the fixed and the variable components respectively. *AP1*, *AP2*, *AP3* and *AP4* represent the four betas of the Acharya and Pedersen liquidity measures. *PS* is the Pastor and Stambaugh liquidity beta. *COSKEW* and *IVOL* are the co-skewness and idiosyncratic volatility, respectively. *MAX* denotes the maximum daily return in a month. *TURN* is the share turnover. *RET5VOL* is the past five-year monthly return volatility. *DISP* measures the analyst earnings forecast dispersion. Panel B reports times-series average of the monthly cross-sectional correlations between the variables in our sample. The sample covers the period from January 1993 to December 2012.

Panel A: Summary Statistics

	Mean	Median	Std Dev	Skewness	Kurtosis
RET	1.316	0.611	12.26	1.09	11.09
CORR	-0.013	-0.014	0.26	0.00	-0.12
BETA	1.260	1.090	0.97	1.45	6.67
LNME	6.523	6.402	1.70	0.40	0.04
LNBM	-0.742	-0.652	0.81	-0.75	2.89
MOM	15.997	8.529	47.22	3.30	37.01
REV	1.986	0.860	13.73	2.81	49.04
ILLIQ	0.387	0.009	3.99	16.03	440.52
VRSPR	0.822	0.436	5.13	8.00	227.88
FT	-2.285	0.444	288.90	-0.59	280.80
VP	0.894	-0.123	69.79	-0.08	212.63
AP1	0.727	0.724	0.14	0.22	-1.00
AP2	0.080	0.008	0.22	5.22	37.32
AP3	-0.031	-0.031	0.01	-0.23	-0.57
AP4	-0.544	-0.065	1.30	-4.60	31.00
PS	0.001	-0.003	0.35	0.02	8.38
COSKEW	-0.688	-0.731	9.63	0.83	22.02
IVOL	2.387	2.029	1.56	3.99	60.19
MAX	6.185	4.930	5.29	6.37	117.47
TURN	0.758	0.479	1.13	8.41	196.56
RET5VOL	12.958	11.335	6.92	2.91	30.34
DISP	0.155	0.036	0.91	20.69	606.44

Table 1 - continued
Panel B: Correlations

	CORR	BETA	LNME	LNBM	MOM	REV	ILLIQ	VRSPR	FT	VP	AP1	AP2	AP3	AP4	PS	COSKEW	IVOL	MAX	TURN	RET5VOL	
BETA	0.034																				
LNME	0.063	-0.083																			
LNBM	-0.037	-0.130	-0.265																		
MOM	0.027	0.042	0.065	-0.154																	
REV	-0.009	0.031	-0.008	0.013	0.006																
ILLIQ	-0.029	-0.044	-0.292	0.123	-0.042	-0.011															
VRSPR	-0.076	-0.008	-0.577	0.161	-0.067	-0.005	0.435														
FT	0.003	0.293	-0.058	0.035	0.027	0.012	0.014	0.024													
VP	0.000	-0.004	-0.027	0.015	0.009	0.003	0.012	0.011	-0.097												
AP1	-0.059	0.020	-0.812	0.215	0.086	0.064	0.298	0.521	0.058	0.040											
AP2	-0.047	-0.025	-0.446	0.129	0.069	0.082	0.441	0.551	0.050	0.035	0.466										
AP3	0.059	-0.022	0.835	-0.220	-0.085	-0.066	-0.325	-0.553	-0.059	-0.038	-0.933	-0.550									
AP4	0.050	0.030	0.484	-0.142	-0.074	-0.083	-0.448	-0.575	-0.054	-0.038	-0.522	-0.987	0.597								
PS	0.005	-0.005	-0.016	0.023	0.029	0.008	0.006	0.019	0.058	0.175	0.011	0.023	-0.014	-0.025							
COSKEW	0.009	0.101	0.091	-0.023	0.002	0.002	-0.041	-0.079	0.157	-0.150	-0.097	-0.069	0.099	0.075	-0.105						
IVOL	0.132	0.292	-0.314	-0.109	0.045	0.024	0.093	0.277	0.033	0.002	0.222	0.202	-0.232	-0.204	0.024	-0.014					
MAX	0.130	0.252	-0.225	-0.084	0.026	0.002	0.055	0.181	0.032	-0.002	0.156	0.149	-0.163	-0.149	0.023	-0.002	0.849				
TURN	0.082	0.276	0.113	-0.217	0.175	0.074	-0.106	-0.154	0.015	-0.009	-0.196	-0.083	0.185	0.097	0.031	0.060	0.430	0.365			
RET5VOL	0.025	0.643	-0.295	-0.207	0.108	0.086	0.009	0.103	0.140	-0.072	0.189	0.111	-0.191	-0.109	0.002	0.050	0.484	0.392	0.359		
DISP	-0.001	0.066	-0.078	0.045	-0.050	-0.006	0.020	0.068	0.002	0.003	0.039	0.015	-0.040	-0.016	0.008	0.002	0.082	0.065	0.031	0.101	

Table 2: Determinants of Return Correlations

Return correlation (*CORR*) is regressed with a set of variables using the Fama-MacBeth (1973) methodology, and all variables except (EA_t) all lagged, and EA_C is concurrent with the return correlation. This table reports the average slope coefficients. Return Correlation (*CORR*) is the correlation between the first half hour return in month t and the return for the rest of the trading day in the same month. *IVOL* is the idiosyncratic volatility. *RET5VOL* is the past five-year monthly return volatility. *TURN* is the shares turnover. *LNME* denotes the natural logarithm of the market capitalization. *VRSPR* is the volume-weighted effective bid-ask spreads of the quotes. *ILLIQ* denotes the Amihud's illiquidity measure. *NASDAQ* is a dummy variable that indicate whether the stock is listed on NASDAQ. *EA* is the indicator variable of whether there is earning announcement in the month. Newey-West t -statistics are reported in parentheses. The sample covers the period from January 1993 to December 2012. Panel A reports results from the quote-based correlation measure, and Panel B reports results from the trade-based correlation measure.

Panel A: Quote-based correlation measure

$Y = CORR_t$	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
$IVOL_{t-1}$	0.000 [0.49]							0.003 [4.12]					
$RET5VOL_{t-1}$		0.071 [5.27]							0.160 [9.79]			0.154 [10.08]	
$TURN_{t-1}$			1.321 [10.07]					0.541 [3.36]					
$LNME_{t-1}$				0.010 [8.18]					0.009 [8.13]		0.009 [8.09]	0.010 [8.59]	
$VRSPR_{t-1}$					-0.027 [-9.12]			-0.026 [-10.02]					
$ILLIQ_{t-1}$						-0.010 [-5.71]			-0.004 [-2.85]			-0.004 [-2.88]	
$NASDAQ_{t-1}$							-0.007 [-1.11]	2.028 [1.22]	-0.003 [-0.50]				
EA_t										0.015 [8.71]	0.010 [7.34]	0.00895 [6.69]	
EA_{t-1}													0.001 [0.67]
Intercept	-0.014 [-3.76]	-0.023 [-5.29]	-0.024 [-5.55]	-0.076 [-8.23]	0.002 [0.56]	-0.012 [-3.21]	-0.004 [-1.05]	-0.005 [-1.08]	-0.087 [-8.54]	-0.018 [-4.93]	-0.078 [-8.34]	-0.104 [-9.48]	-0.014 [-3.85]
N	693,317	618,777	693,388	641,443	687,038	685,073	693,388	686,967	604,942	732,950	641,443	604,942	693,388
R-sq	0.002	0.002	0.006	0.010	0.010	0.002	0.007	0.019	0.018	0.002	0.011	0.016	0.001

Panel B: Trade-based correlation measure

$Y = CORR_t$	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
$IVOL_{t-1}$	0.000 [0.23]							0.008 [8.15]					
$RETSVOL_{t-1}$		0.040 [2.25]							0.240 [12.27]			0.204 [8.16]	
$TURN_{t-1}$			1.032 [9.79]					0.570 [5.81]					
$LNME_{t-1}$				0.012 [12.97]					0.011 [8.92]		0.012 [13.01]	0.013 [10.75]	
$VRSPR_{t-1}$					-0.079 [-13.88]			-0.085 [-15.87]					
$ILLIQ_{t-1}$						-0.609 [-13.36]			-0.339 [-6.97]			-0.343 [-7.28]	
$NASDAQ_{t-1}$							-0.014 [-2.52]	-0.010 [-2.57]	-0.016 [-3.45]				
EA_t										0.012 [9.15]	0.011 [8.19]	0.0102 [7.83]	
EA_{t-1}													-0.005 [-4.57]
Intercept	-0.024 [-6.06]	-0.029 [-6.44]	-0.034 [-10.92]	-0.109 [-17.04]	0.006 [1.42]	-0.017 [-5.15]	-0.014 [-3.22]	-0.008 [-1.67]	-0.119 [-9.59]	-0.030 [-10.69]	-0.112 [-17.62]	-0.139 [-11.99]	-0.023 [-7.41]
N	520,604	470,315	520,639	490,282	517,675	518,624	520,639	517,640	466,465	560,606	490,282	466,465	520,639
R-sq	0.003	0.003	0.004	0.009	0.013	0.006	0.007	0.023	0.022	0.001	0.011	0.018	0.001

Table 3: CORR and Future Returns: Univariate Portfolio Analysis

For each month, NYSE, Amex, and NASDAQ stocks are sorted into ten decile portfolios based on return correlation (*CORR*), which is the monthly correlation between the opening half-hour returns and the remaining return of the day. This table reports the average monthly returns in month t+1 (RET), 4-factor Fama-French (1993) alphas, and the average abnormal returns based on Fama-French 25 size and book-to-market portfolios (AlphaM) for each *CORR* portfolio. Columns “Avg CORR” reports average *CORR* values for each decile portfolio. The last column shows the average market share of each portfolio. The last row shows the 1-10 differences in monthly returns between Low and High *CORR* decile portfolios, the corresponding 4-factor alphas, and the abnormal returns. Average returns and alphas are defined in monthly percentage terms. The entries in Panels A and B are based on the CRSP and NYSE decile breakpoints from the quote-based correlation measure, and the entries in Panels C and D are based on the CRSP and NYSE decile breakpoints from the trade-based correlation measure. Newey-West t-statistics are given in parentheses. The sample covers the period from January 1993 to December 2012.

Panel A: CRSP Decile Breakpoints (Quote-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.58 [4.98]	0.72 [7.29]	0.62 [5.36]	1.06 [3.03]	0.23 [1.41]	0.20 [1.04]	-0.46	7.33
2	1.33 [3.92]	0.45 [5.23]	0.40 [4.17]	0.92 [2.94]	0.13 [1.32]	0.06 [0.46]	-0.28	9.03
3	1.38 [4.01]	0.50 [6.28]	0.47 [5.34]	1.01 [3.23]	0.23 [2.57]	0.13 [1.26]	-0.19	9.78
4	1.49 [4.36]	0.61 [6.70]	0.52 [6.74]	1.01 [3.15]	0.26 [2.82]	0.21 [1.88]	-0.11	10.21
5	1.27 [3.61]	0.36 [4.15]	0.33 [4.05]	0.80 [2.41]	0.06 [0.50]	0.02 [0.18]	-0.05	10.44
6	1.30 [3.76]	0.41 [4.59]	0.34 [3.86]	0.84 [2.50]	0.07 [0.74]	0.05 [0.38]	0.02	10.97
7	1.29 [3.57]	0.37 [4.12]	0.38 [5.16]	0.96 [3.00]	0.19 [1.89]	0.12 [1.10]	0.09	10.82
8	1.17 [3.26]	0.23 [2.93]	0.24 [3.56]	0.70 [2.03]	-0.13 [-1.44]	-0.10 [-0.99]	0.16	10.65
9	1.15 [3.29]	0.23 [3.03]	0.27 [3.36]	0.74 [2.22]	0.05 [0.44]	-0.08 [-0.63]	0.26	11.15
10 (High)	1.21 [3.40]	0.30 [3.15]	0.32 [3.50]	0.37 [0.97]	-0.42 [-3.11]	-0.38 [-2.33]	0.43	9.62
1 - 10 (Low-High)	0.37 [3.26]	0.42 [4.23]	0.29 [2.43]	0.69 [2.39]	0.65 [2.65]	0.59 [2.09]		

Table 3 –continued

Panel B: NYSE Decile Breakpoints (Quote-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.58 [4.92]	0.72 [7.57]	0.62 [5.74]	1.08 [3.19]	0.27 [1.81]	0.19 [1.04]	-0.44	8.61
2	1.31 [3.83]	0.41 [5.05]	0.36 [3.84]	0.96 [3.11]	0.15 [1.47]	0.13 [1.00]	-0.26	9.57
3	1.37 [4.05]	0.50 [5.82]	0.48 [5.41]	0.85 [2.67]	0.08 [0.92]	-0.03 [-0.39]	-0.17	10.19
4	1.45 [4.14]	0.56 [5.27]	0.48 [5.80]	1.06 [3.30]	0.32 [2.59]	0.27 [2.41]	-0.10	10.16
5	1.30 [3.68]	0.40 [4.56]	0.36 [4.32]	0.82 [2.32]	0.07 [0.65]	0.06 [0.44]	-0.03	10.25
6	1.26 [3.60]	0.37 [4.12]	0.30 [3.41]	0.87 [2.81]	0.13 [1.22]	0.06 [0.48]	0.03	10.62
7	1.28 [3.54]	0.36 [4.32]	0.37 [5.24]	0.87 [2.60]	0.08 [0.88]	0.05 [0.46]	0.10	10.42
8	1.15 [3.28]	0.22 [2.70]	0.22 [3.04]	0.68 [1.97]	-0.15 [-1.54]	-0.14 [-1.08]	0.17	10.17
9	1.19 [3.35]	0.26 [3.55]	0.31 [3.55]	0.63 [1.85]	-0.06 [-0.54]	-0.18 [-1.35]	0.26	10.55
10 (High)	1.20 [3.36]	0.28 [2.88]	0.32 [3.42]	0.46 [1.22]	-0.34 [-2.68]	-0.30 [-1.91]	0.44	9.47
1 - 10 (Low-High)	0.38 [3.60]	0.44 [4.37]	0.30 [2.64]	0.62 [2.44]	0.61 [2.86]	0.49 [1.98]		

Table 3 –continued

Panel C: CRSP Decile Breakpoints (Trade-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.65 [4.49]	0.71 [5.69]	0.63 [5.85]	1.03 [2.98]	0.20 [1.29]	0.14 [0.72]	-0.47	6.92
2	1.45 [4.09]	0.55 [5.33]	0.59 [5.67]	0.99 [3.38]	0.24 [2.35]	0.17 [1.25]	-0.30	8.78
3	1.39 [3.61]	0.43 [4.44]	0.45 [4.63]	0.98 [3.02]	0.18 [1.80]	0.11 [0.97]	-0.20	9.78
4	1.44 [3.85]	0.50 [4.54]	0.48 [5.63]	1.02 [3.30]	0.24 [2.91]	0.16 [1.57]	-0.13	10.09
5	1.32 [3.45]	0.41 [4.01]	0.38 [4.42]	0.76 [2.20]	0.01 [0.09]	-0.03 [-0.24]	-0.06	10.46
6	1.26 [3.40]	0.32 [3.55]	0.31 [4.21]	0.86 [2.51]	0.13 [1.15]	0.04 [0.33]	0.01	10.84
7	1.28 [3.29]	0.34 [3.46]	0.32 [4.32]	0.95 [2.95]	0.16 [1.83]	0.11 [1.08]	0.07	11.12
8	1.20 [3.15]	0.24 [3.12]	0.30 [4.13]	0.74 [2.18]	-0.05 [-0.51]	-0.03 [-0.23]	0.15	10.87
9	1.20 [3.23]	0.25 [3.22]	0.26 [3.46]	0.67 [1.93]	-0.08 [-0.81]	-0.17 [-1.41]	0.25	11.22
10 (High)	1.15 [3.03]	0.19 [1.98]	0.29 [3.12]	0.46 [1.22]	-0.31 [-2.52]	-0.28 [-1.82]	0.42	9.92
1 - 10 (Low-High)	0.51 [3.40]	0.52 [3.74]	0.34 [2.70]	0.57 [2.12]	0.50 [2.19]	0.42 [1.63]		

Table 3 –continued

Panel D: NYSE Decile Breakpoints (Trade-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.64 [4.51]	0.71 [6.10]	0.65 [6.31]	0.99 [2.86]	0.16 [1.06]	0.12 [0.63]	-0.45	8.08
2	1.46 [4.00]	0.53 [5.17]	0.58 [5.27]	1.02 [3.53]	0.27 [2.80]	0.17 [1.39]	-0.28	9.37
3	1.34 [3.54]	0.39 [4.10]	0.38 [4.69]	0.92 [2.93]	0.12 [1.42]	0.02 [0.18]	-0.19	10.17
4	1.42 [3.86]	0.49 [4.72]	0.49 [5.77]	0.99 [2.94]	0.22 [2.24]	0.20 [1.89]	-0.11	10.06
5	1.29 [3.28]	0.36 [3.31]	0.31 [3.69]	0.73 [2.19]	0.00 [-0.01]	-0.07 [-0.55]	-0.05	10.43
6	1.22 [3.25]	0.29 [2.99]	0.27 [3.40]	0.90 [2.62]	0.14 [1.25]	0.08 [0.59]	0.02	10.68
7	1.29 [3.36]	0.35 [3.57]	0.37 [5.09]	0.90 [2.92]	0.14 [1.38]	0.07 [0.67]	0.08	10.47
8	1.21 [3.21]	0.25 [3.16]	0.31 [4.03]	0.67 [1.93]	-0.15 [-1.49]	-0.12 [-1.11]	0.16	10.64
9	1.17 [3.09]	0.23 [2.86]	0.26 [3.18]	0.72 [2.10]	0.02 [0.18]	-0.08 [-0.67]	0.25	10.65
10 (High)	1.15 [3.09]	0.20 [1.96]	0.28 [2.95]	0.43 [1.14]	-0.34 [-2.78]	-0.31 [-1.94]	0.43	9.46
1 - 10 (Low-High)	0.49 [3.62]	0.51 [4.04]	0.36 [3.03]	0.56 [2.10]	0.50 [2.20]	0.43 [1.64]		

Table 4: Portfolio Characteristics

For each month, NYSE, Amex, and NASDAQ stocks are sorted into ten decile portfolios based on return correlation (*CORR*), the quote-based correlation between the opening half hour return and the rest of day's return. This table presents the average across the months in the sample of the average values within each month of various characteristics for the stocks in each *CORR* decile. All the variables, except for *RET*, the return in month $t + 1$, are computed for individual firms at the end of the portfolio formation month (month t). Average values are reported for the return correlation (*CORR*), the market beta (*BETA*), the log market capitalization (*LNME*), the book-to-market ratio (*LNBM*), the return over the 11 months prior to portfolio formation (*MOM*), the return in the portfolio formation month (*REV*), the Amihud's illiquidity measure (*ILLIQ*), the volume-weighted effective bid-ask spreads (*VRSPR*), the Sadka's illiquidity risk exposure on the fixed (*FT*) and the variable components (*VP*), the four betas of the Acharya and Pedersen liquidity measure (*AP1*, *AP2*, *AP3* and *AP4*), the Pastor and Stambaugh liquidity beta (*PS*), the monthly co-skewness (*COSKEW*), the monthly idiosyncratic volatility (*IVOL*), the maximum daily return in a month (*MAX*), the turnover in a month (*TURN*), the prior five-year return volatility (*RET5VOL*), the analyst earnings forecast dispersion (*DISP*), the number of shares traded for the whole day (*VOLUME*). The sample covers the period from January 1993 to December 2012.

Decile	1	2	3	4	5	6	7	8	9	10
RET	0.89	1.34	1.56	1.76	1.87	1.90	2.01	2.05	2.08	2.32
CORR	-0.46	-0.28	-0.19	-0.11	-0.05	0.02	0.09	0.16	0.26	0.43
BETA	1.19	1.22	1.24	1.25	1.27	1.26	1.28	1.28	1.30	1.31
LNME	6.18	6.41	6.48	6.54	6.56	6.58	6.62	6.65	6.66	6.55
LNBM	-0.68	-0.71	-0.73	-0.73	-0.74	-0.75	-0.76	-0.77	-0.78	-0.78
MOM	13.41	14.33	14.99	15.34	15.97	16.02	16.59	17.12	18.01	18.24
REV	2.12	2.11	2.08	2.04	1.99	1.90	2.02	1.93	1.92	1.73
ILLIQ	0.65	0.53	0.40	0.37	0.42	0.36	0.30	0.27	0.29	0.30
VRSPR	0.91	0.88	0.79	0.71	0.96	0.81	0.81	0.76	0.65	0.93
FT	-7.31	-3.83	-0.11	-7.22	-6.19	-3.59	3.69	2.35	3.33	-4.02
VP	4.43	-0.39	7.10	-0.23	-0.23	-0.33	-0.58	-0.31	-0.30	-0.22
AP1	0.76	0.73	0.73	0.73	0.73	0.72	0.72	0.72	0.72	0.73
AP2	0.12	0.09	0.08	0.08	0.08	0.08	0.07	0.07	0.07	0.07
AP3	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
AP4	-0.81	-0.62	-0.56	-0.54	-0.53	-0.51	-0.48	-0.46	-0.46	-0.48
PS	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
COSKEW	-0.88	-0.74	-0.69	-0.72	-0.66	-0.65	-0.60	-0.66	-0.55	-0.66
IVOL	2.14	2.19	2.23	2.27	2.32	2.36	2.42	2.48	2.57	2.87
MAX	5.28	5.52	5.68	5.84	5.99	6.13	6.34	6.49	6.79	7.72
TURN	0.60	0.67	0.69	0.72	0.75	0.77	0.80	0.82	0.85	0.92
RET5VOL	12.72	12.80	12.82	12.86	12.92	12.92	12.99	13.05	13.15	13.38
DISP	0.17	0.16	0.15	0.15	0.16	0.15	0.16	0.16	0.15	0.16

Table 5: CORR and Future Returns: Bivariate Portfolio Analysis

This table reports the equal-weighted returns and return differences in month t+1 between low and high correlation (*CORR*) decile portfolios, the corresponding 4-factor alphas, and the abnormal returns after controlling for a given firm characteristic. *CORR* is the quote-based correlation between the opening half hour return and the rest of day's return. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted bid-ask spreads. *PS* is the Pastor and Stambaugh liquidity beta. *COSKEW* and *IVOL* are the co-skewness and idiosyncratic volatility, respectively. *MAX* denotes the maximum daily return in a month. *TURN* is the share turnover. *RET5VOL* is the past five-year monthly return volatility. *DISP* measures the analyst earnings forecast dispersion. In Panel A, stocks are first sorted into control variable quintiles and then, within each control variable quintile, into *CORR* deciles. In Panel B, stocks are independently sorted into control variable and *CORR* quintiles. Panels report average returns of the *CORR* deciles portfolios, averaged across the ten control deciles to produce decile portfolios with dispersion in *CORR* but with similar levels of the control variable. Newey-West t-statistics are reported in parentheses. The sample covers the period from January 1993 to December 2012.

Panel A: Dependent bivariate sorts

	BETA	LNME	LNBM	MOM	REV	ILLIQ	VRSPR	PS	COSKEW	IVOL	MAX	TURN	RET5VOL	DISP
1 (Low)	1.68	1.53	1.58	1.58	1.60	1.61	1.56	1.59	1.54	1.60	1.56	1.54	1.63	1.57
2	1.35	1.34	1.31	1.37	1.34	1.34	1.34	1.39	1.35	1.38	1.41	1.35	1.40	1.27
3	1.33	1.30	1.41	1.38	1.36	1.39	1.42	1.36	1.37	1.36	1.35	1.32	1.32	1.36
4	1.54	1.45	1.48	1.46	1.48	1.46	1.44	1.53	1.48	1.47	1.37	1.43	1.51	1.51
5	1.28	1.27	1.31	1.30	1.29	1.30	1.29	1.27	1.30	1.26	1.32	1.27	1.33	1.26
6	1.33	1.27	1.34	1.27	1.29	1.33	1.40	1.35	1.30	1.34	1.31	1.32	1.36	1.26
7	1.30	1.28	1.22	1.28	1.30	1.28	1.34	1.26	1.23	1.17	1.21	1.26	1.29	1.25
8	1.18	1.18	1.26	1.15	1.13	1.21	1.22	1.16	1.20	1.17	1.19	1.12	1.19	1.12
9	1.17	1.20	1.21	1.15	1.18	1.22	1.25	1.18	1.15	1.13	1.11	1.21	1.18	1.14
10(High)	1.23	1.19	1.24	1.20	1.23	1.26	1.27	1.27	1.20	1.19	1.26	1.27	1.25	1.23
Low - High	0.45	0.34	0.34	0.37	0.37	0.34	0.29	0.32	0.34	0.41	0.30	0.27	0.38	0.34
	[2.68]	[2.04]	[2.36]	[2.48]	[2.48]	[2.06]	[1.96]	[2.2]	[2.27]	[2.71]	[2.14]	[1.96]	[2.63]	[2.40]
AlphaFF	0.46	0.35	0.36	0.38	0.38	0.36	0.31	0.34	0.36	0.41	0.31	0.28	0.40	0.36
	[2.64]	[2.21]	[2.45]	[2.52]	[2.51]	[2.16]	[1.97]	[2.37]	[2.33]	[2.71]	[2.13]	[1.96]	[2.77]	[2.59]
AlphaM	0.38	0.24	0.31	0.30	0.32	0.27	0.19	0.26	0.27	0.38	0.28	0.20	0.33	0.26
	[2.68]	[1.75]	[2.36]	[2.48]	[2.48]	[1.96]	[1.67]	[1.87]	[1.85]	[2.55]	[2.04]	[1.79]	[2.09]	[1.96]

Panel B: Independent bivariate sorts

	BETA	LNME	LNBM	MOM	REV	ILLIQ	VRSPR	PS	COSKEW	IVOL	MAX	TURN	RET5VOL	DISP
1 (Low)	1.64	1.51	1.56	1.59	1.60	1.58	1.55	1.61	1.55	1.62	1.57	1.57	1.60	1.53
2	1.37	1.34	1.34	1.36	1.33	1.36	1.36	1.35	1.33	1.36	1.33	1.31	1.37	1.31
3	1.40	1.36	1.38	1.37	1.38	1.41	1.40	1.39	1.38	1.39	1.36	1.35	1.40	1.34
4	1.50	1.47	1.51	1.48	1.49	1.49	1.50	1.53	1.49	1.50	1.49	1.47	1.51	1.52
5	1.30	1.27	1.29	1.25	1.26	1.29	1.32	1.29	1.26	1.27	1.26	1.27	1.33	1.26
6	1.31	1.29	1.31	1.31	1.31	1.33	1.35	1.31	1.31	1.29	1.29	1.30	1.33	1.28
7	1.30	1.29	1.30	1.27	1.29	1.33	1.35	1.30	1.28	1.26	1.26	1.30	1.32	1.25
8	1.19	1.20	1.21	1.17	1.16	1.22	1.25	1.18	1.17	1.15	1.17	1.19	1.19	1.14
9	1.17	1.16	1.20	1.13	1.15	1.21	1.25	1.17	1.14	1.13	1.15	1.17	1.16	1.13
10(High)	1.23	1.19	1.26	1.20	1.23	1.25	1.24	1.26	1.20	1.18	1.21	1.23	1.25	1.21
Low - High	0.42	0.33	0.30	0.39	0.37	0.34	0.31	0.35	0.35	0.45	0.36	0.34	0.35	0.32
	[2.47]	[1.89]	[2.19]	[2.54]	[2.43]	[1.89]	[1.75]	[2.31]	[2.30]	[2.81]	[2.33]	[2.30]	[2.43]	[2.22]
AlphaFF	0.42	0.34	0.33	0.40	0.38	0.35	0.33	0.37	0.36	0.45	0.37	0.35	0.37	0.33
	[2.47]	[2.02]	[2.27]	[2.63]	[2.44]	[1.97]	[1.96]	[2.53]	[2.34]	[2.82]	[2.33]	[2.32]	[2.55]	[2.35]
AlphaM	0.35	0.22	0.27	0.33	0.31	0.26	0.23	0.27	0.28	0.40	0.32	0.26	0.30	0.25
	[2.03]	[1.64]	[1.91]	[1.97]	[1.94]	[1.63]	[1.62]	[1.95]	[1.78]	[2.47]	[2.06]	[1.87]	[1.99]	[1.94]

Table 6: Monthly Predictive Regressions

Monthly excess stock returns are regressed on a set of lagged predictive variables using the Fama-MacBeth (1973) methodology. This table reports the average slope coefficients. Return Correlation (*CORR*) is the correlation between the first half hour return in month *t* and the return for the rest of the trading day in the same month. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted effective bid-ask spreads. *FT* and *VP* denote Sadka's illiquidity risk exposure on the fixed and the variable components respectively. *AP1*, *AP2*, *AP3* and *AP4* represent the four betas of the Acharya and Pedersen liquidity measures. *PS* is the Pastor and Stambaugh liquidity beta. *COSKEW* and *IVOL* are the co-skewness and idiosyncratic volatility, respectively. *MAX* denotes the maximum daily return in a month. *TURN* is the share turnover. *RET5VOL* is the past five-year monthly return volatility. *DISP* measures the analyst earnings forecast dispersion. Newey-West *t*-statistics are reported in parentheses. The sample covers the period from January 1993 to December 2012. Panel A reports results from the quote-based correlation measure, and Panel B reports results from the trade-based correlation measure.

Panel A: Quote-based correlation measure

$Y = RET_{t+1}$	M1	M2	M3	M4	M5	M6	M7	M8
<i>CORR</i>	-0.274 [-3.05]	-0.265 [-2.78]	-0.263 [-2.86]	-0.226 [-2.58]	-0.219 [-2.37]	-0.260 [-2.66]	-0.229 [-2.42]	-0.216 [-2.12]
<i>BETA</i>	0.239 [1.43]	0.106 [0.72]	0.080 [0.56]	0.108 [0.96]	0.096 [0.82]	0.111 [0.70]	0.155 [1.18]	0.150 [1.09]
<i>LNME</i>	-0.179 [-3.63]	-0.120 [-2.86]	-0.108 [-2.46]	-0.096 [-2.03]	-0.087 [-1.67]	-0.155 [-2.37]	-0.141 [-2.12]	-0.131 [-1.77]
<i>LNBM</i>	0.078 [0.64]	0.090 [0.87]	0.106 [1.03]	0.089 [1.13]	0.045 [0.54]	0.106 [0.96]	0.095 [1.15]	0.052 [0.59]
<i>MOM</i>		0.002 [0.68]	0.002 [0.79]	0.002 [0.93]	0.002 [0.73]	0.002 [0.70]	0.002 [0.81]	0.002 [0.65]
<i>REV</i>		-0.033 [-5.39]	-0.031 [-5.21]	-0.036 [-5.87]	-0.035 [-5.43]	-0.032 [-5.09]	-0.037 [-5.86]	-0.038 [-5.68]
<i>ILLIQ</i>			-0.161 [-1.63]	-0.179 [-2.26]	-0.646 [-3.17]	-0.321 [-2.87]	-0.324 [-3.20]	-0.955 [-3.81]
<i>VRSPR</i>			0.109 [1.13]	0.160 [1.66]	0.180 [1.25]	0.068 [0.58]	0.106 [0.91]	0.091 [0.54]
<i>FT</i>						0.004 [1.26]	0.001 [0.32]	0.000 [-0.05]
<i>VP</i>						-0.010 [-0.85]	-0.015 [-1.16]	-0.015 [-1.18]
<i>AP1</i>						-1.154 [-1.34]	-0.899 [-1.08]	-1.139 [-1.07]
<i>AP2</i>						-1.221 [-0.67]	-2.035 [-1.00]	-13.780 [-1.18]
<i>AP3</i>						0.062 [0.01]	3.051 [0.28]	1.077 [0.07]
<i>AP4</i>						-0.511 [-1.55]	-0.672 [-1.82]	-2.121 [-1.97]
<i>PS</i>				0.054 [0.35]	0.084 [0.51]		0.145 [0.91]	0.203 [1.25]
<i>COSKEW</i>				0.255 [0.36]	0.194 [0.25]		0.306 [0.39]	0.204 [0.25]
<i>IVOL</i>				-0.125	-0.104		-0.139	-0.132

					[-2.10]	[-1.56]		[-2.20]	[-1.89]
MAX					0.037	0.043		0.043	0.052
					[2.22]	[2.37]		[2.44]	[2.77]
TURN					3.601	7.318		4.784	9.326
					[0.38]	[0.65]		[0.47]	[0.78]
RET5VOL					0.145	-0.690		0.251	-0.735
					[0.10]	[-0.47]		[0.16]	[-0.44]
DISP						-0.085			-0.070
						[-1.71]			[-1.31]
Intercept	1.999	1.535	1.416	1.368	1.284	2.384	2.158	2.042	
	[4.64]	[3.64]	[2.95]	[2.59]	[2.16]	[2.60]	[2.43]	[2.08]	
N	591,757	553,139	547,364	521,493	427,012	494,655	469,928	383,792	
R-sq	0.04	0.06	0.06	0.08	0.09	0.07	0.09	0.10	

Panel B: Trade-based correlation measure

$Y = RET_{t+1}$	M1	M2	M3	M4	M5	M6	M7	M8
CORR	-0.310 [-2.83]	-0.312 [-2.71]	-0.274 [-2.47]	-0.242 [-2.18]	-0.199 [-1.79]	-0.288 [-2.44]	-0.270 [-2.24]	-0.238 [-2.03]
BETA	0.187 [1.09]	0.071 [0.47]	0.044 [0.30]	0.095 [0.81]	0.091 [0.77]	0.065 [0.39]	0.145 [1.05]	0.146 [1.05]
LNME	-0.253 [-3.96]	-0.179 [-3.38]	-0.060 [-1.16]	-0.065 [-1.16]	-0.070 [-1.20]	-0.095 [-1.32]	-0.101 [-1.30]	-0.110 [-1.37]
LNBM	0.084 [0.65]	0.094 [0.85]	0.110 [1.02]	0.073 [0.83]	0.051 [0.59]	0.119 [1.02]	0.085 [0.93]	0.058 [0.64]
MOM		0.002 [0.60]	0.002 [0.72]	0.002 [0.80]	0.002 [0.73]	0.001 [0.39]	0.001 [0.43]	0.001 [0.46]
REV		-0.023 [-3.44]	-0.022 [-3.26]	-0.026 [-3.60]	-0.029 [-4.02]	-0.024 [-3.37]	-0.029 [-3.80]	-0.033 [-4.24]
ILLIQ			7.038 [2.63]	4.104 [1.68]	1.028 [0.37]	2.678 [1.09]	0.058 [0.03]	-3.349 [-1.05]
VRSPR			0.503 [2.01]	0.582 [2.55]	0.640 [2.21]	0.511 [1.99]	0.613 [2.80]	0.526 [1.78]
FT				0.670 [0.81]	0.393 [0.46]		0.758 [0.86]	0.443 [0.49]
VP				-0.106 [-1.68]	-0.133 [-1.98]		-0.163 [-2.51]	-0.192 [-2.67]
AP1				0.027 [1.44]	0.041 [2.15]		0.043 [2.18]	0.058 [2.79]
AP2				0.024 [0.14]	0.096 [0.57]		0.121 [0.71]	0.224 [1.36]
AP3				1.433 [0.14]	9.013 [0.75]		2.101 [0.20]	11.310 [0.90]
AP4				-0.237 [-0.16]	-0.722 [-0.45]		-0.080 [-0.05]	-0.664 [-0.37]
PS					-0.084 [-1.40]			-0.074 [-1.12]
COSKEW						0.006 [1.65]	0.001 [0.31]	0.001 [0.15]
IVOL						-0.012 [-0.88]	-0.018 [-1.27]	-0.021 [-1.44]
MAX						-0.767 [-0.76]	-0.392 [-0.38]	-0.762 [-0.70]
TURN						-17.720 [-0.80]	-13.480 [-0.55]	-32.780 [-0.85]
RET5VOL						-0.314 [-0.03]	4.556 [0.33]	6.204 [0.43]
DISP						-5.540 [-2.02]	-4.808 [-1.89]	-8.883 [-1.66]
Intercept	2.705 [4.72]	2.087 [3.90]	0.949 [1.67]	1.085 [1.71]	1.126 [1.70]	1.500 [1.51]	1.443 [1.40]	1.736 [1.64]
N	455,867	429,706	427,036	408,327	374,802	383,411	365,593	334,706
R-sq	0.05	0.07	0.07	0.10	0.10	0.09	0.11	0.11

Table 7: The Effect of Earnings Surprises on CORR

Monthly excess stock returns are regressed on a set of lagged predictive variables using the Fama-MacBeth (1973) methodology. This table reports the average slope coefficients. Return Correlation (*CORR*) is the quote-based correlation between the first half hour return in month *t* and the return for the rest of the trading day in the same month. *EARNINGS* captures the earnings surprises. *CORR*/ES/* indicates the interaction of *CORR* and the absolute value of the earnings surprises (*ES*). *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted effective bid-ask spreads. *COSKEW* and *IVOL* are the co-skewness and idiosyncratic volatility, respectively. *MAX* denotes the maximum daily return in a month. *TURN* is the share turnover. *RETSVOL* is the past five-year monthly return volatility. Newey-West t-statistics are given in parentheses. The sample covers the period from January 1993 to December 2012.

$Y = RET_{t+1}$	M1	M2	M3	M4
CORR	-0.261 [-2.86]	-0.252 [-2.59]	-0.251 [-2.68]	-0.209 [-2.34]
ES	14.040 [2.34]	15.600 [2.75]	16.550 [3.05]	0.092 [0.85]
CORR* ES	-38.960 [-2.32]	-39.050 [-2.34]	-34.430 [-2.05]	-0.101 [-2.17]
BETA	0.237 [1.43]	0.107 [0.73]	0.081 [0.56]	0.089 [1.11]
LNME	-0.179 [-3.63]	-0.121 [-2.88]	-0.108 [-2.48]	13.840 [2.70]
LNBM	0.080 [0.66]	0.094 [0.91]	0.110 [1.07]	-33.800 [-2.06]
MOM		0.002 [0.61]	0.002 [0.71]	0.002 [0.82]
REV		-0.033 [-5.51]	-0.032 [-5.33]	-0.037 [-5.89]
ILLIQ			-0.166 [-1.69]	-0.209 [-2.45]
VRSPR			0.111 [1.17]	0.163 [1.72]
COSKEW				0.092 [0.14]
IVOL				-0.126 [-2.04]
MAX				0.035 [2.02]
TURN				5.911 [0.61]
RETSVOL				0.157 [0.12]
Intercept	2.009 [4.67]	1.546 [3.66]	1.425 [2.98]	1.420 [2.70]
N	591,747	553,133	547,358	547,358
R-sq	0.04	0.06	0.07	0.08

Table 8: Subsample Analysis

Monthly excess stock returns are regressed on a set of lagged predictive variables using the Fama-MacBeth (1973) regression methodology for various sample periods. Recession and Crisis period spans March 2001 to November 2001 and July 2007 to June 2009, whereas the Expansion and Non-Crisis period covers the remaining periods in our 1993-2012 sample. The High VIX periods corresponds to the periods that VIX is higher than 30%, and the Low VIX periods are the time that VIX is less than 15%. This table reports the average slope coefficients and the different in CORR coefficients test. Return Correlation (*CORR*) is the quote-based correlation between the first half hour return in month t and the return for the rest of the trading day in the same month. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted effective bid-ask spreads. Newey-West t-statistics are given in parentheses for the regression coefficients, and the standard t-statistics are reported for the difference test.

$Y = RET_{t+1}$	Recession and Crisis	Expansion and Non-Crisis	High VIX	Low VIX
CORR	-0.695 [-2.56]	-0.193 [-2.11]	-0.505 [-2.70]	-0.104 [-1.11]
BETA	0.118 [0.22]	0.074 [0.53]	0.435 [0.61]	0.225 [1.97]
LNME	-0.310 [-2.12]	-0.075 [-1.77]	-0.063 [-0.51]	-0.087 [-1.76]
LNBM	-0.250 [-1.47]	0.163 [1.43]	-0.337 [-1.45]	0.086 [0.93]
MOM	-0.010 [-0.65]	0.004 [2.30]	-0.020 [-1.32]	0.006 [3.00]
REV	-0.044 [-2.41]	-0.029 [-5.00]	-0.055 [-3.13]	-0.024 [-3.91]
ILLIQ	-0.189 [-1.32]	-0.156 [-1.41]	0.022 [0.12]	-0.107 [-0.98]
VRSPR	0.083 [0.27]	0.113 [1.16]	0.108 [0.38]	0.048 [0.60]
Intercept	0.392 [0.26]	1.579 [3.23]	-2.065 [-1.80]	2.020 [4.44]
N	79,771	467,587	71,701	279,193
R-sq	0.09	0.06	0.10	0.04
Diff		0.502		0.401
T-stats		[2.07]		[1.85]

Table 9: January versus non-January Months

Monthly excess stock returns are regressed on a set of lagged predictive variables using the Fama-MacBeth (1973) regression methodology. This table reports the average slope coefficients. Return Correlation (*CORR*) is the quote-based correlation between the first half hour return in month *t* and the return for the rest of the trading day in the same month. January column reports the results for the January observations in the sample, Non-January column reports the results for the remaining months in the sample. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted effective bid-ask spreads. Newey-West t-statistics are given in parentheses. The sample covers the period from January 1993 to December 2012.

$Y = RET_{t+1}$	January	Non-January
CORR	-0.704 [-2.48]	-0.222 [-2.41]
BETA	-0.304 [-0.66]	0.115 [0.74]
LNME	-0.066 [-0.38]	-0.111 [-2.45]
LNBM	0.149 [0.28]	0.102 [1.15]
MOM	0.005 [1.00]	0.002 [0.67]
REV	-0.016 [-0.66]	-0.033 [-5.26]
ILLIQ	0.136 [0.28]	-0.188 [-1.90]
VRSPR	0.069 [0.23]	0.113 [1.14]
Intercept	0.828 [0.71]	1.469 [2.93]
N	45,097	502,261
R-sq	0.07	0.06
Diff		0.482
t-stat		[1.62]

Table 10: Weighted Least Squares Regressions

The cross section of monthly excess stock returns is regressed on a set of lagged predictive variables using the monthly weighted least squares (WLS) methodology following Asparouhova, Bessembinder, and Kalcheva (2010). The prior-period (one-plus) returns are used as the weighting variable for the WLS estimation. This table reports the average slope coefficients. Return Correlation (*CORR*) is the quote-based correlation between the first half hour return in month *t* and the return for the rest of the trading day in the same month. *BETA*, *LNME*, and *LNBM* denote the market beta, the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *MOM* is the momentum return. *REV* is the short-term reversal. *ILLIQ* denotes the Amihud's illiquidity measure. *VRSPR* is the volume-weighted effective bid-ask spreads. *FT* and *VP* denote Sadka's illiquidity risk exposure on the fixed and the variable components respectively. *AP1*, *AP2*, *AP3* and *AP4* represent the four betas of the Acharya and Pedersen liquidity measures. *PS* is the Pastor and Stambaugh liquidity beta. *COSKEW* and *IVOL* are the co-skewness and idiosyncratic volatility, respectively. *MAX* denotes the maximum daily return in a month. *TURN* is the share turnover. *RET5VOL* is the past five-year monthly return volatility. *DISP* measures the analyst earnings forecast dispersion. Newey-West *t*-statistics are reported in parentheses. The sample covers the period from January 1993 to December 2012.

$Y = RET_{t+1}$	M1	M2	M3	M4	M5	M6	M7
CORR	-0.317 [-3.37]	-0.335 [-3.43]	-0.331 [-3.18]	-0.334 [-3.33]	-0.325 [-3.19]	-0.239 [-2.50]	-0.235 [-2.29]
BETA	0.253 [1.49]	0.105 [0.71]	0.131 [0.78]	0.108 [0.70]	0.127 [0.78]	0.180 [1.34]	0.194 [1.38]
LNME	-0.210 [-4.40]	-0.140 [-3.25]	-0.104 [-2.10]	-0.155 [-2.18]	-0.153 [-2.15]	-0.154 [-2.09]	-0.163 [-1.96]
LNBM	0.036 [0.30]	0.074 [0.71]	0.106 [0.95]	0.091 [0.82]	0.095 [0.86]	0.065 [0.83]	0.003 [0.04]
MOM		0.001 [0.41]	0.001 [0.43]	0.001 [0.42]	0.001 [0.45]	0.002 [0.57]	0.001 [0.47]
REV		-0.037 [-5.55]	-0.036 [-5.43]	-0.036 [-5.51]	-0.036 [-5.45]	-0.041 [-6.07]	-0.041 [-5.67]
ILLIQ			-0.155 [-1.47]	-0.288 [-2.62]	-0.289 [-2.62]	-0.316 [-2.98]	-0.920 [-3.54]
VRSPR			0.209 [2.00]	0.149 [1.25]	0.155 [1.31]	0.221 [1.83]	0.204 [1.06]
FT			0.001 [0.24]		0.000 [0.12]	-0.002 [-0.67]	-0.003 [-0.91]
VP			-0.009 [-0.75]		-0.009 [-0.79]	-0.014 [-1.09]	-0.014 [-1.10]
AP1				-1.097 [-1.22]	-1.192 [-1.33]	-1.060 [-1.19]	-1.402 [-1.24]
AP2				-0.699 [-0.34]	-0.964 [-0.47]	-1.527 [-0.73]	-14.000 [-1.16]
AP3				1.016 [0.10]	-0.038 [-0.00]	5.884 [0.49]	5.540 [0.36]
AP4				-0.392 [-1.02]	-0.443 [-1.16]	-0.599 [-1.54]	-2.185 [-1.93]
PS						0.068 [0.40]	0.129 [0.74]
COSKEW						0.628 [0.77]	0.666 [0.73]
IVOL						-0.142	-0.115

						[-1.98]	[-1.38]
MAX						0.029	0.035
						[1.39]	[1.50]
TURN						-2.812	-0.310
						[-0.27]	[-0.03]
RETSVOL						0.382	-0.946
						[0.23]	[-0.55]
DISP							-0.072
							[-1.26]
Intercept	2.279	1.680	1.296	2.344	2.346	2.430	2.539
	[5.46]	[4.12]	[2.50]	[2.42]	[2.41]	[2.47]	[2.31]
N	591,757	553,139	494,713	494,655	494,655	469,928	383,792
R-sq	0.04	0.06	0.07	0.07	0.08	0.10	0.11

Table 11: Spearman CORR Portfolios: Univariate Portfolio Analysis

For each month, NYSE, Amex, and NASDAQ stocks are sorted into ten decile portfolios based on return correlation (*CORR*), which is the monthly Spearman correlation between the opening half-hour returns and the remaining return of the day. This table reports the average monthly returns in month t+1 (RET), 3-factor Fama-French (1993) alphas, and the average abnormal returns based on Fama-French 25 size and book-to-market portfolios (AlphaM) for each *CORR* portfolio. Columns “Avg CORR” reports average *CORR* values for each decile portfolio. The last column shows the average market share of each portfolio. The last row shows the 1-10 differences in monthly returns between Low and High *CORR* decile portfolios, the corresponding 3-factor alphas, and the abnormal returns. Average returns and alphas are defined in monthly percentage terms. The entries in Panels A and B are based on the CRSP and NYSE decile breakpoints from the quote-based correlation measure, and the entries in Panels C and D are based on the CRSP and NYSE decile breakpoints from the trade-based correlation measure. Newey-West t-statistics are given in parentheses. The sample covers the period from January 1993 to December 2012.

Panel A: CRSP Decile Breakpoints (Quote-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.53 [4.71]	0.67 [7.20]	0.57 [5.14]	1.15 [3.50]	0.32 [2.26]	0.26 [1.74]	-0.42	7.84
2	1.37 [4.16]	0.51 [5.77]	0.41 [4.29]	0.81 [2.61]	0.04 [0.39]	-0.04 [-0.27]	-0.26	8.91
3	1.38 [4.03]	0.50 [5.75]	0.44 [5.42]	0.89 [2.85]	0.12 [1.32]	0.03 [0.32]	-0.17	9.76
4	1.39 [3.97]	0.50 [6.02]	0.45 [5.89]	0.82 [2.52]	0.07 [0.76]	0.07 [0.69]	-0.10	10.13
5	1.34 [3.90]	0.44 [5.31]	0.40 [4.57]	1.03 [3.18]	0.22 [2.20]	0.24 [1.79]	-0.04	10.16
6	1.27 [3.54]	0.36 [3.86]	0.31 [4.04]	0.86 [2.40]	0.14 [1.31]	0.05 [0.41]	0.02	10.92
7	1.25 [3.45]	0.33 [3.92]	0.33 [4.40]	0.83 [2.41]	0.01 [0.15]	0.05 [0.40]	0.09	10.73
8	1.29 [3.68]	0.36 [4.96]	0.38 [5.56]	0.76 [2.34]	-0.02 [-0.20]	-0.04 [-0.33]	0.16	10.79
9	1.13 [3.26]	0.20 [2.20]	0.26 [2.73]	0.73 [2.17]	0.01 [0.06]	-0.10 [-0.72]	0.24	10.55
10 (High)	1.22 [3.41]	0.31 [3.31]	0.33 [3.52]	0.40 [1.10]	-0.35 [-2.69]	-0.37 [-2.33]	0.40	10.22
1 - 10 (Low-High)	0.31 [2.96]	0.36 [3.59]	0.25 [2.22]	0.75 [2.85]	0.67 [2.86]	0.64 [2.63]		

Table 11 –continued

Panel B: NYSE Decile Breakpoints (Quote-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.53 [4.72]	0.67 [7.34]	0.58 [5.42]	1.11 [3.40]	0.30 [2.04]	0.23 [1.46]	-0.41	9.21
2	1.35 [4.02]	0.47 [5.42]	0.39 [4.13]	0.80 [2.57]	0.00 [-0.05]	-0.04 [-0.33]	-0.24	9.33
3	1.36 [3.97]	0.48 [5.47]	0.40 [5.06]	0.83 [2.64]	0.09 [0.79]	-0.02 [-0.15]	-0.16	9.93
4	1.37 [3.91]	0.48 [5.64]	0.46 [5.50]	0.91 [2.79]	0.14 [1.88]	0.14 [1.52]	-0.09	10.21
5	1.33 [3.86]	0.43 [5.11]	0.35 [4.55]	0.94 [2.76]	0.16 [1.59]	0.11 [0.94]	-0.03	10.18
6	1.28 [3.59]	0.36 [4.08]	0.32 [4.27]	0.89 [2.68]	0.15 [1.25]	0.10 [0.79]	0.03	10.30
7	1.24 [3.44]	0.32 [3.64]	0.32 [4.16]	0.85 [2.52]	0.07 [0.74]	0.08 [0.64]	0.09	10.45
8	1.27 [3.60]	0.33 [4.34]	0.39 [5.10]	0.79 [2.40]	0.00 [-0.04]	-0.01 [-0.09]	0.16	10.29
9	1.14 [3.24]	0.21 [2.38]	0.25 [2.75]	0.67 [1.92]	-0.08 [-0.67]	-0.18 [-1.32]	0.25	10.21
10 (High)	1.22 [3.45]	0.31 [3.45]	0.33 [3.59]	0.42 [1.17]	-0.34 [-2.55]	-0.33 [-2.07]	0.41	9.90
1 - 10 (Low-High)	0.31 [3.17]	0.37 [3.83]	0.25 [2.47]	0.69 [2.53]	0.64 [2.62]	0.57 [2.24]		

Table 11 –continued

Panel C: CRSP Decile Breakpoints (Trade-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.74 [4.85]	0.83 [6.73]	0.72 [6.69]	1.08 [3.01]	0.25 [1.38]	0.16 [0.76]	-0.44	7.33
2	1.43 [3.92]	0.51 [4.29]	0.52 [4.84]	0.87 [2.87]	0.14 [1.37]	0.02 [0.17]	-0.28	8.88
3	1.40 [3.60]	0.45 [4.53]	0.46 [5.12]	1.05 [3.56]	0.25 [2.72]	0.21 [1.93]	-0.19	9.53
4	1.28 [3.46]	0.36 [3.87]	0.34 [4.76]	0.92 [2.78]	0.20 [1.64]	0.11 [1.13]	-0.12	9.95
5	1.36 [3.51]	0.43 [4.27]	0.43 [4.20]	0.92 [2.60]	0.12 [1.09]	0.11 [0.87]	-0.05	10.40
6	1.31 [3.49]	0.35 [4.26]	0.36 [5.00]	0.86 [2.55]	0.12 [1.20]	0.04 [0.41]	0.01	10.37
7	1.29 [3.31]	0.34 [3.29]	0.33 [4.04]	0.93 [2.68]	0.12 [1.15]	0.11 [0.86]	0.07	10.87
8	1.31 [3.46]	0.36 [4.15]	0.38 [4.32]	0.70 [2.08]	-0.05 [-0.52]	-0.09 [-0.73]	0.14	11.15
9	1.10 [2.93]	0.16 [1.82]	0.20 [2.68]	0.69 [1.95]	-0.07 [-0.74]	-0.16 [-1.11]	0.23	11.01
10 (High)	1.14 [3.02]	0.18 [1.78]	0.28 [2.89]	0.44 [1.21]	-0.32 [-2.31]	-0.32 [-2.01]	0.39	10.52
1 - 10 (Low-High)	0.60 [3.89]	0.65 [4.54]	0.45 [3.43]	0.65 [2.01]	0.57 [1.98]	0.48 [1.54]		

Table 11 –continued

Panel D: NYSE Decile Breakpoints (Trade-based correlation measure)

Decile	<i>Equal-Weighted</i>			<i>Value-Weighted</i>			Avg CORR	Mkt Share
	RET	AlphaFF	AlphaM	RET	AlphaFF	AlphaM		
1 (Low)	1.71 [4.74]	0.79 [6.62]	0.71 [6.51]	1.04 [3.03]	0.21 [1.39]	0.14 [0.79]	-0.42	8.53
2	1.38 [3.69]	0.45 [3.83]	0.47 [4.51]	0.90 [2.92]	0.13 [1.31]	0.04 [0.26]	-0.26	9.46
3	1.36 [3.64]	0.43 [4.19]	0.42 [4.96]	0.98 [3.24]	0.21 [2.65]	0.15 [1.54]	-0.17	9.75
4	1.28 [3.40]	0.35 [3.75]	0.37 [4.34]	0.92 [2.82]	0.16 [1.28]	0.13 [1.05]	-0.10	10.14
5	1.34 [3.48]	0.41 [4.13]	0.38 [4.13]	0.92 [2.57]	0.14 [1.50]	0.09 [0.79]	-0.04	10.22
6	1.31 [3.49]	0.35 [4.01]	0.36 [5.29]	0.70 [2.04]	-0.06 [-0.54]	-0.10 [-0.96]	0.02	10.36
7	1.33 [3.36]	0.37 [3.49]	0.39 [3.64]	1.14 [3.36]	0.34 [3.06]	0.32 [2.16]	0.08	10.46
8	1.22 [3.28]	0.28 [3.12]	0.30 [4.48]	0.58 [1.73]	-0.17 [-1.78]	-0.23 [-2.01]	0.15	10.65
9	1.10 [2.95]	0.16 [1.75]	0.21 [2.59]	0.69 [2.02]	-0.05 [-0.46]	-0.13 [-0.94]	0.24	10.56
10 (High)	1.15 [3.05]	0.20 [1.84]	0.28 [2.82]	0.46 [1.27]	-0.29 [-2.00]	-0.32 [-1.84]	0.40	9.87
1 - 10 (Low-High)	0.56 [3.65]	0.60 [4.10]	0.43 [3.19]	0.58 [1.95]	0.51 [1.87]	0.46 [1.59]		