# Transitory Price, Resiliency, and the Cross-Section of Stock Returns

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This paper suggests a new measure of resiliency and investigates whether resiliency is a systematic component of liquidity that generates cross-sectional variations in stock returns. Resiliency is defined as quickness of transitory price recovery from a liquidity shock. Using the Beveridge-Nelson decomposition and the spectral analysis in the frequency domain, we measure resiliency as the speed of mean reversion of transitory price components. Main finding is that a zero-investment portfolio that is long in low-resiliency stocks and short in high-resiliency stocks earns significant abnormal returns. Furthermore, we find that our resiliency measure is complementary to existing liquidity measures.

*JEL classification:* G12, G14

*Keywords*: resiliency; liquidity; stock returns; transitory price

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# Transitory Price, Resiliency, and the Cross-Section of Stock Returns


## Abstract

This paper suggests a new measure of resiliency and investigates whether resiliency is a systematic component of liquidity that generates cross-sectional variations in stock returns. Resiliency is defined as quickness of transitory price recovery from a liquidity shock. Using the Beveridge-Nelson decomposition and the spectral analysis in the frequency domain, we measure resiliency as the speed of mean reversion of transitory price components. Main finding is that a zero-investment portfolio that is long in low-resiliency stocks and short in high-resiliency stocks earns significant abnormal returns. Furthermore, we find that our resiliency measure is complementary to existing liquidity measures.



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## 1. Introduction

Depth, breadth, and resiliency are basic requirements for liquid stock markets as described in Bernstein (1987). Among these requirements, depth and breadth have been studied extensively as the two main categories of characterizing liquidity dimensions.[1] One side of the liquidity dimension is trading activity such as total trading volume or share turnover, which represents how actively market investors trade assets. The other side is trading cost, generally estimated using the Amihud (2002) illiquidity or bid–ask spread measures that capture the price impact that investors should bear when executing market orders. Regarding these two categories, measures of liquidity have been well defined and widely discussed in the literature. However, a measure for another side of the liquidity dimension, *resiliency*, has yet to be clearly defined and remains to be an issue that needs further investigation. This study intends to fill this gap by suggesting a new measure of resiliency for individual stocks, and based on the suggested measure, investigating whether resiliency generates cross-sectional variations in stock returns, independently of the existing liquidity and other well-known systematic risk factors.

The concept of resiliency has been introduced in several previous studies. Black (1971) describes a liquid market as a continuous and efficient market in which securities can be bought or sold immediately at very near the current price. Kyle (1985) mentions that resiliency is the speed of the price recovery from an uninformative random shock. He describes the role of informed traders in the market such that *"the resiliency of prices is determined by insider. Noise trading causes the price to wander aimlessly, with no tendency to return an underlying value"*. Bernstein (1987) explains resiliency in terms of order imbalance by arguing that resiliency means a large order flow countervailing a transaction price change attributable to temporary order imbalances. Harris (2003) specifies that resiliency refers to how quickly prices revert to fundamental values driven by value traders after price changes in response to large order flow imbalances initiated by liquidity demanders

[1] Harris (2003) explains that "depth" means the size which investors can trade at a given price and "breadth" means the price at which investors can trade a given size.

or uninformed traders. He also mentions that "*value traders make markets resilient by standing ready to trade when prices move away from fundamental values*". These descriptions indicate that resiliency can be characterized as the speed of price that reverts to its fundamental value from a prior transitory impact driven by informed traders, and that informed traders play a central role in generating market resiliency by buying (selling) if the price is lower (higher) than the fundamental value to earn profits from uninformed traders. It is also suggestive that higher fraction (either in the number or in the size of order flows) of informed traders may lead to more resilient price reversion by responding to a transitory deviation more expeditiously. In short, a stock with higher speed of reversion indicates that it recovers from a prior transitory price impact more quickly, and thus investors can regard it as a more liquid one.

On the basis of the concept from the literature, we first suggest a measure of resiliency. To derive the resiliency measure, we need to decompose daily stock prices into their fundamental components and transitory components because resiliency represents the speed of a transitory price reverting to its fundamental value.[2] To extract transitory stock prices, we use the trend-cycle decomposition methodology introduced by Beveridge and Nelson (1981, hereafter the B-N decomposition). After performing the B-N decomposition, we transform the estimated series of transitory prices into a spectral functional form in the frequency domain to derive the speed of the transitory price recovery as our measure of resiliency.

Some recent empirical studies suggest resiliency measures that can be classified into two types. One type is the degree of mean reversion given that resiliency appears when stock prices revert to fundamental values. Dong et al. (2007) define resiliency as the mean reversion parameter of the stock's intraday pricing-error process, and show that expected stock returns of individual firms are

[2] A number of studies also mention that liquidity measures are related to transitory price effects. Roll (1984) derives bid–ask spreads using the characteristics of the negative autocovariance of the transitory price change. Hasbrouck (1993) and Boehmer (2009) mention that temporary deviations from the efficient price may arise from the transaction costs or dealer inventory effects. Easley, Hvidkjaer, and O'Hara (2010) explain that total price effects can be divided into a permanent component attributable to information and a temporary component attributable to liquidity. Bao, Pan and Wang (2011) argue that the magnitude of transitory price movements reflects the degree of illiquidity because the lack of liquidity causes transitory components in asset prices.

negatively related to resiliency. Alan et al. (2015) calculate resiliency as the intraday serial correlation of the opening half-hour stock returns with those of the remaining hours per trading day. They show that resiliency has a negative relationship with the cross-section of stock returns through both individual firm-level and portfolio-level analyses. The other type of resiliency measures focuses on the recovery process in terms of trading cost measures such as the bid–ask spread or market depth. Anand et al. (2013) suggest a resiliency measure as the average percentage of months that trading costs exceed a two-standard deviation threshold relative to the pre-crisis period during and after the financial crisis. They show that the liquidity supply of buy-side institutions is the main factor for recovery from a liquidity shock in the post-crisis period. Kempf et al. (2015) define resiliency as the mean reversion parameter of a trading cost flow using intraday data, and provide an empirical evidence that supports Foucault et al. (2005) in that resiliency is positively correlated with the proportion of patient traders and negatively correlated with the order arrival rate.

A main distinction of this study is that our resiliency measure is directly derived as the speed of a transitory price recovery. By applying spectral analysis in the frequency domain to cyclical components of stock prices, we obtain the distance and time components of the transitory price recovery, which are combined to calculate the speed. We believe that our measure fits well with the literal definition of resiliency from the previous literature. In addition, our resiliency measure is constructed to overcome the problem that existing studies only examine resiliency over a short horizon, which is pointed out by Anand et al. (2013). Our measure explicitly considers that the transitory price movement has more than one frequency component that reverts to its fundamental value, so that it can capture the speed of the recovery movement over both a short and long horizons. Finally, regarding the data structure, while many previous studies used intraday microstructure data, we use daily stock price data to calculate the monthly resiliency of individual firms, following Amihud (2002).[3]

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[3] Amihud (2002) mentions that intraday microstructure data are not available in many stock markets and do not cover long periods even when available. Following Amihud (2002), we can cover longer period from 1965 to 2013 to implement the asset pricing test and examine a longer–horizon of price recovery movements from the

Based on the suggested measure, we classify individual stocks according to their resiliency and investigate whether the resiliency is a systematic risk factor in asset pricing. Our empirical findings show that resiliency generates cross-sectional variations in stock returns. Expected stock returns are a decreasing function of resiliency, which implies that stocks with lower resiliency need to compensate investors with a higher risk premium. During our sample period of 1965–2013, the result of Fama-Macbeth regression with individual stocks shows that our resiliency measure has a significant predictive power on their expected stock returns. In addition, we find that a resiliency-based portfolio strategy produces positive abnormal returns that are statistically and economically significant after controlling for the six risk factors that are widely adopted in the literature: the market, size and book-to-market factors of Fama and French (1993), the momentum factor of Jegadeesh and Titman (1993), and the two liquidity factors of Pastor and Staumbaugh (2003) and Charoenrook and Conrad (2008). We also find that our resiliency measure is complementary to existing liquidity measures. In the Fama-MacBeth regression, the effect of resiliency does not eliminate the positive predictive power of the Amihud or Roll measure on the stock returns. The result of a double-sorted portfolio analysis based on the Amihud illiquidity measure and our resiliency measure also shows that resiliency can capture additional risk premium in addition to that from the Amihud illiquidity measure. This finding suggests that resiliency can supplement the liquidity dimension and generate additional cross-sectional variations in stock returns that are not explained by existing liquidity measures.

This paper is organized as follows. In Section 2, we describe the construction of resiliency measure and a description of the data. In Section 3, we present the empirical results that show the effect of resiliency on an individual firm’s stock returns and single/double-sorted portfolio analysis. Section 4 concludes.

## 2. Constructing a resiliency measure

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price impact.

Following prior studies such as Roll (1984), Hasbrouck (1993), Boehmer (2009), Easley et al. (2010), and Bao et al. (2011), the stock price can be decomposed into two components. One is the permanent or random walk component that represents the fundamental value of the stock moving along with an informational shock, that is, when new information arrives. The other is a transitory or stationary component that contains temporary price movement deviating from its fundamental value. As previously discussed, resiliency represents how quickly the stock price recovers to its fundamental value from the transitory price impact. In this regard, we measure resiliency as the average speed of the recovery movement of the transitory price component. More specifically, to calculate the measure of a stock's resiliency, we implement the following two-step procedure: First, we decompose an individual stock price into a permanent component and a transitory component. Second, we compute the speed of price recovery of a transitory component using spectral analysis in the frequency domain. This procedure is described in detail in the following sections.

## 2.1. Decomposition of the stock price

To decompose the stock price into permanent and transitory components, we use the B-N decomposition methodology. Assume that the stock price can be decomposed into a random walk component with drift, $q_t$, and a stationary process, $z_t$. Then we model the stock price, $p_t$, as the sum of $q_t$ and $z_t$,

$$p_t = q_t + z_t, \tag{1}$$

$$q_t = q_{t-1} + \mu + \eta_t, \tag{2}$$

$$z_t = \phi z_{t-1} + \varepsilon_t, \tag{3}$$

where $p_t$ is the natural log of a stock price at time t, μ is an expected drift, and $\eta_t$ and $\varepsilon_t$ are shocks at time t. We assume that $z_t$ follows an AR(1) process. We extend this model to incorporate more general processes in the later section

Using this model, we represent the stock return as follows:

$$r_t = p_t - p_{t-1} = \mu + \eta_t + \Delta z_t, \tag{4}$$

where $\Delta z_t = z_t - z_{t-1}$. Because $p_t$ is modeled as the sum of the random walk component and the AR(1) process, the return $r_t^* = r_t - \mu$ follows an ARMA(1,1) process,

$$r_t^* = \phi r_{t-1}^* + \epsilon_t + \theta \epsilon_{t-1}. \tag{5}$$

In the state-space representation, this ARMA(1,1) process can be described as,

$$\widetilde{r_t} = F \cdot \widetilde{r_{t-1}} + R\epsilon_t, \tag{6}$$

where $\widetilde{r_t} = \begin{bmatrix} r_t^* \\ \epsilon_t \end{bmatrix}, F = \begin{bmatrix} \phi & \theta \\ 0 & 0 \end{bmatrix}, R = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

Then, we can obtain the permanent component, $q_t$, and the stationary transitory component, $z_t$, using the following relationship as described in Morley (2002),

$$q_t = p_t + [1\ 0] \sum_{j=1}^{\infty} F^j \widetilde{r_t}$$

$$= p_t + [1\ 0] F(I - F)^{-1} \widetilde{r_t}, \tag{7}$$

$$z_t = p_t - q_t\ , \tag{8}$$

where $I$ is an identity matrix.

## 2.2. Measuring resiliency

The estimated transitory component of a stock price is a stationary series that reverts to the permanent price component. A stock with a higher speed of reversion indicates that it can recover more quickly from a prior transitory price impact. Thus, investors regard this stock as more resilient and, accordingly, more liquid one. On the other hand, a stock with slower reversion of transitory price is regarded as a riskier asset. To measure the speed of recovery, we transform the estimated transitory price to a spectral functional form in the frequency domain using a Fourier transform. We assume that the transitory price series is a finite signal that contains more than one frequency component reverting to its fundamental value. A finite time series has the following discrete Fourier transform relation between the time domain and the frequency domain,

$$Z_k = \sum_{t=1}^{D} z_t e^{-\frac{i2\pi kt}{D}}, \qquad (k = 1, 2, \cdots, D) \quad (9)$$

where $z_t$ is a finite times series data, $Z_k$ represents the spectral function of $z_t$, and *k* is the indicator for the frequency domain. *D* is the total trading days and $i$ denotes imaginary unit. To estimate the pure magnitude of the spectral function without the influence of the number of trading days, we normalize $Z_k$ with *D*. Then, we obtain a normalized functional form, $\tilde{Z}_k$,[4] as

$$\tilde{Z}_k = \frac{1}{D} Z_k \, , \qquad (10)$$

Using equation (10), we compute the magnitude of the normalized spectral function, $|\tilde{Z}_k|$. Because the frequency is defined as the number of cycles per unit time, the period (cycle), $T_k$ $(= \frac{D}{k})$, can be represented as the reciprocal of the scaled version of the frequency component, $f_k \left(= \frac{k}{D}\right)$.[5] The magnitude, $|\tilde{Z}_k|$, indicates the distance to the peak of the swings of the transitory price that deviates from its fundamental value in each frequency level. The period, $T_k$, captures the quickness at which the cycle of each reverting swing is completed. Therefore, the speed of the transitory price

[4] When we implement a discrete Fourier transform, the spectral function contains a scaled sample size term on the magnitude axis. This sample size term is matched with the $2\pi$ term of the magnitude axis in the continuous version of a Fourier transform. Thus, we use the normalized form, $\tilde{Z}_k$, which is divided by its sample size to compute the pure magnitude.

[5] The frequency axis of a spectral function is also scaled by $\frac{1}{D}$ to avoid the influence of the number of trading days and to present the time of each period (cycle) in a day unit. We denote this scaled version of the frequency component as $f_k$.

movement in each frequency level can be obtained by dividing $|\tilde{Z}_k|$ by its corresponding period, $T_k$. Accordingly, our resiliency measure, which is the average speed of the transitory price recovery, can be obtained using the following equation:

$$Resiliency_{i,t} = \frac{1}{[\frac{D_{i,t}}{2}]} \sum_{k=1}^{[D_{i,t}/2]} \frac{2|\tilde{Z}_{k,i,t}|}{T_{k,i,t}} = \frac{1}{[\frac{D_{i,t}}{2}]} \sum_{k=1}^{[D_{i,t}/2]} 2|\tilde{Z}_{k,i,t}| \cdot f_{k,i,t}\ , \tag{11}$$

where $D_{i,t}$ is the number of sample days for which data are available for stock $i$ in the rolling window at the end of each month t. In this study, we use a three-month rolling window to compute stocks' resiliency month by month. $[\frac{D_{i,t}}{2}]$ is the nearest integer to $\frac{D_{i,t}}{2}$.[6] To avoid the effect of outliers, we eliminate the estimated observations of $Resiliency_{i,t}$ at the highest or lowest 1% tails of the distribution.

### 2.3 Data and variable descriptions

We estimate our resiliency measure for the sample of all stocks listed on the NYSE, AMEX and NASDAQ during 1964–2013, using return and volume data from the CRSP database and the merged COMPUSTAT accounting database. Stocks with prices less than $5 at the end of the previous month are excluded and at least 24-month return observations are required for inclusion in the sample. At the end of each month, the B-N decomposition is implemented repeatedly using all available past return data in order to separate the permanent and transitory prices. We then calculate the level of resiliency for individual stocks as in equation (11) using quarter-length (three-month) rolling window month by month.[7] Although daily return data are not required to be consecutive, a stock should have

[6] For the numerator in equation (11), the symmetric property of the spectral function leads to summing up twice the absolute magnitude value with the range of $k = 1, \cdots, [D_{i,t}/2]$ on the frequency axis, which is matched with the range of $0$ to $\pi$ in the continuous version of the Fourier transform.

[7] We also calculate the level of resiliency using other length of rolling windows and find that the results are qualitatively similar to the case of quarter-length rolling window.

observations of more than 70% of trading days in a given quarter to be included in our sample, following Pastor and Stambaugh (2003). To improve the accuracy and reliability of the spectral function calculated through a discrete Fourier transform, we use a longer data series—a quarter as opposed to the month used in Pastor and Stambaugh (2003)—as the length of the rolling window.

With the estimated measures, we proceed to investigate whether the stock resiliency is a systematic risk factor that generates risk premia through the regression analyses. We use two categories of variables that are associated with market liquidity as the control variables in the subsequent regressions. First, to control for the effect of investors' trading activity in the market, we use trading volume and share turnover. Trading volume (*TrdVol*) is defined as the sum of the trading volume during the given month. Share turnover (*TURN*), which is defined as the monthly average of the daily share turnover (the number of shares traded divided by the number of shares outstanding), is also used to control for the trading activeness for a stock given its outstanding amount.

As the second category of liquidity-related variables, we use two trading cost measures developed by Amihud (2002) and Roll (1984), which are widely adopted measures for capturing price impact or market illiquidity. The Amihud illiquidity measure (*Amihud*) is defined as the annual average ratio of the daily absolute returns, $|r_{i,d,t}|$, to the dollar trading volume, $Vol_{i,d,t}$, on that day,

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum\nolimits_d \frac{|r_{i,d,t}|}{Vol_{i,d,t}}, \qquad (12)$$

where $N_{i,t}$ is the number of trading days for which data are available for stock *i* in year *t*.[8] We also include the Roll measure (*Roll*) to capture bid-ask spread of a stock. *Roll* is defined as

$$Roll_{i,t} = 2\sqrt{-Cov(\Delta p_{i,d}, \Delta p_{i,d-1})}\,, \qquad (13)$$

where $\Delta p_d = p_d - p_{d-1}$ for which daily data $p_d$ are available for stock *i* in month *t*. If positive

[8] Following the Amihud (2002) methodology, we calculate the average illiquidity for each stock in a year from daily data and multiply by $10^6$ for scaling.

autocovariance occurs, we force it negative and use the Roll estimate, following Lesmond (2005). *Roll* implies that serially negatively correlated price movements can be interpreted as a bid-ask bounce. We compute *Roll* in a given month only if more than 15 observations of return data exist in its corresponding month.

Additional control variables are included in the regression model. Following Fama and French (1992), we include market beta, firm size, and the book-to-market ratio. To obtain market beta (*Beta*), pre-ranking betas are estimated on 60 monthly returns (minimum 24 monthly returns) in June of year t, and then we double sort the individual stocks using deciles of size and pre-ranking beta. After sorting stocks, we calculate the post ranking monthly returns of each portfolio for the next 12 months, from July of year t to June of year t+1. Finally, we estimate post-ranking betas on 100 portfolios using the full sample period with the CRSP value-weighted portfolio market index. For firm size (*Ln_ME*), we use the natural logarithm of a firm's market capitalization for June of year t. For the book-to-market ratio (*Ln_BM*), we use a firm's book value of stockholders' equity plus deferred taxes and investment tax credit, minus the book value of preferred stock for the last fiscal year end divided by the market equity value at the end of December of year t-1. The volatility measure (*Vol*) is the standard deviation of the monthly returns of a stock for the past 60 months (minimum 24 months).

<Table 1 here>

Table 1 shows the descriptive statistics of the main variables used in our empirical analysis. The summary statistics are reported in Panel A including the $5^{th}$, $25^{th}$, $50^{th}$, $75^{th}$, and $95^{th}$ percentile values, as well as the mean and the standard deviation of each variable. In Panel B, we report the pair-wise correlation matrix of the variables. The estimated correlation coefficients between *Resiliency* and other liquidity variables such as *Roll*, *Amihud*, *TrdVol*, and *TURN* are relatively low with the range from -0.049 to 0.302. This is consistent with our hypotheses that resiliency captures an additional liquidity dimension.

## 3. Empirical results

An important issue in the study of stock market resiliency is whether resiliency has an independent role to capture another dimension of liquidity risk. In order to provide a preliminary answer to this issue and to motivate our empirical analysis, we begin by presenting the estimates of liquidity risk premia from two different sources of liquidity in Figure 1. We first divide the sample stocks into small, medium, and large groups based on the firm size, and then independently double sort each group of stocks to construct quintile portfolios by the Amihud illiquidity measure and the suggested resiliency measure, respectively. For each size group, the illiquidity premium is derived by the return difference between the simple average of the high and low Amihud illiquidity portfolios, and the resiliency premium comes from the return difference between the simple average of the high and low resiliency portfolios. Then we further calculate the return difference between the portfolio with high Amihud illiquidity and high resiliency (AHRH) and that with low Amihud illiquidity and low resiliency (ALRL) to represent the relative return performance of two portfolios with contrasting liquidity profiles. That is, AHRH is exposed to high Amihud illiquidity but highly resilient, and ALRL is liquid in the Amihud sense but illiquid with low resiliency.

<Figure 1 here>

Figure 1 shows that, while both high Amihud illiquidity and low resiliency generate positive and significant risk premia, the return difference between AHRH and ALRL becomes insignificant. If resiliency does not capture an independent aspect of liquidity, then either the resiliency cannot generate a significant risk premium or the return difference should be close to the Amihud illiquidity premium. However, the insignificant return difference observed in Figure 1 indicates that the Amihud illiquidity premium is offset by contrasting resiliency profile. This result, combined with the significant resiliency premium, suggests that resiliency is potentially a systematic component of asset market liquidity. While a close overlapping between Amihud liquidity and resiliency might be raised as one possibility to explain the observed risk premia, this argument cannot be accepted with the low correlation between the Amihud illiquidity and the resiliency in the range from 0.054 (large size) to

0.291 (small size). Motivated with this figure, we will perform a formal regression analysis to investigate whether resiliency is a systematic component of liquidity that generates cross-sectional variations in stock returns after controlling for various firm characteristics, including other dimensions of liquidity, in the subsequent sections.

## 3.1. Cross-sectional analysis with individual stocks

In this section, we implement a monthly predictive regression to investigate the predictive power of our resiliency measure for the future returns at the individual firm level. The test procedure first follows the Fama and MacBeth (1973) method, and we also run the Fama-MacBeth regression using weighted least squares, following the suggestion by Asparouhavova et al. (2010).

<Table 2 here>

Table 2 presents the results of the Fama-MacBeth cross-sectional regression to verify the predictive power of the resiliency measure on monthly stock returns. For each t, the regression is run, as follows:

$$R_{i,t+1} = \alpha_{t+1} + \gamma_{t+1} Resiliency_{i,t} + \varphi_{t+1} X_{i,t} + \varepsilon_{i,t+1} \, , \tag{14}$$

where $R_{i,t+1}$ is the monthly excess stock return of firm $i$ in month $t+1$, $Resiliency_{i,t}$ represents our resiliency measure, and $X_{i,t}$ is a vector of control variables for stock $i$ in month $t$, respectively. In Panel A, we report the standard Fama-MacBeth regression results. Model 1 is our base model with *Beta*, *Ln_ME* and *Ln_BM* as control variables. These variables are also included in Model 2 to Model 6. Model 2 contains trading cost measures, Model 3 contains a stock return volatility measure, and Model 4 contains both trading activity and trading cost measures. All control variables are included in Model 5, and Model 6 further controls for the January effect. The results show that the sample averages of the coefficients of resiliency are significantly negative for all regression models. These results are consistent with our hypothesis that stocks with low resiliency predict higher returns.

Among the control variables, the coefficients of *Amihud* are positive and statistically significant in all regression models. The coefficient of *Roll* is also positive and statistically significant with *Resiliency and Amihud* (Model 2), although its significance is weakened when we include the trading activity variables in the model (Model 4). Even though trading cost measures are somewhat positively correlated with resiliency as shown in Table 1, their predicting effects for the monthly return have opposite signs indicating that illiquidity in both resiliency and trading cost dimensions require risk premia. For example, in Model 2, the estimated coefficient of resiliency measure is -7.333, whereas the estimated coefficients of *Amihud* and *Roll* are 0.058 and 2.416, respectively. For the trading activity variables, the coefficients of share turnover (*TURN*) and trading volume (*TrdVol*) are not significant and the direction of signs is unclear, and the significance of the estimated coefficients for return volatility (*Vol*) is also limited.

In addition, Panel B reports the estimation results of the Fama-MacBeth regression with weighted least squares. Asparouhova et al. (2010) suggest that the Fama-MacBeth regression by weighted least squares using prior-month gross return as a weighting variable can alleviate the effect of bias arising from noisy prices. Similar to Panel A, the sample averages of the coefficient estimates of our resiliency measure in Model 1 to Model 6 are all significantly negative. The predictive power of *Amihud* is also positive and significant for the entire models. Given the results of the estimated coefficients of *Resiliency*, after including several control variables and correcting for a possible bias arising from noisy prices, we can conclude that our resiliency measure has a predictive power for individual stock returns.

## 3.2 Portfolio analysis: sorting by resiliency

In addition to the Fama-MacBeth cross-sectional regression analysis at the individual stock level, we further perform a portfolio analysis to examine the effect of resiliency on expected stock returns. At the end of each year, all stocks in the sample are sorted into decile portfolios on the basis of the resiliency measure. Then, we obtain monthly value-weighted and equal-weighted returns of each portfolio during the next 12 months. To investigate whether the portfolios sorted by resiliency have abnormal returns, the time-series of returns of the decile portfolios in excess of the risk free rate are regressed on various risk factors that are widely adopted in the literature. We use the Fama-French three factors (*MKT, SMB, HML*), the momentum factor (*MOM*) of Jegadeesh and Titman (1993), and the liquidity risk factor (*LIQ*) suggested by Pastor and Stambaugh (2003).[9] In addition to the five factors, we construct the Amihud illiquidity factor (*AMI*) and include it in our regressions, following Charoenrook and Conrad (2008) and Easley et al. (2010). Then, the resiliency-sorted portfolio excess return, $R_{i,t}$, is regressed on the selected factors as follows:

$$R_{i,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + m_i MOM_t + l_i LIQ_t + a_i AMI_t + \epsilon_{i,t}\,, \qquad (15)$$

<Table 3 here>

Panel A in Table 3 presents the average values of market capitalization and resiliency, and Panel B and C present the monthly raw returns and alphas of value-weighted and equal-weighted decile portfolios sorted on resiliency, respectively. Stocks with the lowest resiliency are grouped in the decile 1 portfolio and stocks with the highest resiliency are grouped in the decile 10 portfolio. Panel A shows that market capitalization decreases almost monotonically as resiliency increases, which seems to be somewhat counterintuitive considering that illiquid stocks tend to have relatively small market capitalization based on the traditional concept of liquidity. However, as is already discussed, informed traders are the main driving force to provide stock market resiliency, and several empirical studies provide an evidence of negative relationship between the proportion of informed traders and firm size. Hasbrouck (1991) shows that the relative proportion of potentially informed traders is larger for firms with smaller market values, and Chung and Charonenwong (1998) find that the percentage of insider trading as a direct measure of informed trading is larger for smaller firms. Easley, Kiefer, O'Hara, and

[9] The Fama-French three-factors and the momentum factor are obtained from Kenneth French's website and the Pastor and Stambaugh liquidity factor is obtained from Robert Stambaugh's website. We thank Kenneth French and Robert Stambaugh for making the factor data available on the web.

Paperman (1996), Easley, Hvidkjaer, and O'Hara (2002, 2010) also mention that the probability of information-based trade (PIN) increases monotonically as the average firm size decreases.[10] In this regard, our empirical finding that a portfolio with higher resiliency has relatively lower market capitalization is consistent with the previous literature from the viewpoint of the role of informed traders in making stocks more resilient. Futhermore, additional evidence that the firm size is not a sole determinant of the level of stock resiliency will be provided in the subsequent tables.

In panel B, we report the monthly returns and alphas of value-weighted portfolios. In accordance with our hypothesis, portfolios with lower resiliency have higher average returns and portfolios with higher resiliency have lower average returns. For example, the monthly return of decile 1 is 0.934 percent per month and that of decile 10 is 0.454 percent per month, respectively. The average return of the decile portfolio decreases almost monotonically with resiliency. We also construct a zero-investment portfolio which is long in the lowest-resiliency portfolio (decile 1) and short in the highest-resiliency portfolio (decile 10). This zero-investment portfolio has an average return of 0.479 percent per month with statistical and economic significance. This result shows that a resiliency-based trading strategy can give an excess return of 5.748 percent per year to investors.

Abnormal returns are also shown to decrease almost monotonically with resiliency. Alphas from the selected six-factor model are distributed from 0.078 percent in decile 1 to -0.539 percent in decile 10. The zero-investment portfolio has also significant alphas. The Fama-French three-factor alpha is 0.627 percent per month and the four- and six-factor alphas are 0.613 and 0.617, respectively. Interestingly, including liquidity factors (*LIQ*, *AMI*) rarely affects the magnitude of the zero-investment portfolio's alpha, so that the resiliency-based strategy provides investors with an annualized 7.404 percent. This result supports our hypothesis that resiliency is another systematic component of stock market liquidity. We also test the hypothesis that the all alphas are jointly equal to

[10] While these papers may provide a possible explanation for a negative relationship between firm size and resiliency from a perspective of the distribution of informed traders, the resiliency measure is distinguished from the PIN measure. PIN is estimated conditional on the occurrence of information events to capture the risk of asymmetric information, but resiliency is derived not from the information risk but based on transitory price movements to focus on the role of informed traders to recover price from a liquidity shock.

zero, using the test of Gibbons, Ross, and Shanken (1989, hereafter GRS test). The results of the GRS test show that the null hypothesis is rejected at the one percent significance level. Panel C reports the results of the equal-weighted portfolios, where the portfolio returns and alphas show analogous results with those of the value-weighted portfolios. The zero-investment portfolio's monthly returns and alphas are slightly lower than those of the value-weighted case but are still statistically and economically significant. The Fama-French three-factor alpha is 0.471 percent per month and the six-factor alpha is 0.436 percent per month. We perform the GRF test again and the null hypothesis is strongly rejected, as in the case of the value-weighted portfolios. Overall, our empirical findings support the hypothesis that resiliency is systematically priced.

<Table 4 here>

Table 4 reports the simple average of resiliency for each portfolio that is dependently double-sorted on the basis of market capitalization (size) and resiliency. The average resiliency decrease as we move from small- to large-size stocks, which is consistent with the results in Table 3. Regarding the relation between resiliency and firm size, the distribution of average resiliency should be rarely overlapped if it is mainly explained by firm size since we first sort the stocks based on firm size, and then sort again based on resiliency. However Table 4 shows that the distributions of resiliency level are quite overlapped among the size groups. For example, the average level of estimated resiliency for the highest resiliency portfolio in the 'Top' size group is 0.031 which is compare to those for the 9$^{th}$ resiliency portfolio in 'Middle' size group and for the 7$^{th}$ resiliency portfolio in 'Bottom' size group. Therefore this result implies that firm size is not a dominant determinant of resiliency although the estimated resiliency has the opposite pattern with the firm size broadly as we mentioned in terms of the role of informed traders in the market.

<Table 5 here>

To investigate the patterns of risk exposure of the resiliency-sorted portfolios, we regress the excess returns of the resiliency decile portfolios and the zero-investment portfolio on the selected six factors, and Table 5 reports the factor loadings. The results show that the effect of resiliency is in the opposite direction to the well-known size effect. For the value-weighted zero-investment portfolio in Panel A, *SMB* is a strongly significant factor in explaining the zero-investment portfolio return with the estimated coefficient of -0.992, and the corresponding t-value of -18.40. A negative and significant factor loading on *SMB* implies that the zero-investment portfolio behaves like large firms. These results are consistent with those of Panel A in Table 3 in that average market capitalization of the decile portfolios decreases almost monotonically as resiliency increases. However, the average returns of the decile portfolio decrease with resiliency, so that the zero-investment portfolio generates a positive risk premium, which is contrary to the general size effect of small stocks having higher risk premia than large stocks. This result implies that, while the market capitalization tends to be negatively related to the level of resiliency, the size effect is not strong in the resiliency-sorted decile portfolios and dominated by the resiliency risk premium.

Pastor and Stambaugh (2003) also show quite similar pattern with our findings. They construct a liquidity measure of volume-related return reversals and report that the level of return reversal is negatively correlated with firm's market capitalization. Specifically, portfolio with the lowest level of predicted liquidity betas has the highest level of return reversals and the lowest market capitalization, while portfolio with the highest liquidity betas has relatively low level of return reversals and high market capitalization. [11] Furthermore, they also find that firm size and liquidity are not the sole determinants of predicted liquidity betas by constructing decile portfolios sorted on the basis of firm size. We discuss the effect of resiliency after controlling related liquidity measures as well as firm size in detail in the following section.

### 3.3 Double-sorted portfolios: resiliency and other risk factors

In this section, we apply a double-sorted portfolio strategy to further examine whether

[11] See Pastor and Stambaugh ((2003), P. 667).

resiliency is systematically priced after controlling for other risk factors. As previously discussed, certain variables related to market capitalization, trading activity, and trading cost are correlated with resiliency which make it possible that they partially affect the resiliency risk premia. To control for the influence of these variables, we implement a double-sorting portfolio analysis between resiliency and market capitalization, the Amihud illiquidity, and the trading volume as control variables. [12] To implement this strategy, we sort all sample firms into tercile groups (bottom 30%, middle 40%, top 30%) on the basis of control variables, at the end of each year. We then independently sort the same firms into 10 groups on the basis of resiliency and take intersections.

<Table 6 here>

Table 6 presents the returns and alphas of the independently double-sorted portfolios. Panel A shows the results of the value-weighted portfolio double sorted based on resiliency and market capitalization.[13] The first to third rows ("Size") report the monthly raw returns of size-controlled resiliency decile portfolios. The fourth row ("Avg.size") reports the returns of the resiliency decile portfolios averaged across the three firms' market capitalization portfolios. The bottom three rows report alphas of the averaged resiliency decile portfolios with respect to the Fama-French three-factors, *MOM*, and the two liquidity factors, *LIQ*, and *AMI*. The "Low-High" column represents the returns and alphas of zero-investment portfolios that buy the lowest resiliency portfolio and sell the highest resiliency portfolio. All alphas of the zero-investment portfolios are shown to be positive and significant. The size-controlled zero-investment portfolio gives a risk premium of 0.501 percent per

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[12] Easley, Hvidkjaer, and O'Hara (2002) mention that the estimated PIN is strongly correlated with trading volume or firm size. Duarte and Young (2009) show that the effect of PIN disappears after controlling Amihud illiquidity. Since resiliency is possibly related to PIN from a perspective of the distribution of informed traders, we implement double-sorted portfolio analysis with firm size, trading volume and Amihud illiquidity to verify the distinguished effect of resiliency from that of PIN as well as other liquidity effects. Using these control variables also allow us to cover longer period than directly using PIN which is estimated from intraday microstructure data.

[13] Asparouhova et al. (2013) show that the estimated alphas of the equal-weighted portfolios are biased because of noisy prices. Therefore, hereafter we only report the results of the value-weighted portfolio case in this paper. However, the results of the equal-weighted portfolio case are qualitatively similar to those of value weighted case.

month and its six-factor alpha is 0.557 percent per month. We also find that the effect of resiliency is still significant after controlling that of trading volume in Panel B. The trading volume-controlled zero-investment portfolio gives a risk premium of 0.403 percent per month and six-factor alpha is 0.534 percent per month.[14]

Panel C in Table 6 reports the results of the independently double-sorted portfolios between Amihud illiquidity and resiliency. Similar to the results of Panel A and Panel B, all the alphas of the Amihud illiquidity-controlled zero-investment portfolio are statistically and economically significant. For example, the averaged zero-investment portfolio gives a risk premium of 0.561 percent per month and its six-factor alpha is 0.592 percent per month. Similar to the results of Table 2, we also find the evidence that the effect of our resiliency measure is complementary to those of the existing trading cost measure in portfolio analysis. The average return for the portfolio with the lowest resiliency and in the top-ranked group of Amihud illiquidity (portfolio with the most illiquid stocks in terms of resiliency and Amihud illiquidity) is 1.373 percent per month, and the average return of the portfolio with the highest resiliency and in the bottom-ranked group of Amihuid illiquidity (portfolio with the most liquid stocks in terms of resiliency and Amihud illiquidity) is 0.254 percent per month. The average return difference of these two portfolios is 1.119 percent per month. Considering that the average Amihud illiquidity risk premium is 0.432 percent per month and the average Amihud illiquidity-controlled zero-investment portfolio sorted by resiliency is 0.561 percent per month, this result implies that our resiliency measure can generate additional cross-sectional variations of stock returns.

Because the correlation between two variables might cause the problem that the number of firms in some portfolios is not enough to eliminate an individual firm's idiosyncratic risk, we repeat the same analysis with dependently double-sorted portfolios. First, we sort all sample firms into

[14] Our analyses include stock data for the NYSE, AMEX, and NASDAQ following Pastor and Stambaugh (2003). However reported trading volumes for the stocks in NASDAQ include interdealer trades, those may overstated relative to NYSE and AMEX. Therefore we repeat the double-sorted portfolio analyses with the trading volume and the Amihud illiquidity using data for the NYSE and AMEX only. These results are qualitatively similar to those reported in Table 6.

tercile groups (bottom 30%, middle 40%, top 30%) on the basis of their market capitalizations or Amihud illiquidity at the end of the each year. We then sort the sample firms within each market capitalization or Amihud illiquidity measure group into decile portfolios on the basis of resiliency.

<Table 7 here>

Table 7 presents the results. Panel A in Table 6 shows the results of dependently double-sorted portfolios based on market capitalization and resiliency. As is similar to the results of independently sorted portfolios, the average risk premium of the size-controlled zero-investment portfolio ("Avg.size") is 0.482 per month and alphas range from 0.514 to 0.575 per month, which are all significant at a one percent level. Panel B in Table 6 presents the dependently double-sorted results with the trading volume and resiliency. The trading volume-controlled zero-investment portfolio gives a significant risk premium of 0.391 percent per month and the estimated alphas range from 0.508 to 0.563 percent per month. In Panel C, we also report the results of the dependently sorted portfolios with Amihud illiquidity and resiliency. The average risk premium of the Amihud illiquidity-controlled zero-investment portfolio is 0.429 per month and all alphas are positively significant. Overall, we conclude that the pricing capability of our resiliency measure is still valid after controlling the correlated variables.

## 3.4 Robustness check

### 3.4.1. Stock price decomposition with extended ARMA models

In section 2.1, we assume that a stock price can be decomposed into a random walk component and a stationary component following AR(1) process. To capture a wider range of autoregressive effects of stationary prices, we generalize this assumption to enable the stationary component can has up to the third-order autoregressive structure rather than only the first order. To decide the number of optimal lags of the autoregressive model for the stationary component, we use the Bayesian Information Criterion (BIC). At the end of each month, we estimate the coefficients of the

ARMA(1,1), ARMA(2,2), and ARMA(3,3) models using all of the available historical return series of each firm corresponding to the AR(1), AR(2), and AR(3) models in the stationary component, respectively. We then apply the BIC rules to these three estimated model parameters to detect the optimal number of the autoregressive lag order. Once the proper coefficients of the ARMA models are estimated, the level of each firm's resiliency is calculated in the same manner as in section 2 using the B-N decomposition and frequency domain analysis.[15]

<Table 8 here>

Table 8 shows the returns and alphas of decile portfolios sorted on resiliency that is calculated from the extended ARMA models. The zero-investment portfolio return is 0.425 percent per month with significance and the estimate alphas are distributed within the range of 0.556 to 0.585 percent per month. We also test double-sorted portfolios by resiliency and firm size, resiliency and trading volume, and also resiliency and Amihud illiquidity.

<Table 9 here>

The results of the independently double-sorted portfolios estimated from the extended ARMA models are reported in Table 9. The premium of the zero-investment portfolio is 0.457 percent per month for size-controlled double sorts, 0.377 percent per month for trading volume-controlled double sorts, and 0.501 percent per month for Amihud illiquidity-controlled double sorts, respectively. The estimated alphas of the zero-investment portfolio with size controlled are statistically and economically significant in the range from 0.457 to 0.517 percent per month. The alphas of the zero-investment portfolio after controlling for trading volume and Amihud illiquidity are also distributed within the range from 0.485 to 0.516, and from 0.533 to 0.590 percent per month with significance, respectively.

<Table 10 here>

[15] As noted in section 2.1, a non-stationary series contains a random walk process and an AR process can be transformed into the ARMA model.

The estimated results of the dependently double-sorted portfolios are reported in Table 10, which shows a similar pattern to the results of independently double-sorted portfolios. The premium of zero-investment portfolios is 0.498 percent per month for size-controlled double sorts and 0.406 percent per month for Amihud illiquidity controlled double sorts, respectively. The estimated alphas are also statistically and economically significant for both cases.

### 3.4.2 Sub-period analysis

In order to investigate a potentially time-varying pattern of the resiliency effect, we perform the sub-period analysis by dividing the full sample period into two sub-periods with similar length: Sub-period 1 is from January 1965 to December 1989 and sub-period 2 is from January 1990 to December 2013. Table 11 presents the results of the sub-period analysis, which show that the magnitude of the zero-investment portfolio return of sub-period 2 is substantially higher than that of sub-period 1. The Low-High return premium of sub-period 2 is 0.619 percent per month with statistical significance, whereas that of sub-period 1 is 0.346 percent per month which is not statistically significant. The estimated patterns of alpha are also similar to those of the zero-investment portfolio returns. The alphas are distributed in the range from 0.753 percent to 0.844 percent per month in sub-period 2 and from 0.468 percent to 0.624 percent in sub-period 1, respectively. In this regard, we conclude that the effect of resiliency has strengthened in more recent period in explaining the cross sections of expected stock returns.

<Table 11 here>

### 3.4.3 Role of frequency component

As we discussed in section 2.2, the speed of transitory price recovery is calculated by considering two components; absolute magnitude (distance) and frequency (time). The calculated speed will increase as distance of transitory price wave from peak to trough increases or its cycle decreases. Therefore, if the level of our resiliency measure mainly depends on the distance component, a stock with larger transitory deviation will also have higher speed of recovery regardless of its frequency component. To address this issue, we further implement the following robustness check to verify the role of the frequency component by varying the contribution of frequency in measuring resiliency and constructing respective decile portfolios, in order to investigate the corresponding return variation. First, we re-estimate the equation (11) without considering the frequency component using the following equation that denotes the average absolute value of magnitude (*Avg.Magnitude*).

$$Avg.Magnitude_{i,t} = \frac{1}{[\frac{D_{i,t}}{2}]} \sum_{k=1}^{[D_{i,t}/2]} 2\left|\tilde{Z}_{k,i,t}\right| \tag{16}$$

Second, we divide the frequency axis into three parts by the level, and also re-estimate the speed of transitory price recovery on the low-frequency and high-frequency axes separately. Using these three frequency-adjusted measures, we construct decile portfolios and estimate the 'Low-High' portfolio return differences again.

Panel A in Table 12 shows the returns of the decile portfolios and the 'Low-High' zero-investment portfolio that are sorted by *Avg.Magnitude*, the low-frequency resiliency, and the high-frequency resiliency, respectively. The premium of the zero-investment portfolio is 0.247 percent per month for *Avg.Magnitude* and 0.224 percent per month for the low-frequency resiliency, but they are insignificant. In contrast, the zero-investment portfolio return for the high-frequency resiliency is 0.469 percent per month with significance. We also find that this return premium is still significant, after controlling for the risk factors. Panel B in Table 12 shows that the estimated alphas of the zero-investment portfolio for the high-frequency resiliency range from 0.527 percent to 0.624 percent per month and significant at the one percent level. Therefore, the level of estimated return premium and the abnormal returns for the high-frequency resiliency are shown to be most comparable to the results with our suggested resiliency measure in Table 3. In this regard, we can conclude that the effect of resiliency does not come from the magnitude of transitory deviation alone. The speed of transitory price recovery estimated in the high frequency level accounts for the most part of resiliency effect that generates cross-sectional variation in stock returns. These results also imply that the speed of recovery process completed in relatively short-term horizon plays an important role in asset pricing.

<Table 12 here>

## 4. Conclusion

This paper proposes a new measure of stock market resiliency and investigates whether resiliency is a systematic component of liquidity that generates cross-sectional variations in stock returns. Resiliency is defined as quickness of price recovery from a liquidity shock. Using this definition, we focus on measuring resiliency and investigating its effect on stock returns. To measure resiliency, we first decompose the stock price into the fundamental and transitory components, and then transform the transitory price into a spectral functional form in the frequency domain to calculate the speed of transitory price recovery. The level of resiliency of an individual stock can be obtained by dividing the magnitude component by its cycle in the frequency domain.

Based on the suggested resiliency measure, we perform the regression analyses at the individual stock and portfolio levels to investigate whether resiliency can independently explains additional dimension of liquidity. Our empirical findings show that resiliency is a systematic component of liquidity that generates cross-sectional variations in stock returns. Expected stock returns are a decreasing function of resiliency, which implies that stocks with lower resiliency are compensated with higher risk premia. During the sample period of 1965–2013, we find that a zero-investment portfolio that is long in low resiliency stocks and short in high resiliency stocks earns a statistically and economically significant abnormal return with respect to various risk factors that are widely adopted in the literature. Furthermore, we find that the effects of resiliency on the expected stock returns are complementary to those of existing trading cost-based liquidity. A significant predictive power of resiliency on expected stock returns is not diminished by the trading cost measure on expected stock returns. In addition, we show that resiliency generates additional cross-sectional variations in stock returns in addition to that of the Amihud illiquidity and trading volume. These results imply that resiliency can capture an additional dimension of liquidity that is not explained by existing liquidity measures.

## References


Alan, N.S., J. Hua, L. Peng, and R.A. Schwartz. 2015. Stock Resiliency and Expected Returns. Working Paper, version April 2015.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-Section and Times-Series Effects. *Journal of Financial Markets* 5:31–56.

Anand, A., P. Irvine, A. Puckett, and K. Venkataraman. 2013. Institutional Trading and Stock Resiliency: Evidence from the 2007–2009 Financial Crisis. *Journal of Financial Economics* 108:773–797.

Asparouhova E., H. Bessembinder, and I. Kalcheva. 2010. Liquidity Biases in Asset Pricing Tests. *Journal of Financial Economics* 96:215–237.

Asparouhova E., H. Bessembinder, and I. Kalcheva. 2013. Noisy Prices and Inference Regarding Returns. *Journal of Finance* 68:665–714.

Bao, J., J. Pan, and J. Wang. 2011. The Illiquidity of Corporate Bonds. *Journal of Finance* 66:911–946.

Bernstein, P.L. 1987. Liquidity, Stock Markets, and Market Makers. *Financial Management* 16:54–62.

Beveridge, S., and C.R. Nelson. 1981. A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle'. *Journal of Monetary Economics* 7:151–174.

Black, F. 1971. Toward a Fully Automated Stock Exchange. Part 1. *Financial Analysts Journal* 27:29–34.

Boehmer, E., and E.K. Kelley. 2009. Institutional Investors and the Informational Efficiency of

Prices. *Review of Financial Studies* 22:3563–3594.

Charoenrook, A., and J. Conrad. 2008. Identifying Risk-Based Factors. Working Paper, version August 2008.

Chordia, T., R. Roll, and A. Subrahmanyam. 2001. Market Liquidity and Trading Activity. *Journal of Finance* 56:501–530.

Daniel, K., and S. Titman. 1997. Evidence on the Characteristics of Cross-Sectional Variation in Stock Returns. *Journal of Finance* 52:1–33.

Datar, V.T., N.Y. Naik, and R. Radcliffe. 1998. Liquidity and Stock Returns: An Alternative Test. *Journal of Financial Markets* 1:203–219.

Dong, J., A. Kempf, and P.K. Yadav. 2007. Resiliency, the Neglected Dimension of Market Liquidity: Empirical Evidence from the New York Stock Exchange. Working Paper.

Duarte, J., and L. Young. 2009. Why is PIN Priced? *Journal of Financial Economics*, 91:119–138.

Easley, D., S. Hvidkjaer, and M. O'Hara. 2002. Is Information Risk a Determinant of Asset Returns? *Journal of Finance* 57:2185–2221.

Easley, D., S. Hvidkjaer, and M. O'Hara. 2010. Factoring Information into Returns. *Journal of Financial and Quantitative Analysis* 45:293–309.

Easley, D., N. Kiefer, M. O'Hara and J. Paperman. 1996. Liquidity, Information, and Less-Frequently Traded Stocks. *Journal of Finance* 51:1405–1436.

Fama, E., and J. MacBeth. 1973. Risk, Return and Equilibrium: Empirical Tests. *Journal of Political Economy* 81:607–636.

Fama, E., and K. French. 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance* 47:427–465.

Fama, E., and K. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33:3–56.

Foucault, T., O. Kadan, and E. Kandel. 2005. Limit Order Book as a Market for Liquidity. *Review of Financial Studies* 18:1171–1217.

Friewald, N., R. Jankowitsch, and M.G. Subrahmanyam. 2012. Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market During Financial Crises. *Journal of Financial Economics* 105:18–36.

Gibbons, M., S. Ross, and J. Shanken. 1989. A Test of the Efficiency of a Given Portfolio. *Econometrica* 57:1121–1152.

Harris, L. 2003. *Trading & Exchanges: Market Microstructure for Practitioner.* Oxford University Press.

Hasbrouck, J. 1991. Measuring the Information Content of Stock Trades. *Journal of Finance* 46:179–207.

Hasbrouck, J. 1993. Assessing the Quality of a Security Market: A New Approach to Transaction-Cost Measurement. *Review of Financial Studies* 6:191–212.

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

Kempf, A., D. Mayston, M. Gehde-Trapp, P. Yadav. 2015. Resiliency: A Dynamic View of Liquidity. Working Paper.

Kyle, A. 1985. Continuous Auctions and Insider Trading. *Econometrica* 5: 1315–1335.

Leland, B.J. 1991, *Signals, Systems, and Transforms*. Addison-Wesley Publishing Company.

Lesmond, D.A. 2005. Liquidity of Emerging Markets. *Journal of Financial Economics* 77:411–452.

Morley, J. 2002. A State-Space Approach to Calculating the Beveridge-Nelson Decomposition. *Economics Letters* 75:123–127.

Newey, W., and K. West. 1987. A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55:703–706.

Roll, R. 1984. A simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *Journal of Finance* 39:1127–1139.

Pastor, L., and R. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111:642–685.

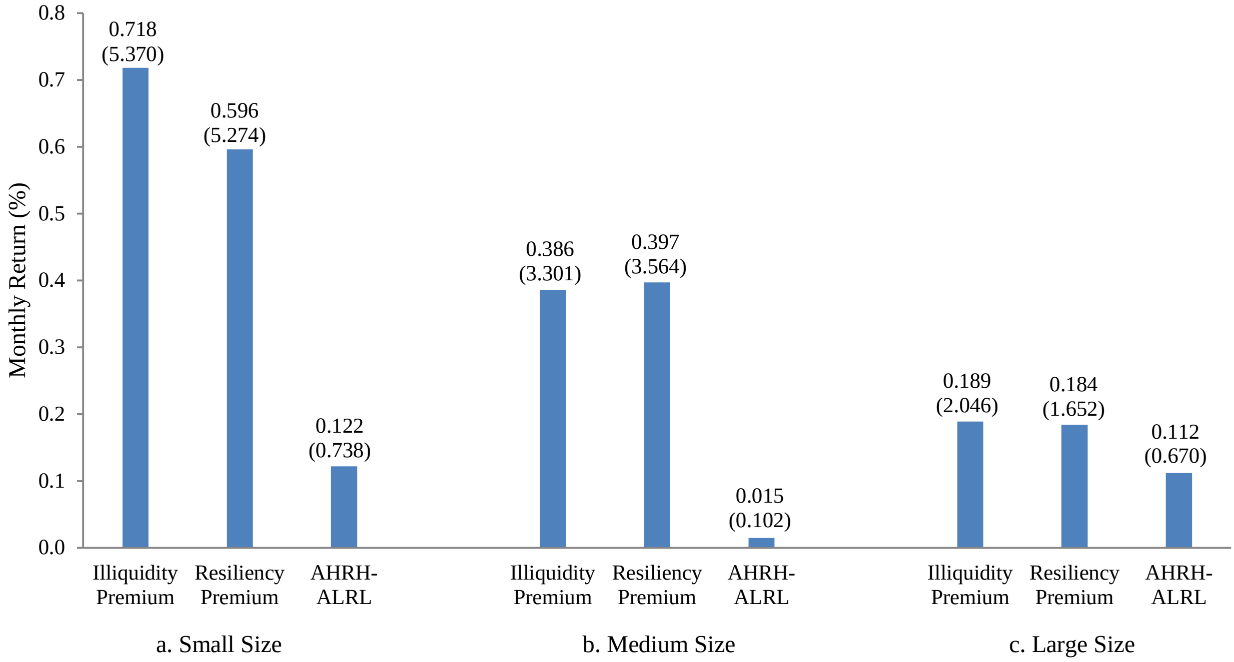


**Fig.1.** Amihud illiquidity premium and effect of resiliency. All available stocks are divided into small, medium and large size groups, and then independently double-sorted into quintile portfolios on the basis of the Amihud illiquidity and estimated resiliency, respectively. The value-weighted monthly returns of the each portfolio are estimated from 1965 to 2013. For each size group, we plot the illiquidity premium which represents the Amihud illiquidity premium, the resiliency premium, and “AHRH-ALRL”. “AHRH” denotes the portfolio with high Amihud illiquidity and high resiliency, and “ALRL” denotes the portfolio with low Amihud illiquidity and low resiliency. “AHRH-ALRL” presents the return difference between “AHRH” and “ALRL”. The t-statistics are shown in parentheses.

**Table 1**
Descriptive statistics.

Panel A reports the summary statistics of the explanatory variables. *Beta* denotes the post-ranking market beta estimated using the Fama and French (1992) method. *Ln_ME*, *LN_BM* denotes the natural logarithm of the market capitalization, and of the book-to-market equity ratio, respectively. *Resiliency* denotes the speed of the transitory price recovery. Stocks with resiliency at the extreme 1% upper and lower values are excluded. *Roll* is the Roll (1984) bid–ask spread measure and *Amihud* is the Amihud (2002) illiquidity measure. *TrdVol*, which denotes trading volume, is defined as the sum of the trading volume during the given month. *TURN* denotes share turnover, which is defined as the monthly average of the daily share turnover, or the number of shares traded divided by the number of shares outstanding. *Vol* is the standard deviation of the monthly return of a stock for the past 60 months. Stocks with share prices less than $5 at the end of the previous month are excluded and at least 24-month return observations are required to be included in the sample. Panel B reports the pair-wise correlation matrix between the explanatory variables in our sample. The samples cover the period from January 1965 to December 2013.

A. Summary statistics

| Variable | Mean | Std. Dev. | Percentile | | | | |
|---|---|---|---|---|---|---|---|
| | | | 5th | 25th | 50th | 75th | 95th |
| *Beta* | 1.084 | 0.332 | 0.582 | 0.821 | 1.057 | 1.319 | 1.734 |
| *Ln_ME* | 12.262 | 1.887 | 9.406 | 10.923 | 12.134 | 13.471 | 15.577 |
| *Ln_BM* | -7.308 | 1.063 | -8.865 | -7.864 | -7.309 | -6.815 | -5.895 |
| *Resiliency* | 0.021 | 0.025 | 0.002 | 0.006 | 0.013 | 0.026 | 0.070 |
| *Roll* | 0.006 | 0.026 | -0.033 | -0.011 | 0.008 | 0.020 | 0.048 |
| *Amihud* | 0.732 | 2.493 | 0.000 | 0.007 | 0.056 | 0.406 | 3.435 |
| *TrdVol* | 86.525 | 647.705 | 0.039 | 1.171 | 5.849 | 31.982 | 309.243 |
| *TURN* | 6.977 | 73.816 | 0.282 | 1.044 | 2.510 | 6.076 | 20.147 |
| *Vol* | 0.113 | 0.059 | 0.043 | 0.074 | 0.102 | 0.138 | 0.218 |

Panel B : Correlation Matrix

| | *Beta* | *Ln_ME* | *Ln_BM* | *Resiliency* | *Roll* | *Amihud* | *TrdVol* | *TURN* | *Vol* |
|---|---|---|---|---|---|---|---|---|---|
| *Beta* | 1.000 | | | | | | | | |
| *Ln_ME* | 0.017 | 1.000 | | | | | | | |
| *Ln_BM* | -0.129 | -0.303 | 1.000 | | | | | | |
| *Resiliency* | -0.062 | -0.328 | -0.036 | 1.000 | | | | | |
| *Roll* | -0.043 | -0.120 | 0.016 | 0.268 | 1.000 | | | | |
| *Amihud* | -0.064 | -0.362 | 0.116 | 0.302 | 0.108 | 1.000 | | | |
| *TrdVol* | 0.055 | 0.283 | -0.079 | -0.049 | -0.006 | -0.075 | 1.000 | | |
| *TURN* | 0.158 | 0.107 | -0.044 | 0.035 | -0.035 | -0.047 | 0.156 | 1.000 | |
| *Vol* | 0.548 | -0.226 | -0.142 | 0.167 | 0.013 | 0.112 | 0.025 | 0.252 | 1.000 |

**Table 2**
Resiliency and Fama-Macbeth cross-section regressions.

Panel A reports the time series averages of the estimated coefficients form the monthly, firm-level cross-sectional regressions. The monthly excess returns are regressed on a set of lagged variables using the standard Fama-MacBeth (1973) methodology. *Beta* denotes the post-ranking market beta estimated using the Fama and French (1992) method. *Ln_ME*, *LN_BM* denotes the natural logarithm of the market capitalization, and of the book-to-market equity ratio, respectively. *Resiliency* denotes the speed of the transitory price recovery. Stocks with resiliency at the extreme 1% upper and lower values are excluded. *Roll* is the Roll (1984) bid–ask spread measure and *Amihud* is the Amihud (2002) illiquidity measure. *TrdVol*, which denotes trading volume, is defined as the sum of the trading volume during given month. *TURN* denotes share turnover defined as the monthly average of the daily share turnover, or the number of shares traded divided by the number of shares outstanding. *Vol* is the standard deviation of the monthly return of a stock for the past 60 months. Stocks with share prices less than $5 at the end of the previous month are excluded. The samples cover the period from January 1965 to December 2013 in Model (1) to Model (5), and Model (6) control for the January effect. Panel B reports the time series averages of the estimated coefficients from the monthly, firm-level cross-sectional regressions using weighted least squares suggested by Asparouhova, Bessembinder, and Kalcheva (2010). The Newey-West (1987) t-statistics are given in parentheses and Significance at the 10% level is indicated in **bold**.

A. Fama-MacBeth regression

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | *Ret* | *Ret* | *Ret* | *Ret* | *Ret* | *Ret* |
| *Beta* | -0.0947 | 0.005 | 0.133 | 0.006 | 0.201 | 0.202 |
| | (-0.379) | (0.0189) | (0.643) | (0.0278) | (0.914) | (0.897) |
| *Ln_ME* | -0.0533 | -0.013 | **-0.067** | 0.009 | -0.029 | 0.067 |
| | (-1.555) | (-0.375) | **(-1.769)** | (0.198) | (-0.665) | (1.448) |
| *Ln_BM* | **0.154** | **0.165** | **0.108** | **0.155** | **0.117** | **0.094** |
| | **(3.095)** | **(3.148)** | **(2.190)** | **(3.013)** | **(2.066)** | **(1.868)** |
| *Resiliency* | **-7.650** | **-7.333** | **-5.148** | **-5.119** | **-5.339** | **-6.544** |
| | **(-3.814)** | **(-3.324)** | **(-3.088)** | **(-1.657)** | **(-2.096)** | **(-2.190)** |
| *Amihud* | | **0.058** | | **0.077** | **0.050** | **0.058** |
| | | **(2.029)** | | **(2.340)** | **(1.811)** | **(1.779)** |
| *Roll* | | **2.416** | | 1.673 | **3.741** | 2.040 |
| | | **(1.752)** | | (1.213) | **(2.593)** | (1.563) |
| *TURN* | | | | 0.010 | 0.009 | 0.039 |
| | | | | (0.366) | (0.339) | (1.345) |
| *TrdVol* | | | | -0.0235 | -0.026 | -0.054 |
| | | | | (-0.569) | (-0.805) | (-1.402) |
| *Vol* | | | -2.550 | | -2.589 | **-3.583** |
| | | | (-1.108) | | (-1.363) | **(-1.771)** |
| *Constant* | **2.665** | **2.143** | **2.544** | **1.819** | **2.121** | 0.765 |
| | **(5.550)** | **(4.078)** | **(4.747)** | **(3.067)** | **(3.494)** | (1.315) |
| Observations | 1,218,175 | 1,128,687 | 985,429 | 1,128,644 | 919,753 | 844,751 |
| R-squared | 0.054 | 0.063 | 0.064 | 0.073 | 0.079 | 0.076 |

B. Fama-MacBeth regression by weighted least squares

| | Model 1 *Ret* | Model 2 *Ret* | Model 3 *Ret* | Model 4 *Ret* | Model 5 *Ret* | Model 6 *Ret* |
|---|---|---|---|---|---|---|
| *Beta* | -0.271 | -0.062 | 0.191 | 0.003 | 0.230 | 0.216 |
| | (-1.076) | (-0.247) | (0.909) | (0.0135) | (1.029) | (0.960) |
| *Ln_ME* | -0.031 | -0.002 | **-0.072** | 0.009 | -0.035 | 0.062 |
| | (-0.891) | (-0.0645) | **(-1.873)** | (0.200) | (-0.791) | (1.341) |
| *Ln_BM* | **0.172** | **0.171** | **0.104** | **0.156** | **0.115** | **0.095** |
| | **(3.505)** | **(3.259)** | **(2.095)** | **(3.032)** | **(2.021)** | **(1.878)** |
| *Resiliency* | **-8.845** | **-8.426** | **-5.615** | **-5.414** | **-5.508** | **-6.665** |
| | **(-4.301)** | **(-3.731)** | **(-3.345)** | **(-1.764)** | **(-2.161)** | **(-2.234)** |
| *Amihud* | | **0.047** | | **0.072** | **0.049** | **0.054** |
| | | **(1.660)** | | **(2.178)** | **(1.763)** | **(1.672)** |
| *Roll* | | **3.218** | | 1.873 | **3.806** | 1.983 |
| | | **(2.189)** | | (1.353) | **(2.619)** | (1.501) |
| *TURN* | | | | 0.010 | 0.009 | 0.039 |
| | | | | (0.335) | (0.351) | (1.339) |
| *TrdVol* | | | | -0.024 | -0.026 | -0.054 |
| | | | | (-0.564) | (-0.788) | (-1.381) |
| *Vol* | | | -3.101 | | -2.908 | **-3.745** |
| | | | (-1.353) | | (-1.543) | **(-1.854)** |
| *Constant* | **2.671** | **2.095** | **2.568** | **1.837** | **2.183** | 0.838 |
| | **(5.401)** | **(3.934)** | **(4.794)** | **(3.084)** | **(3.601)** | (1.444) |
| Observations | 1,218,175 | 1,128,687 | 985,429 | 1,128,644 | 919,753 | 844,751 |
| R-squared | 0.058 | 0.067 | 0.068 | 0.077 | 0.083 | 0.080 |

**Table 3**
Portfolio analysis: Sorting by resiliency.

At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency, and then monthly portfolio returns are obtained during the subsequent 12 months. *Resiliency* denotes the speed of the transitory price recovery. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A presents the average market capitalization in natural logarithm form and the simple average of resiliency for each decile portfolio. Panel B reports value-weighted monthly returns and alphas of the decile portfolios, and Panel C reports the equal weighted case. "Low-High" column denotes the average raw returns and alphas of the zero-investment portfolio. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (three-factor alpha), on the Fama-French factor with the momentum factor (four-factor alpha), and on the four-factor model with two liquidity factors—the Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A. Portfolio Characteristics | | | | | | | | | | |
| *Ln_ME* | 12.566 | 12.585 | 12.509 | 12.474 | 12.321 | 12.156 | 11.938 | 11.650 | 11.275 | 10.800 | |
| *Resiliency* | 0.005 | 0.006 | 0.008 | 0.010 | 0.013 | 0.016 | 0.021 | 0.027 | 0.037 | 0.058 | |
| | B. Value-weighted Portfolio return and alpha | | | | | | | | | | |
| Raw Return | 0.934 | 0.877 | 0.963 | 0.960 | 0.877 | 0.853 | 0.809 | 0.728 | 0.745 | 0.454 | 0.479 |
| | (5.601) | (4.909) | (5.052) | (4.866) | (4.248) | (3.892) | (3.512) | (2.934) | (2.798) | (1.558) | (2.277) |
| Three-factor alpha | 0.027 | 0.009 | 0.060 | 0.036 | -0.069 | -0.092 | -0.141 | -0.233 | -0.318 | -0.600 | 0.627 |
| | (0.449) | (0.172) | (1.221) | (0.706) | (-1.229) | (-1.409) | (-1.812) | (-2.435) | (-3.185) | (-4.877) | (4.415) |
| Four-factor alpha | 0.076 | 0.031 | 0.084 | 0.115 | 0.013 | 0.019 | -0.022 | -0.162 | -0.131 | -0.537 | 0.613 |
| | (1.255) | (0.556) | (1.667) | (2.319) | (0.229) | (0.297) | (-0.292) | (-1.673) | (-1.378) | (-4.286) | (4.220) |
| Six-factor alpha | 0.078 | 0.037 | 0.076 | 0.111 | 0.011 | 0.019 | -0.022 | -0.150 | -0.125 | -0.539 | 0.617 |
| | (1.289) | (0.668) | (1.521) | (2.230) | (0.195) | (0.302) | (-0.293) | (-1.553) | (-1.317) | (-4.306) | (4.269) |

| | Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | C. Equal-weighted Portfolio return and alpha | | | | | | | | | | |
| Raw Return | 1.134 | 1.137 | 1.118 | 1.082 | 1.043 | 1.072 | 1.046 | 0.986 | 1.003 | 0.766 | 0.368 |
| | (6.234) | (5.879) | (5.597) | (5.207) | (4.855) | (4.895) | (4.645) | (4.202) | (4.120) | (3.049) | (3.045) |
| Three-factor alpha | 0.069 | 0.045 | 0.023 | -0.036 | -0.087 | -0.054 | -0.093 | -0.169 | -0.178 | -0.402 | 0.471 |
| | (1.438) | (0.982) | (0.493) | (-0.770) | (-1.840) | (-1.157) | (-2.004) | (-3.172) | (-2.804) | (-4.493) | (5.169) |
| Four-factor alpha | 0.124 | 0.104 | 0.096 | 0.049 | 0.010 | 0.050 | 0.000 | -0.087 | -0.099 | -0.328 | 0.452 |
| | (2.578) | (2.297) | (2.124) | (1.078) | (0.226) | (1.173) | (0.00875) | (-1.674) | (-1.572) | (-3.633) | (4.851) |
| Six-factor alpha | 0.121 | 0.104 | 0.094 | 0.048 | 0.010 | 0.049 | 0.003 | -0.080 | -0.091 | -0.315 | 0.436 |
| | (2.651) | (2.394) | (2.188) | (1.129) | (0.239) | (1.173) | (0.0731) | (-1.568) | (-1.445) | (-3.503) | (4.826) |

**Table 4**
Average resiliency in double-sorted portfolios.
This table reports the simple average of resiliency for each portfolio that is dependently double-sorted on the basis of market capitalization (size) and resiliency. Resiliency denotes the speed of the transitory price recovery. At the end of each year between 1964 and 2012, all available stocks are sorted into tercile portfolios on the basis of the firm's market capitalization, and then within each market capitalization, stocks are grouped into decile portfolios on the basis of resiliency. Stocks with resiliency at the extreme 1% upper and lower values and with share prices less than $5 at the end of the each year are excluded.

| | Resiliency Decile Portfolio | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) |
| Size (Bottom) | 0.007 | 0.01 | 0.013 | 0.017 | 0.022 | 0.027 | 0.034 | 0.042 | 0.052 | 0.073 |
| Size (Middle) | 0.005 | 0.007 | 0.009 | 0.011 | 0.014 | 0.017 | 0.021 | 0.026 | 0.033 | 0.049 |
| Size (Top) | 0.003 | 0.004 | 0.006 | 0.007 | 0.009 | 0.011 | 0.013 | 0.016 | 0.020 | 0.031 |

**Table 5**
Portfolio analysis: Factor loadings.

At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency, and then monthly portfolio returns are obtained during the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. The factor loadings are estimated as the coefficients from the regressions of excess portfolio returns on six factors including the Fama-French factor (MKT, SMB, HML), the momentum factor (MOM), the Pastor and Stambaugh liquidity factor (LIQ) and the Amihud illiquidity factor (AMI). Panel A presents the factor loadings of the value-weighted portfolios sorted by resiliency. Panel B reports the factor loadings of the equal-weighted case. “Low-High” column denotes the zero-investment’s factor loadings. The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A. Value-weighted Portfolio factor loading | | | | | | | | | | |
| *MKT* | 0.852 | 0.936 | 1.014 | 1.012 | 1.046 | 1.064 | 1.065 | 1.017 | 1.109 | 1.046 | -0.193 |
| | (57.16) | (67.88) | (82.03) | (82.47) | (78.71) | (68.95) | (56.95) | (42.55) | (47.45) | (33.87) | (-5.426) |
| *SMB* | -0.083 | -0.086 | -0.056 | -0.029 | -0.102 | 0.001 | 0.098 | 0.414 | 0.575 | 0.909 | -0.992 |
| | (-3.665) | (-4.137) | (-3.008) | (-1.539) | (-5.061) | (0.0514) | (3.456) | (11.47) | (16.25) | (19.47) | (-18.40) |
| *HML* | 0.172 | 0.069 | 0.035 | -0.010 | -0.024 | -0.117 | -0.182 | -0.254 | -0.162 | -0.277 | 0.449 |
| | (7.544) | (3.249) | (1.836) | (-0.532) | (-1.166) | (-4.941) | (-6.365) | (-6.957) | (-4.517) | (-5.866) | (8.237) |
| *LIQ* | 1.773 | 1.348 | -2.803 | -0.907 | 1.436 | 1.617 | 1.620 | 4.482 | 0.245 | -2.345 | 4.118 |
| | (1.646) | (1.352) | (-3.138) | (-1.023) | (1.496) | (1.450) | (1.200) | (2.598) | (0.145) | (-1.051) | (1.599) |
| *MOM* | -0.053 | -0.025 | -0.026 | -0.086 | -0.087 | -0.120 | -0.129 | -0.079 | -0.210 | -0.072 | 0.019 |
| | (-3.827) | (-1.989) | (-2.258) | (-7.621) | (-7.114) | (-8.424) | (-7.478) | (-3.561) | (-9.702) | (-2.520) | (0.583) |
| *AMI* | 0.067 | -0.045 | -0.005 | 0.039 | 0.122 | 0.086 | 0.089 | 0.015 | -0.109 | -0.088 | 0.155 |
| | (2.906) | (-2.089) | (-0.282) | (2.054) | (5.906) | (3.595) | (3.059) | (0.404) | (-3.000) | (-1.838) | (2.808) |
| Adj. R-squared | 0.881 | 0.911 | 0.937 | 0.942 | 0.938 | 0.926 | 0.902 | 0.862 | 0.885 | 0.833 | 0.571 |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | B. Equal-weighted Portfolio factor loading | | | | | | | | | | |
| *MKT* | 0.823 | 0.874 | 0.893 | 0.918 | 0.942 | 0.949 | 0.933 | 0.934 | 0.937 | 0.897 | -0.074 |
| | (72.72) | (81.41) | (84.49) | (87.41) | (90.37) | (92.48) | (88.04) | (73.82) | (60.32) | (40.44) | (-3.336) |
| *SMB* | 0.364 | 0.410 | 0.426 | 0.456 | 0.496 | 0.545 | 0.665 | 0.760 | 0.903 | 0.990 | -0.625 |
| | (21.31) | (25.28) | (26.69) | (28.73) | (31.50) | (35.11) | (41.53) | (39.74) | (38.45) | (29.51) | (-18.53) |
| *HML* | 0.252 | 0.231 | 0.181 | 0.174 | 0.152 | 0.115 | 0.106 | 0.092 | 0.134 | 0.120 | 0.131 |
| | (14.56) | (14.06) | (11.23) | (10.84) | (9.505) | (7.341) | (6.554) | (4.762) | (5.657) | (3.550) | (3.851) |
| *LIQ* | 1.615 | 2.079 | 1.607 | 2.264 | 2.277 | 1.272 | 2.288 | 3.256 | 2.249 | 3.247 | -1.631 |
| | (1.977) | (2.681) | (2.106) | (2.984) | (3.025) | (1.716) | (2.990) | (3.563) | (2.004) | (2.027) | (-1.012) |
| *MOM* | -0.057 | -0.062 | -0.077 | -0.091 | -0.104 | -0.113 | -0.102 | -0.089 | -0.089 | -0.084 | 0.027 |
| | (-5.433) | (-6.293) | (-7.911) | (-9.327) | (-10.84) | (-11.86) | (-10.39) | (-7.648) | (-6.165) | (-4.104) | (1.326) |
| *AMI* | 0.132 | 0.117 | 0.137 | 0.141 | 0.126 | 0.101 | 0.074 | 0.054 | -0.036 | -0.084 | 0.216 |
| | (7.536) | (7.009) | (8.330) | (8.635) | (7.794) | (6.329) | (4.470) | (2.725) | (-1.475) | (-2.431) | (6.238) |
| Adj. R-squared | 0.942 | 0.954 | 0.958 | 0.962 | 0.965 | 0.967 | 0.967 | 0.957 | 0.940 | 0.884 | 0.489 |

**Table 6**
Portfolio analysis: Independently double sorting by resiliency and control variables.

At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency and into tercile portfolios on the basis of the control variables, respectively. The value-weighted monthly returns of each portfolio are estimated by taking the intersection during the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A reports the results of independently double sorting between resiliency and market capitalization. "Low-High" column presents the average raw returns and alphas of the zero-investment portfolio. "Bottom", "Middle", and "Top" denote the average raw returns of the controlled resiliency decile portfolios. "Avg." portfolio denotes the average raw returns of the resiliency decile portfolios averaged across the each control variable. The alphas are estimated as intercepts from the regressions of the controlled excess portfolio returns on the Fama-French factor (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). Panel B and Panel C reports the results of independently double sorting between resiliency and the trading volume, and resiliency and the Amihud illiquidity, respectively. The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A-1. Double sorting with Firm's market capitalization: Portfolio return | | | | | | | | | | |
| Size (Bottom) | 1.179 | 1.239 | 1.124 | 1.102 | 1.134 | 1.142 | 1.231 | 1.141 | 1.154 | 0.853 | 0.326 |
| | (6.038) | (5.903) | (5.451) | (5.077) | (4.942) | (4.981) | (5.195) | (4.805) | (4.821) | (3.464) | (2.955) |
| Size (Middle) | 1.211 | 1.154 | 1.145 | 1.108 | 1.070 | 1.082 | 0.996 | 0.918 | 0.875 | 0.518 | 0.693 |
| | (5.940) | (5.342) | (5.238) | (4.915) | (4.725) | (4.636) | (4.121) | (3.624) | (3.244) | (1.763) | (4.413) |
| Size (Top) | 0.909 | 0.863 | 0.954 | 0.954 | 0.865 | 0.833 | 0.801 | 0.687 | 0.698 | 0.426 | 0.483 |
| | (5.466) | (4.836) | (5.002) | (4.834) | (4.182) | (3.776) | (3.417) | (2.695) | (2.513) | (1.323) | (1.915) |
| Avg. size | 1.100 | 1.085 | 1.075 | 1.055 | 1.023 | 1.019 | 1.009 | 0.915 | 0.909 | 0.599 | 0.501 |
| | (6.248) | (5.769) | (5.591) | (5.246) | (4.902) | (4.734) | (4.502) | (3.919) | (3.677) | (2.249) | (3.515) |
| | A-2. Double sorting with Firm's market capitalization: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.070 | 0.045 | 0.023 | -0.015 | -0.069 | -0.070 | -0.086 | -0.183 | -0.220 | -0.507 | 0.577 |
| | (1.378) | (0.943) | (0.470) | (-0.309) | (-1.342) | (-1.398) | (-1.667) | (-3.299) | (-3.419) | (-5.604) | (5.727) |
| Four-factor alpha | 0.121 | 0.091 | 0.076 | 0.069 | 0.014 | 0.035 | 0.012 | -0.111 | -0.105 | -0.436 | 0.557 |
| | (2.378) | (1.891) | (1.587) | (1.483) | (0.278) | (0.741) | (0.245) | (-2.027) | (-1.711) | (-4.772) | (5.414) |
| Six-factor alpha | 0.125 | 0.098 | 0.075 | 0.071 | 0.016 | 0.035 | 0.015 | -0.102 | -0.100 | -0.432 | 0.557 |
| | (2.480) | (2.045) | (1.576) | (1.552) | (0.338) | (0.765) | (0.304) | (-1.885) | (-1.620) | (-4.723) | (5.439) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | B-1. Double sorting with trading volume: Portfolio return | | | | | | | | | | |
| TrdVol (Bottom) | 1.229 | 1.183 | 1.192 | 1.240 | 1.114 | 1.306 | 1.201 | 1.237 | 1.384 | 1.004 | 0.226 |
| | (6.934) | (6.425) | (6.628) | (6.454) | (5.666) | (6.876) | (5.870) | (6.179) | (6.781) | (4.592) | (1.789) |
| TrdVol (Middle) | 1.129 | 1.180 | 1.074 | 1.123 | 1.124 | 0.969 | 1.061 | 0.993 | 0.897 | 0.698 | 0.431 |
| | (6.222) | (6.174) | (5.686) | (5.843) | (5.618) | (4.730) | (5.111) | (4.421) | (3.692) | (2.527) | (2.737) |
| TrdVol (Top) | 0.906 | 0.768 | 0.974 | 0.926 | 0.831 | 0.891 | 0.758 | 0.654 | 0.498 | 0.354 | 0.552 |
| | (5.430) | (4.320) | (5.038) | (4.609) | (3.978) | (3.970) | (3.113) | (2.406) | (1.705) | (1.046) | (2.116) |
| Avg. TrdVol | 1.088 | 1.043 | 1.080 | 1.096 | 1.023 | 1.055 | 1.007 | 0.961 | 0.926 | 0.685 | 0.403 |
| | (6.648) | (6.102) | (6.203) | (6.001) | (5.398) | (5.456) | (4.960) | (4.447) | (4.033) | (2.676) | (2.811) |
| | B-2. Double sorting with trading volume: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.104 | 0.055 | 0.074 | 0.066 | -0.028 | 0.025 | -0.053 | -0.105 | -0.165 | -0.474 | 0.577 |
| | (1.968) | (1.086) | (1.507) | (1.282) | (-0.532) | (0.493) | (-1.025) | (-1.916) | (-2.746) | (-5.771) | (6.113) |
| Four-factor alpha | 0.153 | 0.097 | 0.116 | 0.134 | 0.054 | 0.108 | 0.025 | -0.038 | -0.084 | -0.377 | 0.531 |
| | (2.894) | (1.881) | (2.340) | (2.642) | (1.054) | (2.231) | (0.497) | (-0.702) | (-1.416) | (-4.619) | (5.521) |
| Six-factor alpha | 0.154 | 0.100 | 0.113 | 0.129 | 0.048 | 0.105 | 0.024 | -0.033 | -0.083 | -0.380 | 0.534 |
| | (2.969) | (1.965) | (2.297) | (2.641) | (0.990) | (2.262) | (0.492) | (-0.610) | (-1.392) | (-4.636) | (5.595) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | C-1. Double sorting with Amihud illiquidity measure: Portfolio return | | | | | | | | | | |
| Amihud(Bottom) | 0.914 | 0.878 | 1.002 | 0.978 | 0.941 | 0.928 | 0.937 | 0.693 | 0.623 | 0.254 | 0.660 |
| | (5.417) | (4.861) | (5.223) | (4.977) | (4.529) | (4.202) | (4.094) | (2.776) | (2.231) | (0.772) | (2.612) |
| Amihud (Middle) | 1.138 | 1.183 | 1.095 | 1.157 | 1.117 | 0.938 | 1.052 | 0.962 | 0.916 | 0.524 | 0.614 |
| | (6.016) | (5.885) | (5.315) | (5.691) | (5.233) | (4.323) | (4.716) | (4.154) | (3.602) | (1.838) | (3.738) |
| Amihud (Top) | 1.373 | 1.307 | 1.312 | 1.069 | 1.315 | 1.420 | 1.280 | 1.165 | 1.263 | 0.965 | 0.408 |
| | (6.185) | (5.739) | (5.919) | (4.687) | (5.875) | (6.098) | (5.545) | (4.922) | (5.162) | (3.844) | (2.314) |
| Avg. Amihud | 1.141 | 1.123 | 1.136 | 1.068 | 1.124 | 1.095 | 1.090 | 0.940 | 0.934 | 0.581 | 0.561 |
| | (6.429) | (5.991) | (5.941) | (5.472) | (5.560) | (5.204) | (5.069) | (4.174) | (3.839) | (2.168) | (3.606) |
| | C-2. Double sorting with Amihud illiquidity measure: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.104 | 0.071 | 0.074 | 0.008 | 0.040 | 0.017 | -0.007 | -0.157 | -0.185 | -0.560 | 0.664 |
| | (1.649) | (1.203) | (1.284) | (0.144) | (0.781) | (0.346) | (-0.126) | (-2.981) | (-2.852) | (-6.157) | (6.002) |
| Four-factor alpha | 0.133 | 0.096 | 0.124 | 0.043 | 0.094 | 0.070 | 0.048 | -0.124 | -0.116 | -0.458 | 0.591 |
| | (2.074) | (1.592) | (2.129) | (0.760) | (1.815) | (1.400) | (0.916) | (-2.311) | (-1.790) | (-5.046) | (5.269) |
| Six-factor alpha | 0.132 | 0.096 | 0.117 | 0.039 | 0.088 | 0.065 | 0.045 | -0.126 | -0.118 | -0.459 | 0.592 |
| | (2.139) | (1.602) | (2.034) | (0.724) | (1.800) | (1.343) | (0.874) | (-2.406) | (-1.827) | (-5.057) | (5.383) |

**Table 7**
Portfolio analysis: Dependently double sorting by resiliency and control variables.

At the end of each year between 1964 and 2012, all available stocks are sorted into tercile portfolios on the basis of the control variables, and then within each control variable, grouped into decile portfolios on the basis of resiliency. The value-weighted monthly returns of each portfolio are estimated during the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A reports the results of dependently double sorting between resiliency and market capitalization. "Low-High" column presents the average raw returns and alphas of the zero-investment portfolio. "Bottom", "Middle", and "Top" denote the average raw returns of the controlled resiliency decile portfolios. "Avg." portfolio denotes the average raw returns of the resiliency decile portfolios averaged across the each control variable. The alphas are estimated as intercepts from the regressions of the controlled excess portfolio returns on the Fama-French factor returns (three-factor alpha), on the Fama-French with momentum factor returns (four-factor alpha), and on the four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and the Amihud illiquidity factor (six-factor alpha). Panel B and Panel C reports the results of dependently double sorting between resiliency and the trading volume, and resiliency and the Amihud illiquidity, respectively. The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A-1. Double sorting with Firm's market capitalization: Portfolio return | | | | | | | | | | |
| Size (Bottom) | 1.190 | 1.102 | 1.128 | 1.185 | 1.229 | 1.147 | 1.208 | 1.135 | 0.999 | 0.672 | 0.518 |
| | (6.215) | (5.396) | (5.194) | (5.266) | (5.219) | (4.912) | (5.069) | (4.612) | (4.117) | (2.636) | (4.382) |
| Size (Middle) | 1.200 | 1.192 | 1.090 | 1.111 | 1.103 | 1.011 | 1.033 | 0.868 | 0.896 | 0.545 | 0.654 |
| | (5.876) | (5.491) | (5.045) | (4.894) | (4.796) | (4.305) | (4.286) | (3.437) | (3.350) | (1.890) | (4.389) |
| Size (Top) | 0.884 | 0.935 | 0.834 | 1.003 | 1.014 | 0.813 | 0.920 | 0.852 | 0.754 | 0.610 | 0.274 |
| | (5.388) | (5.333) | (4.516) | (5.200) | (5.025) | (4.012) | (4.346) | (3.888) | (3.183) | (2.305) | (1.533) |
| Avg. size | 1.091 | 1.076 | 1.017 | 1.100 | 1.115 | 0.990 | 1.054 | 0.952 | 0.883 | 0.609 | 0.482 |
| | (6.230) | (5.793) | (5.272) | (5.436) | (5.299) | (4.715) | (4.860) | (4.242) | (3.774) | (2.397) | (3.937) |
| | A-2. Double sorting with Firm's market capitalization: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.070 | 0.023 | -0.033 | 0.030 | 0.021 | -0.105 | -0.049 | -0.149 | -0.212 | -0.506 | 0.575 |
| | (1.373) | (0.490) | (-0.667) | (0.658) | (0.434) | (-2.159) | (-1.044) | (-2.854) | (-3.687) | (-6.843) | (6.837) |
| Four-factor alpha | 0.116 | 0.076 | 0.020 | 0.098 | 0.104 | -0.026 | 0.030 | -0.067 | -0.127 | -0.405 | 0.520 |
| | (2.269) | (1.612) | (0.410) | (2.199) | (2.179) | (-0.547) | (0.666) | (-1.327) | (-2.259) | (-5.554) | (6.094) |
| Six-factor alpha | 0.118 | 0.083 | 0.025 | 0.098 | 0.103 | -0.024 | 0.033 | -0.060 | -0.122 | -0.396 | 0.514 |
| | (2.346) | (1.774) | (0.521) | (2.208) | (2.178) | (-0.523) | (0.737) | (-1.190) | (-2.166) | (-5.450) | (6.093) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | B-1. Double sorting with trading volume: Portfolio return | | | | | | | | | | |
| TrdVol (Bottom) | 1.226 | 1.174 | 1.174 | 1.248 | 1.287 | 1.281 | 1.225 | 1.278 | 1.143 | 0.981 | 0.246 |
| | (7.104) | (6.503) | (6.932) | (6.346) | (6.942) | (6.557) | (6.203) | (6.216) | (5.459) | (4.288) | (1.849) |
| TrdVol (Middle) | 1.137 | 1.163 | 1.087 | 1.089 | 1.111 | 0.974 | 1.089 | 0.986 | 0.950 | 0.674 | 0.463 |
| | (6.280) | (6.128) | (5.761) | (5.568) | (5.548) | (4.730) | (5.296) | (4.380) | (3.951) | (2.485) | (3.062) |
| TrdVol (Top) | 0.862 | 0.832 | 0.910 | 1.045 | 0.827 | 0.855 | 0.970 | 0.739 | 0.737 | 0.398 | 0.465 |
| | (5.274) | (4.732) | (4.785) | (5.284) | (4.069) | (4.161) | (4.363) | (3.084) | (2.908) | (1.276) | (2.025) |
| Avg. TrdVol | 1.075 | 1.056 | 1.057 | 1.127 | 1.075 | 1.037 | 1.095 | 1.001 | 0.943 | 0.684 | 0.391 |
| | (6.657) | (6.225) | (6.040) | (6.136) | (5.817) | (5.444) | (5.598) | (4.829) | (4.336) | (2.719) | (2.854) |
| | B-2. Double sorting with trading volume: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.097 | 0.056 | 0.051 | 0.095 | 0.045 | -0.009 | 0.031 | -0.067 | -0.132 | -0.465 | 0.563 |
| | (1.820) | (1.158) | (1.022) | (1.938) | (0.900) | (-0.184) | (0.669) | (-1.382) | (-2.456) | (-6.344) | (6.422) |
| Four-factor alpha | 0.144 | 0.095 | 0.097 | 0.165 | 0.099 | 0.056 | 0.103 | 0.012 | -0.068 | -0.367 | 0.510 |
| | (2.662) | (1.939) | (1.935) | (3.411) | (1.999) | (1.157) | (2.316) | (0.264) | (-1.268) | (-5.065) | (5.731) |
| Six-factor alpha | 0.144 | 0.097 | 0.094 | 0.160 | 0.093 | 0.056 | 0.103 | 0.013 | -0.066 | -0.364 | 0.508 |
| | (2.737) | (1.991) | (1.920) | (3.380) | (1.955) | (1.220) | (2.371) | (0.285) | (-1.239) | (-5.108) | (5.773) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | C-1. Double sorting with Amihud illiquidity measure: Portfolio return | | | | | | | | | | |
| Amihud (Bottom) | 0.895 | 0.915 | 1.014 | 0.966 | 0.939 | 0.963 | 0.945 | 0.938 | 0.778 | 0.620 | 0.275 |
| | (5.305) | (5.235) | (5.352) | (5.009) | (4.640) | (4.698) | (4.391) | (4.178) | (3.269) | (2.295) | (1.570) |
| Amihud (Middle) | 1.148 | 1.197 | 1.047 | 1.127 | 1.117 | 1.013 | 1.047 | 1.012 | 0.903 | 0.599 | 0.549 |
| | (6.044) | (5.964) | (5.118) | (5.548) | (5.277) | (4.640) | (4.763) | (4.472) | (3.590) | (2.208) | (3.747) |
| Amihud (Top) | 1.336 | 1.315 | 1.245 | 1.391 | 1.317 | 1.208 | 1.197 | 1.302 | 1.022 | 0.871 | 0.465 |
| | (6.336) | (5.946) | (5.766) | (6.166) | (5.874) | (5.062) | (4.958) | (5.097) | (4.376) | (2.983) | (2.280) |
| Avg. Amihud | 1.126 | 1.142 | 1.102 | 1.161 | 1.124 | 1.061 | 1.063 | 1.084 | 0.901 | 0.697 | 0.429 |
| | (6.392) | (6.195) | (5.847) | (5.945) | (5.599) | (5.118) | (5.035) | (4.901) | (3.986) | (2.694) | (3.095) |
| | C-2. Double sorting with Amihud illiquidity measure: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.094 | 0.099 | 0.046 | 0.087 | 0.042 | -0.042 | -0.038 | -0.012 | -0.178 | -0.436 | 0.529 |
| | (1.629) | (1.840) | (0.831) | (1.754) | (0.812) | (-0.871) | (-0.832) | (-0.231) | (-3.376) | (-5.697) | (5.585) |
| Four-factor alpha | 0.124 | 0.101 | 0.079 | 0.126 | 0.075 | -0.024 | 0.017 | 0.006 | -0.118 | -0.356 | 0.479 |
| | (2.104) | (1.838) | (1.385) | (2.510) | (1.442) | (-0.493) | (0.363) | (0.121) | (-2.248) | (-4.649) | (4.970) |
| Six-factor alpha | 0.123 | 0.101 | 0.070 | 0.118 | 0.073 | -0.027 | 0.014 | 0.002 | -0.123 | -0.357 | 0.480 |
| | (2.180) | (1.886) | (1.272) | (2.411) | (1.463) | (-0.577) | (0.309) | (0.041) | (-2.333) | (-4.653) | (5.057) |

**Table 8**

Extended ARMA model: Sorting by resiliency.

At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency, which is calculated from the extended ARMA model. The value-weighted monthly returns are obtained during the subsequent 12 months. Resiliency denotes the speed of the transitory price recovery. Stocks with resiliency at the extreme 1% upper and lower values and with share prices less than $5 at the end of the previous month are excluded. Panel A presents the average market capitalization in natural logarithm form and the simple average of resiliency for each decile portfolio. Panel B reports the value-weighted monthly returns and alphas of the decile portfolios and Panel C reports the equal weighted case. "Low-High" column denotes the average raw returns and alphas of the zero-investment portfolio. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A. Portfolio Characteristics | | | | | | | | | | |
| *Ln_ME* | 12.43 | 12.47 | 12.43 | 12.39 | 12.23 | 12.03 | 11.81 | 11.53 | 11.17 | 10.73 | |
| *Resiliency* | 0.005 | 0.007 | 0.009 | 0.011 | 0.014 | 0.017 | 0.021 | 0.028 | 0.037 | 0.059 | |
| | B. Value-weighted Portfolio return and alpha | | | | | | | | | | |
| Raw Return | 0.930 | 0.847 | 0.986 | 0.953 | 0.898 | 0.895 | 0.845 | 0.721 | 0.704 | 0.505 | 0.425 |
| | (5.446) | (4.584) | (5.313) | (4.983) | (4.499) | (4.288) | (3.720) | (2.874) | (2.662) | (1.762) | (2.124) |
| Three-factor alpha | 0.022 | -0.044 | 0.108 | 0.031 | -0.033 | -0.035 | -0.097 | -0.248 | -0.348 | -0.534 | 0.556 |
| | (0.347) | (-0.725) | (2.413) | (0.624) | (-0.624) | (-0.599) | (-1.255) | (-2.533) | (-3.478) | (-4.383) | (4.006) |
| Four-factor alpha | 0.095 | -0.012 | 0.126 | 0.086 | 0.029 | 0.014 | 0.026 | -0.156 | -0.146 | -0.485 | 0.580 |
| | (1.498) | (-0.200) | (2.746) | (1.729) | (0.543) | (0.246) | (0.346) | (-1.587) | (-1.553) | (-3.905) | (4.089) |
| Six-factor alpha | 0.096 | -0.008 | 0.121 | 0.084 | 0.025 | 0.012 | 0.031 | -0.143 | -0.141 | -0.488 | 0.585 |
| | (1.526) | (-0.129) | (2.648) | (1.679) | (0.479) | (0.205) | (0.414) | (-1.458) | (-1.503) | (-3.934) | (4.144) |

**Table 9**

Extended ARMA model: Independently double sorting by resiliency and control variables.

At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency, which is calculated from the extended ARMA models and into tercile portfolios on the basis of the control variables, respectively. The value-weighted monthly returns of each portfolio are estimated by taking the intersection during the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A reports the results of independently double sorting between resiliency and market capitalization. “Low-High” column presents the average raw returns and alphas of the zero-investment portfolio. “Bottom”, “Middle”, and “Top” denote the controlled resiliency decile portfolios. “Avg.” portfolio denotes the average raw returns of the resiliency decile portfolios averaged across the each control variable. The alphas are estimated as intercepts from the regressions of controlled excess portfolio returns on the Fama-French factor returns (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). Panel B and Panel C reports the results of independently double sorting between resiliency and the trading volume, and resiliency and the Amihud illiquidity, respectively. The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A-1. Double sorting with Firm's market capitalization : Portfolio return | | | | | | | | | | |
| Size (Bottom) | 1.202 | 1.206 | 1.160 | 1.193 | 1.025 | 1.184 | 1.203 | 1.172 | 1.080 | 0.839 | 0.363 |
| | (6.220) | (5.872) | (5.750) | (5.469) | (4.452) | (5.183) | (5.113) | (4.944) | (4.521) | (3.414) | (3.294) |
| Size (Middle) | 1.198 | 1.166 | 1.103 | 1.150 | 1.073 | 1.069 | 0.960 | 0.967 | 0.849 | 0.500 | 0.698 |
| | (5.918) | (5.418) | (5.133) | (5.159) | (4.701) | (4.554) | (4.016) | (3.768) | (3.161) | (1.706) | (4.546) |
| Size (Top) | 0.967 | 0.994 | 1.035 | 0.963 | 0.985 | 0.919 | 0.843 | 0.722 | 0.632 | 0.656 | 0.311 |
| | (5.652) | (5.504) | (5.406) | (4.775) | (4.683) | (4.211) | (3.615) | (2.792) | (2.249) | (2.065) | (1.279) |
| Avg. size | 1.122 | 1.122 | 1.099 | 1.102 | 1.028 | 1.057 | 1.002 | 0.954 | 0.854 | 0.665 | 0.457 |
| | (6.318) | (5.907) | (5.724) | (5.430) | (4.882) | (4.903) | (4.485) | (4.014) | (3.451) | (2.513) | (3.286) |
| | A-2. Double sorting with Firm’s market capitalization : Alpha | | | | | | | | | | |
| Three-factor alpha | 0.079 | 0.0478 | 0.038 | 0.000 | -0.068 | -0.037 | -0.097 | -0.160 | -0.271 | -0.438 | 0.517 |
| | (1.584) | (0.982) | (0.770) | (0.010) | (-1.398) | (-0.771) | (-1.983) | (-2.987) | (-4.583) | (-5.013) | (5.234) |
| Four-factor alpha | 0.114 | 0.099 | 0.099 | 0.075 | 0.006 | 0.056 | 0.002 | -0.073 | -0.159 | -0.348 | 0.462 |
| | (2.252) | (2.036) | (1.995) | (1.539) | (0.122) | (1.227) | (0.052) | (-1.397) | (-2.830) | (-3.977) | (4.601) |
| Six-factor alpha | 0.116 | 0.098 | 0.099 | 0.078 | 0.008 | 0.054 | 0.003 | -0.067 | -0.154 | -0.341 | 0.457 |
| | (2.342) | (2.094) | (2.032) | (1.665) | (0.175) | (1.224) | (0.068) | (-1.299) | (-2.744) | (-3.904) | (4.614) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | B-1. Double sorting with trading volume: Portfolio return | | | | | | | | | | |
| TrdVol (Bottom) | 1.228 | 1.022 | 1.065 | 1.247 | 0.957 | 1.212 | 1.089 | 1.210 | 1.236 | 0.980 | 0.249 |
| | (6.544) | (5.540) | (5.957) | (6.518) | (4.926) | (6.349) | (5.536) | (6.273) | (6.169) | (4.694) | (1.721) |
| TrdVol (Middle) | 1.150 | 1.150 | 1.061 | 1.092 | 1.119 | 0.959 | 1.048 | 0.996 | 0.897 | 0.689 | 0.461 |
| | (6.243) | (6.146) | (5.719) | (5.731) | (5.467) | (4.710) | (5.030) | (4.428) | (3.688) | (2.499) | (2.777) |
| TrdVol (Top) | 0.893 | 0.872 | 0.998 | 1.007 | 0.965 | 0.984 | 0.779 | 0.745 | 0.581 | 0.473 | 0.420 |
| | (5.240) | (4.924) | (5.196) | (5.105) | (4.742) | (4.633) | (3.323) | (2.833) | (1.983) | (1.429) | (1.616) |
| Avg. TrdVol | 1.091 | 1.015 | 1.041 | 1.116 | 1.014 | 1.052 | 0.972 | 0.984 | 0.905 | 0.714 | 0.377 |
| | (6.568) | (5.979) | (6.030) | (6.163) | (5.411) | (5.550) | (4.869) | (4.619) | (3.955) | (2.862) | (2.639) |
| | B-2. Double sorting with trading volume: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.101 | 0.016 | 0.035 | 0.076 | -0.031 | 0.025 | -0.081 | -0.086 | -0.197 | -0.415 | 0.516 |
| | (1.641) | (0.269) | (0.640) | (1.397) | (-0.548) | (0.483) | (-1.612) | (-1.600) | (-3.395) | (-5.364) | (5.454) |
| Four-factor alpha | 0.156 | 0.052 | 0.084 | 0.138 | 0.048 | 0.096 | -0.003 | -0.033 | -0.114 | -0.329 | 0.485 |
| | (2.521) | (0.886) | (1.512) | (2.542) | (0.863) | (1.918) | (-0.065) | (-0.615) | (-1.997) | (-4.257) | (5.021) |
| Six-factor alpha | 0.156 | 0.049 | 0.080 | 0.135 | 0.045 | 0.091 | -0.003 | -0.031 | -0.114 | -0.329 | 0.485 |
| | (2.625) | (0.392) | (1.477) | (2.589) | (0.857) | (1.930) | (-0.062) | (-0.588) | (-2.009) | (-4.254) | (5.148) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | C-1. Double sorting with Amihud illiquidity measure : Portfolio return | | | | | | | | | | |
| Amihud (Bottom) | 0.895 | 0.901 | 1.000 | 1.001 | 0.907 | 0.957 | 0.865 | 0.798 | 0.602 | 0.454 | 0.441 |
| | (5.197) | (5.026) | (5.223) | (5.082) | (4.478) | (4.460) | (3.920) | (3.203) | (2.156) | (1.461) | (1.891) |
| Amihud (Middle) | 1.145 | 1.175 | 1.065 | 1.150 | 1.135 | 0.962 | 1.042 | 0.988 | 0.893 | 0.450 | 0.695 |
| | (6.042) | (5.834) | (5.248) | (5.668) | (5.300) | (4.383) | (4.698) | (4.234) | (3.518) | (1.583) | (4.279) |
| Amihud (Top) | 1.334 | 1.342 | 1.361 | 1.108 | 1.289 | 1.380 | 1.219 | 1.208 | 1.247 | 0.966 | 0.368 |
| | (6.108) | (5.936) | (6.093) | (4.744) | (5.727) | (5.906) | (5.320) | (5.090) | (5.158) | (3.836) | (2.099) |
| Avg. Amihud | 1.125 | 1.140 | 1.142 | 1.086 | 1.110 | 1.100 | 1.042 | 0.998 | 0.914 | 0.623 | 0.501 |
| | (6.344) | (6.103) | (5.982) | (5.519) | (5.551) | (5.233) | (4.919) | (4.431) | (3.780) | (2.381) | (3.380) |
| | C-2. Double sorting with Amihud illiquidity measure : Alpha | | | | | | | | | | |
| Three-factor alpha | 0.088 | 0.094 | 0.088 | 0.025 | 0.031 | 0.019 | -0.048 | -0.101 | -0.198 | -0.502 | 0.590 |
| | (1.402) | (1.604) | (1.478) | (0.468) | (0.587) | (0.380) | (-0.969) | (-1.835) | (-3.157) | (-5.756) | (5.593) |
| Four-factor alpha | 0.126 | 0.119 | 0.119 | 0.044 | 0.076 | 0.067 | 0.002 | -0.070 | -0.112 | -0.406 | 0.533 |
| | (1.976) | (2.007) | (1.972) | (0.808) | (1.435) | (1.313) | (0.040) | (-1.247) | (-1.807) | (-4.665) | (4.965) |
| Six-factor alpha | 0.126 | 0.117 | 0.114 | 0.040 | 0.072 | 0.059 | -0.002 | -0.071 | -0.112 | -0.410 | 0.536 |
| | (2.062) | (1.991) | (1.921) | (0.761) | (1.419) | (1.217) | (-0.048) | (-1.294) | (-1.819) | (-4.700) | (5.120) |

**Table 10**
Extended ARMA model: Dependently double sorting by resiliency and control variables.

At the end of each year between 1964 and 2012, all available stocks are sorted into tercile portfolios on the basis of the control variables, and then within each market control variable, grouped into decile portfolios on the basis of resiliency, which is calculated from the extended ARMA models. The value-weighted monthly returns of each portfolio are estimated during the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A reports the results of dependently double sorting between resiliency and market capitalization. "Low-High" column presents the average raw returns and alphas of the zero-investment portfolio. "Bottom", "Middle", and "Top" denote the controlled resiliency decile portfolios. "Avg." portfolio denotes the average raw returns of the resiliency decile portfolios averaged across the each control variable. The alphas are estimated as intercepts from the regressions of controlled excess portfolio returns on the Fama-French factor returns (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). Panel B and Panel C reports the results of independently double sorting between resiliency and the trading volume, and resiliency and the Amihud illiquidity, respectively. The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A-1. Double sorting with Firm's market capitalization : Portfolio return | | | | | | | | | | |
| Size (Bottom) | 1.235 | 1.139 | 1.126 | 1.139 | 1.240 | 1.086 | 1.237 | 1.112 | 1.028 | 0.648 | 0.587 |
| | (6.461) | (5.707) | (5.174) | (5.051) | (5.308) | (4.641) | (5.165) | (4.568) | (4.186) | (2.553) | (4.942) |
| Size (Middle) | 1.175 | 1.193 | 1.115 | 1.111 | 1.119 | 0.976 | 1.030 | 0.877 | 0.877 | 0.576 | 0.599 |
| | (5.801) | (5.543) | (5.140) | (4.988) | (4.849) | (4.171) | (4.272) | (3.443) | (3.258) | (1.999) | (4.091) |
| Size (Top) | 0.940 | 1.027 | 1.062 | 1.038 | 0.949 | 0.927 | 0.926 | 0.955 | 0.829 | 0.631 | 0.310 |
| | (5.565) | (5.683) | (5.728) | (5.379) | (4.724) | (4.569) | (4.284) | (4.315) | (3.460) | (2.270) | (1.685) |
| Avg. size | 1.117 | 1.120 | 1.101 | 1.096 | 1.103 | 0.996 | 1.064 | 0.981 | 0.911 | 0.618 | 0.498 |
| | (6.309) | (5.965) | (5.602) | (5.405) | (5.230) | (4.697) | (4.873) | (4.345) | (3.845) | (2.403) | (4.037) |
| | A-2. Double sorting with Firm's market capitalization : Alpha | | | | | | | | | | |
| Three-factor alpha | 0.080 | 0.045 | 0.017 | 0.001 | -0.013 | -0.111 | -0.044 | -0.128 | -0.201 | -0.497 | 0.577 |
| | (1.661) | (0.919) | (0.351) | (0.0109) | (-0.261) | (-2.205) | (-0.941) | (-2.578) | (-3.574) | (-6.857) | (7.006) |
| Four-factor alpha | 0.111 | 0.098 | 0.075 | 0.074 | 0.065 | -0.029 | 0.026 | -0.049 | -0.105 | -0.397 | 0.508 |
| | (2.275) | (1.993) | (1.544) | (1.532) | (1.325) | (-0.603) | (0.576) | (-1.010) | (-1.927) | (-5.563) | (6.115) |
| Six-factor alpha | 0.111 | 0.099 | 0.076 | 0.073 | 0.063 | -0.025 | 0.030 | -0.047 | -0.102 | -0.390 | 0.501 |
| | (2.356) | (2.063) | (1.638) | (1.553) | (1.337) | (-0.544) | (0.658) | (-0.989) | (-1.881) | (-5.468) | (6.150) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | B-1. Double sorting with trading volume: Portfolio return | | | | | | | | | | |
| TrdVol (Bottom) | 1.226 | 1.009 | 1.081 | 1.185 | 1.114 | 1.201 | 1.193 | 1.212 | 1.113 | 0.930 | 0.296 |
| | (6.842) | (5.484) | (5.943) | (6.078) | (5.884) | (6.333) | (6.101) | (6.075) | (5.384) | (4.294) | (2.083) |
| TrdVol (Middle) | 1.155 | 1.112 | 1.120 | 1.052 | 1.086 | 0.986 | 1.052 | 1.001 | 0.911 | 0.712 | 0.443 |
| | (6.300) | (5.978) | (5.937) | (5.472) | (5.361) | (4.816) | (5.086) | (4.416) | (3.795) | (2.634) | (2.817) |
| TrdVol (Top) | 0.852 | 0.925 | 0.945 | 1.011 | 1.001 | 0.924 | 1.044 | 0.790 | 0.778 | 0.543 | 0.309 |
| | (5.034) | (5.206) | (4.964) | (5.251) | (5.019) | (4.569) | (4.876) | (3.478) | (3.071) | (1.770) | (1.376) |
| Avg. TrdVol | 1.078 | 1.016 | 1.049 | 1.083 | 1.067 | 1.037 | 1.096 | 1.001 | 0.934 | 0.728 | 0.349 |
| | (6.590) | (5.972) | (5.973) | (5.972) | (5.770) | (5.538) | (5.674) | (4.927) | (4.287) | (2.969) | (2.605) |
| | B-2. Double sorting with trading volume: Alpha | | | | | | | | | | |
| Three-factor alpha | 0.093 | 0.006 | 0.032 | 0.040 | 0.031 | -0.006 | 0.033 | -0.070 | -0.149 | -0.396 | 0.489 |
| | (1.557) | (0.098) | (0.606) | (0.731) | (0.556) | (-0.128) | (0.713) | (-1.420) | (-2.745) | (-5.729) | (5.732) |
| Four-factor alpha | 0.141 | 0.054 | 0.079 | 0.102 | 0.078 | 0.064 | 0.094 | 0.012 | -0.101 | -0.295 | 0.437 |
| | (2.352) | (0.941) | (1.469) | (1.865) | (1.401) | (1.317) | (2.065) | (0.253) | (-1.857) | (-4.360) | (5.044) |
| Six-factor alpha | 0.140 | 0.051 | 0.071 | 0.098 | 0.077 | 0.064 | 0.092 | 0.012 | -0.101 | -0.295 | 0.435 |
| | (2.435) | (0.924) | (1.398) | (1.871) | (1.465) | (1.389) | (2.077) | (0.262) | (-1.851) | (-4.345) | (5.144) |

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | C-1. Double sorting with Amihud illiquidity measure : Portfolio return | | | | | | | | | | |
| Amihud (Bottom) | 0.880 | 0.922 | 0.995 | 1.001 | 0.910 | 0.981 | 0.922 | 0.947 | 0.788 | 0.677 | 0.203 |
| | (5.147) | (5.213) | (5.247) | (5.204) | (4.560) | (4.845) | (4.419) | (4.318) | (3.370) | (2.503) | (1.167) |
| Amihud (Middle) | 1.157 | 1.171 | 1.061 | 1.140 | 1.115 | 1.023 | 1.050 | 1.003 | 0.877 | 0.593 | 0.564 |
| | (6.113) | (5.772) | (5.297) | (5.575) | (5.235) | (4.668) | (4.742) | (4.464) | (3.496) | (2.186) | (3.875) |
| Amihud (Top) | 1.284 | 1.332 | 1.234 | 1.439 | 1.345 | 1.171 | 1.202 | 1.283 | 1.046 | 0.833 | 0.451 |
| | (6.011) | (6.204) | (5.557) | (6.340) | (5.943) | (4.864) | (5.049) | (5.078) | (4.478) | (2.850) | (2.132) |
| Avg. Amihud | 1.107 | 1.142 | 1.097 | 1.193 | 1.123 | 1.058 | 1.058 | 1.077 | 0.904 | 0.701 | 0.406 |
| | (6.298) | (6.154) | (5.778) | (6.085) | (5.581) | (5.108) | (5.064) | (4.950) | (4.041) | (2.722) | (2.957) |
| | C-2. Double sorting with Amihud illiquidity measure : Alpha | | | | | | | | | | |
| Three-factor alpha | 0.076 | 0.090 | 0.044 | 0.121 | 0.036 | -0.050 | -0.031 | -0.017 | -0.170 | -0.430 | 0.506 |
| | (1.281) | (1.689) | (0.791) | (2.493) | (0.667) | (-1.066) | (-0.684) | (-0.354) | (-3.122) | (-5.678) | (5.367) |
| Four-factor alpha | 0.109 | 0.106 | 0.064 | 0.137 | 0.074 | -0.030 | -0.000 | 0.014 | -0.106 | -0.342 | 0.451 |
| | (1.811) | (1.944) | (1.144) | (2.765) | (1.377) | (-0.638) | (-0.003) | (0.293) | (-1.959) | (-4.536) | (4.710) |
| Six-factor alpha | 0.109 | 0.104 | 0.054 | 0.131 | 0.072 | -0.032 | -0.003 | 0.009 | -0.111 | -0.344 | 0.452 |
| | (1.886) | (1.976) | (1.004) | (2.711) | (1.399) | (-0.711) | (-0.073) | (0.192) | (-2.047) | (-4.543) | (4.818) |

**Table 11**
Sub-period analysis.
At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the estimated resiliency, and then value-weighted monthly returns are obtained for the subsequent 12 months. Stocks with resiliency at the extreme 1% upper and lower values, and with share prices less than $5 at the end of the each year are excluded. Panel A presents average raw returns and alphas of the decile portfolios from 1965 to 1989. Panel B reports the estimated results from 1990 to 2013. The “Low-High” column presents the average raw returns and alphas of the zero-investment portfolio. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the Four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). The t-statistics are in parentheses.

| | Resiliency Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A. January 1965-December 1989 | | | | | | | | | | |
| Return | 0.914 | 0.999 | 0.981 | 1.028 | 0.927 | 0.907 | 0.867 | 0.765 | 0.768 | 0.569 | 0.346 |
| | (3.736) | (3.946) | (3.725) | (3.772) | (3.235) | (3.092) | (2.786) | (2.400) | (2.200) | (1.510) | (1.462) |
| Three-factor alpha | -0.059 | 0.066 | 0.049 | 0.0915 | 0.063 | -0.004 | -0.062 | -0.235 | -0.335 | -0.527 | 0.468 |
| | (-0.607) | (0.870) | (0.803) | (1.478) | (0.985) | (-0.054) | (-0.694) | (-2.719) | (-3.632) | (-4.374) | (2.942) |
| Four-factor alpha | 0.087 | 0.116 | 0.0747 | 0.155 | 0.099 | 0.066 | 0.002 | -0.188 | -0.259 | -0.489 | 0.576 |
| | (0.904) | (1.487) | (1.191) | (2.455) | (1.506) | (0.863) | (0.023) | (-2.106) | (-2.742) | (-3.909) | (3.510) |
| Six-factor alpha | 0.110 | 0.148 | 0.0532 | 0.163 | 0.092 | 0.065 | 0.003 | -0.168 | -0.261 | -0.514 | 0.624 |
| | (1.140) | (1.891) | (0.847) | (2.560) | (1.389) | (0.846) | (0.031) | (-1.884) | (-2.732) | (-4.062) | (3.776) |
| | B. January 1990-December 2013 | | | | | | | | | | |
| Raw Return | 0.954 | 0.751 | 0.945 | 0.888 | 0.824 | 0.797 | 0.748 | 0.691 | 0.722 | 0.336 | 0.619 |
| | (4.221) | (2.975) | (3.416) | (3.107) | (2.767) | (2.433) | (2.193) | (1.800) | (1.781) | (0.748) | (1.755) |
| Three-factor alpha | 0.127 | -0.0628 | 0.0550 | -0.0323 | -0.165 | -0.196 | -0.235 | -0.284 | -0.349 | -0.717 | 0.844 |
| | (1.846) | (-0.803) | (0.705) | (-0.400) | (-1.875) | (-1.874) | (-1.839) | (-1.676) | (-1.994) | (-3.333) | (3.610) |
| Four -factor alpha | 0.131 | -0.0582 | 0.0729 | 0.0536 | -0.0640 | -0.075 | -0.099 | -0.211 | -0.131 | -0.659 | 0.791 |
| | (1.870) | (-0.732) | (0.921) | (0.699) | (-0.773) | (-0.766) | (-0.815) | (-1.239) | (-0.812) | (-3.027) | (3.334) |
| Six-factor alpha | 0.117 | -0.0507 | 0.0724 | 0.0411 | -0.0857 | -0.091 | -0.126 | -0.221 | -0.108 | -0.636 | 0.753 |
| | (1.717) | (-0.639) | (0.915) | (0.549) | (-1.086) | (-0.941) | (-1.074) | (-1.307) | (-0.675) | (-2.932) | (3.225) |

**Table 12**
Role of frequency component.
'Avg.magnitude' denotes the average absolute value of magnitude for transitory price wave in the frequency domain. 'Low-frequency' and 'High-frequency' denotes the speed of transitory price recovery estimated in low-frequency and high-frequency level, respectively. At the end of each year between 1964 and 2012, all available stocks are sorted into decile portfolios on the basis of the frequency-adjusted measures. The value-weighted monthly returns are obtained during the subsequent 12 months. Panel A reports the average monthly returns of the decile portfolio and 'Low-High' zero-investment portfolio sorted by *Avg.Magnitude*, low-frequency resiliency, and high-frequency resiliency, respectively. Panel B reports estimated alphas of the decile portfolio and 'Low-High' zero-investment portfolio sorted by high-frequency resiliency. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (three-factor alpha), on the Fama-French with momentum factor (four-factor alpha), and on the Four-factor model with two liquidity factors—Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (six-factor alpha). The t-statistics are in parentheses.

| | Decile Portfolio | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10(High) | Low-High |
| | A. Portfolio Return | | | | | | | | | | |
| *Avg.Magnitude* | 0.934 | 0.867 | 0.998 | 0.958 | 0.849 | 0.866 | 0.783 | 0.767 | 0.711 | 0.687 | 0.247 |
| | (5.607) | (4.772) | (5.101) | (4.812) | (4.032) | (3.922) | (3.559) | (3.381) | (2.830) | (2.698) | (1.501) |
| Low-frequency | 0.953 | 0.961 | 0.941 | 0.936 | 0.832 | 0.822 | 0.782 | 0.856 | 0.809 | 0.728 | 0.224 |
| | (5.543) | (5.218) | (4.832) | (4.597) | (4.003) | (3.829) | (3.659) | (4.043) | (3.474) | (2.997) | (1.509) |
| High-frequency | 0.967 | 0.832 | 0.962 | 1.034 | 0.866 | 0.854 | 0.861 | 0.764 | 0.550 | 0.498 | 0.469 |
| | (5.769) | (4.727) | (5.070) | (5.285) | (4.235) | (3.830) | (3.683) | (3.018) | (2.046) | (1.604) | (2.022) |
| | B. High-frequency alpha | | | | | | | | | | |
| Three-factor alpha | 0.051 | -0.037 | 0.076 | 0.096 | -0.068 | -0.096 | -0.085 | -0.252 | -0.453 | -0.573 | 0.624 |
| | (0.792) | (-0.705) | (1.608) | (1.889) | (-1.224) | (-1.414) | (-0.984) | (-2.773) | (-4.606) | (-4.257) | (3.955) |
| Four-factor alpha | 0.110 | -0.013 | 0.108 | 0.149 | -0.003 | 0.024 | 0.063 | -0.133 | -0.365 | -0.425 | 0.535 |
| | (1.689) | (-0.251) | (2.248) | (2.913) | (-0.0504) | (0.362) | (0.757) | (-1.485) | (-3.685) | (-3.163) | (3.335) |
| Six-factor alpha | 0.110 | -0.008 | 0.102 | 0.141 | -0.006 | 0.027 | 0.069 | -0.131 | -0.359 | -0.417 | 0.527 |
| | (1.715) | (-0.145) | (2.128) | (2.780) | (-0.109) | (0.415) | (0.834) | (-1.456) | (-3.637) | (-3.117) | (3.323) |