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

Jinyong Kim* and Yongsik Kim**

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Keywords: resiliency; liquidity; stock returns; transitory price

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* School of Management Engineering, Korea Advanced Institute of Science and Technology, 85, Hoegi-ro, Dongdaemun-gu, Seoul, 130-722 Korea; Tel.: +82 2-958-3425; Email: jinyongkim@business.kaist.ac.kr

** Corresponding author, School of Management Engineering, Korea Advanced Institute of Science and Technology, 85, Hoegi-ro, Dongdaenun-gu, Seoul, 130-722 Korea; Tel.: +82 2-958-3150; Email: yskim83@business.kaist.ac.kr

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Abstract

This paper investigates whether resiliency is a systematic risk factor that generates cross-sectional variations of stock returns. Resiliency is defined as quickness of price recovery from a liquidity shock. Using the Beveridge-Nelson decomposition and the spectral analysis in frequency domain, we measure resiliency for individual stocks as the speed of mean reversion of transitory price components. Our main finding is 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. Furthermore, we find that our resiliency measure is complementary to existing liquidity measures to capture a full dimension of liquidity and to capture additional liquidity risk premia.

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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 is trading activity such as total volume of trading or share turnover which represents how the market investors trade assets actively. The other side of liquidity dimension is trading cost, generally estimated by Amihud (2002) illiquidity measure or bid-ask spread measures in order to capture the level of price impact that investors should bear when executing market orders. Regarding these two categories, liquidity measures have been well-defined in large numbers of literatures. However, measure for another side of liquidity dimension, *resiliency*, has not been clearly defined yet.

The concept of resiliency has been introduced in several previous studies. Black (1971) describes a liquid market is a continuous and efficient market where securities can be bought or sold immediately at very near the current price. Kyle (1985) mentions that resiliency is the speed of price recovery from an uninformative random shock. Bernstein (1987) explains resiliency in terms of order imbalance. He argues that resiliency means a large order flow countervailing transaction price change due to the temporary order imbalances. Harris (2003) specifies that resiliency refers to how quickly prices revert to fundamental values driven by value trader after price changes in response to large order flow imbalances initiated by liquidity demander or uninformed trader. In this regard, resiliency can be characterized as the speed of price recovery that reverts to its fundamental value from the prior transitory price impact driven by informed trader.

On the basis of these definitions, this study measures resiliency and investigates whether the resiliency has an effect on the cross section of stock returns. To compute the level of resiliency, first we need to decompose daily stock prices into the fundamental components and the transitory components because the resiliency represents the reversion of transitory price to fundamental value as

[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.

we discussed above.[2] For decomposition of stock prices, we use the trend-cycle decomposition methodology introduced by Beveridge and Nelson (1981, hereafter B-N decomposition). After performing B-N decomposition, we transform the estimated daily series of transitory price into spectral functional form in frequency domain to derive the speed of transitory price recovery as our measure of resiliency.

Some of recent empirical studies have suggested resiliency measures. These resiliency measures can be classified into two types. One is that resiliency represents the mean reverting in terms of stock price. This approach mainly focuses on the movement of stock price itself. Dong et al. (2007) define resiliency as mean reversion parameter of the stock's intraday pricing-error process between period t-1 and t. They show that expected stock returns of individual firm are negatively related with resiliency. Alan et al. (2015) calculate resiliency as the intraday serial correlation of the opening half-hour stock returns with those of the remainder trading day. They also find that the resiliency has a negative relationship with the cross-section of stock returns through individual firm level and portfolio level analysis. The other type of resiliency measures focuses on recovery process in terms of trading cost measure such as bid-ask spread or market depth. Anand et al. (2013) suggest irresiliency measure as the average percentage of months during and after the financial crisis period (from May 2008 to December 2009) that trading cost exceed a two-sigma threshold relative to pre-crisis period. They show that liquidity supplying of buy-side institutions is the main factor for recovery from a liquidity shock in the post-crisis period. Kempf et al. (2015) also use trading cost measure to calculate resiliency. Similar to Dong, et al. (2007), Kempf et al. (2015) define resiliency as the mean reversion parameter of the previous level of trading cost and current trading cost flow using intraday data.

A main distinction of this study is that our resiliency measure measures the speed of transitory

[2] A number of studies also have mentioned that liquidity measures are related to the transitory price effects. Roll (1984) derive bid-ask spreads using the characteristics of the negative autocovariance of the transitory price change. Easley, Hvidkjaer, and O'Hara (2010) explain that total price effects can be divided into a permanent component due to information and a temporary component due to liquidity. Bao, Pan and Wang (2011) argue that the magnitude of transitory price movement reflects the degree of illiquidity because the lack of liquidity causes transitory components in asset prices.

price recovery directly. By the spectral analysis in frequency domain, we obtain the concept of distance and recovery time of transitory price. We then calculate speed from the distance divide by recovery time. Thus we contend that our measure fits better to the literal definition of resiliency than the previous literatures. In addition, our resiliency measure is modeled to overcome the problem which Anand et al. (2013) point out that the existing studies only examine resiliency over a short horizon. We model the transitory price movement has more than one frequency component reverting to fundamental value which implies that our resiliency measure can capture the speed over a long-horizon recovery movement as well as over a short-horizon. Regarding data structure, much of previous studies use intraday microstructure data to compute the level of resiliency. In contrast with these studies, we use daily stock data to calculate monthly resiliency of individual firms following the spirit of Amihud (2002)[3].

Our empirical findings show that resiliency plays a significant role as a systematic risk factor in asset pricing. Expected stock returns are a decreasing function of resiliency which implies that stocks with lower resiliency need to compensate a higher risk premium to investors. During our sample period for the years 1965-2013, we find that resiliency-based trading 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 Amihud (2002). We also find that our resiliency measure is complementary to existing trading cost measure. The result of the Fama-Macbeth regression on individual stocks shows that our resiliency measure has a significantly negative predicting power on their expected stock returns. What should be noted is that resiliency does not reduce the positive predicting power of Amihud (2002) or Roll (1984) measure on stock returns. The

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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 of time even when available. Following Amihud (2002), we can cover longer time period from 1965 to 2013 to implement asset pricing test and examine longer-horizon of price recovery movement from the price impact.

result of double-sorted portfolio analysis based on resiliency and Amihud illiquidity measure also shows that resiliency can capture additional risk premium in addition to that of Amihud illiquidity measure. This suggests that our resiliency measure can generate additional cross-sectional variations and liquidity dimension of stock returns which are not explained by existing liquidity measure.

This paper is organized as follows. In Section 2, we describe the construction of resiliency measure and data description. In Section 3, we present cross-section estimates results that include the effect of resiliency on individual firm's stock returns and univariate/bivariate portfolio level analysis. The last section is a conclusion.

2. Constructing a resiliency measure

The stock price can be decomposed into two components. One is a permanent or random walk component which represents stock's fundamental value that moves along with the informational shock. The other is a transitory or stationary component that contains temporary price movement deviating from its fundamental value. As discussed above, resiliency represents how quickly the stock price recovers to its fundamental value from the transitory price impact. In this regard, we measure as the average speed of the recovery movement of the transitory price component to its fundamental value. More specifically, to calculate the measure of stock's resiliency, we implement following two-step procedure: First, we decompose 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 frequency domain. This procedure is described in the following sections.

2.1. A decomposition of stock price

To decompose the stock price into permanent and transitory components, we use the methodology of B-N decomposition. Assume that the stock price can be decomposed into a random walk component with drift, q_t, and AR(1) stationary process, z_t. Then we can model 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 η_t and ε_t are shocks at time t. Based on this model, we can represent stock return as follows:

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

where $\Delta z_t = z_t - z_{t-1}$.

The series p_t can be derived as the sum of the random walk component and AR(1) process, which follows ARIMA(1,1,1) process. Therefore, $r_t^* = r_t - \mu$ follows 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 a 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 higher speed of reversion indicates that it can recover from a prior transitory price impact more quickly. Thus, investors regard this stock as more resilient, and accordingly more liquid, one. In other words, 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 frequency domain by using Fourier transform. If a stock has higher speed of reversion, its spectral function will be mainly distributed at a higher frequency level, while if it has lower speed of reversion, its spectral function will be distributed at a lower frequency. Here, we assume that the transitory price series is a finite signal which contain 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, $\mathrm{Z_k}$ represents the spectral function of z_t, and k is the indicator for frequency domain. D is the total trading days and i denotes imaginary unit. To estimate pure magnitude of spectral function without influence of the number of trading days, we normalize Z_k with *D*. Then, we obtain normalized functional form, $\tilde{Z}_k$, as

$$\tilde{Z}_k = \frac{1}{D} Z_k, \qquad (k = 1, 2, \cdots, D) \quad (10)$$[4]

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

By equation (10), we compute the magnitude of normalized spectral function, $|\tilde{Z}_k|$. Since the frequency is defined as the number of cycles per unit time, consequently the period (cycle), T_k $(=\frac{D}{k})$, can be represented as the reciprocal of the scaled version of frequency component, $f_k(=\frac{k}{D})$[5]. The magnitude, $|\tilde{Z}_k|$, indicates the distance to the peak of swings of transitory price deviating from its fundamental value in each frequency level. The period, *T*, captures how quickly the cycle of each reverting swing is completed. Therefore, the speed of transitory price movement in each frequency level can be obtained by dividing $|\tilde{Z}_k|$ by its corresponding period. Accordingly, our resiliency measure, which is the average speed of the transitory price recovery, can be obtained by the following equation:

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

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 3-month rolling window for computing 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 $Resiliency_{i,t}$ at the highest or lowest 1% tails of distribution.

2.3 Data and variable description

We estimate our resiliency measure for the sample of all common stocks listed in the NYSE,

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[5] Frequency axis of spectral function is also scaled by $\frac{1}{D}$ to avoid 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 frequency component as f_k.

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

AMEX and NASDAQ during the years 1964-2013, using return and volume data from CRSP data base 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 to be included 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 price. We then calculate the level of resiliency for individual stocks as in equation (11) using quarter-length (3 months) rolling window month by month. Daily return data are not required to be consecutive, but a stock should have observations of more than 70% of trading days in a given quarter, in order to be included in our sample, following Pastor and Stambaugh(2003). To improve accuracy and reliability of the spectral function calculated through discrete Fourier transform, we use longer data series, a quarter, as a length of rolling window than a month as in Pastor and Stambaugh (2003).

With the estimated measures, this study proceeds to investigate whether the stock resiliency is a systematic risk factor to generate risk premia based on various regression analyses. As control variables used in the subsequent regressions, we use two categories of variables that are associated with market liquidity. 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 indicate the trading activeness for a stock to its given share outstandings.

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 to capture price impact and market illiquidity. Amihud illiquidity measure (*Amihud*) is defined as the annual average ratio of the daily absolute returns, $|r_{i,d}|$, to the dollar trading volume, $Vol_{i,d}$, on that day, i.e.,

$$Amihud_{i,y} = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \frac{|r_{i,d}|}{Vol_{i,d}}, \tag{12}$$

where $D_{i,y}$ is the number of trading days for which data are available for stock *i* in year *y*.[7] We also include the Roll measure (*Roll*) to capture bid-ask spread of a stock. Roll measure is defined as,

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

where $\Delta p_d = p_d - p_{d-1}$ for which data are available for stock *i* in month *m*. *Roll* implies that, serially negatively correlated price movements can be interpreted as a bid-ask bounce under certain circumstances. We compute *Roll* in a given month only if there are more than 15 observations of return data in its corresponding month.

Additional control variables such as market beta, market size, book to market ratio and volatility measures are also included in the regression model. Following Fama and French (1992), we estimate market beta, firm size and book to market ratio. To obtain market beta (*Beta*), pre-ranking betas are calculated on 60 monthly returns (minimum 24 monthly returns) before July of year t, and then we assign the individual stocks based on double sorted portfolios base on deciles of size and pre-ranking beta portfolios in June. After assigning stocks, we calculate the post ranking monthly returns of each portfolio for the next 12months, from July of year t to June of year t+1. Finally, we estimate post-ranking betas on 100 portfolio using the full sample period with the CRSP value-weighted portfolio index. For the firm size (*Ln_ME*), we use a firm's market equity value in natural logarithm 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 in t-1 divided by market equity value at the end of December of year t-1. Volatility measure (Vol) is the standard deviation of the monthly return of a stock for the past 60 months (minimum 24 months).

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

3. Empirical results

3.1. Cross-sectional analysis with individual stocks

In this section, we implement a monthly predictive regression to check the predicting power of our resiliency measure for the future monthly return at an individual firm level. The test procedure follows the Fama and Macbeth (1973) method first, and then, we run Fama-Macbeth regression by weighted least squares.

Table 1 shows the descriptive statistics of the main variables used in our empirical analysis. Summary statistics are reported in Panel A. For each variable, the 5th, 25th, 50th, 75th, and 95th percentile values are reported as well as the mean and standard deviation in this panel. In Panel B, we report pair-wise correlation matrix of the variables. Table 2 presents the results of the Fama-MacBeth cross-sectional regression results to verify the predictive power of resiliency measure on monthly stock returns. The regression is run, for each t, 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 usual 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. Model (3) contains stock return volatility measure, and model (4) contains trading activity measures with trading cost measures. All control variables are included in model (5). Model (6) represents non-January model. The results show that the sample averages of the coefficients of resiliency are significantly negative in the entire 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 the entire regression model. 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 variables of the trading activity 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 while the estimated coefficient of *Amihud* and *Roll* is 0.058 and 2.416 respectively. Meanwhile, for the trading activity variables, the coefficients of share turnover (*TURN*) and trading volume (*TrdVol*) are not significant and the direction of signs is not clear. The significance of estimated coefficients for return volatility (*Vol*) is also limited.

In addition, we report the estimation results of the Fama-Macbeth regression with weighted least square in Panel B, following Asparouhavova et al. (2010). They suggest that Fama-Macbeth regression by weighted least squared using previous month return as a weighting variable can alleviate the effect of bias due to the noisy price. Similar to Panel A, the sample averages of the coefficient estimates of our resiliency measure in Model (1) to (6) are all significantly negative. The predicting power of *Amihud* is also positive and significant for the entire Model (1)-(6). With the results with the estimated coefficient of *Resiliency*, we can conclude that our resiliency measure has a negative predicting power for an individual stock return after including several control variables and correcting a possible bias arising from noisy price.

3.2 Portfolio analysis: sorting by resiliency

In addition to the Fama-Macbeth cross-sectional regression analysis at the individual stock level, we examine the effect of resiliency on expected stock returns by the portfolio analysis. At the end of each year, all stocks in the sample are sorted into decile portfolios based on 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, alpha, the time-series of returns of the ten portfolios in excess of risk free rate are regressed on various risk factors that are widely adopted in the literature. We use the Fama-French 3 factors (MKT, SMB, HML), the momentum factor (MOM) of Carhart (1997) and the liquidity risk factor (LIQ) suggested by Pastor and Stambaugh (2003).[8] Additionally, we construct Amihud illiquidity factor (AMI) and include in our regressions in addition to the five factors, following Charoenrook and Concrad (2005) and Easley et al. (2010). Then, the resiliency-sorted portfolio excess return, $R_{i,t}$, is regressed on the selected factors as follows:

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

Table 3 presents characteristics of portfolios in Panel A, and monthly raw returns and alphas of value-weighted and equal-weighted decile portfolios sorted on resiliency in Panel B and C, respectively. Stocks with lowest resiliency are grouped in the decile 1 portfolio and stocks with highest resiliency are grouping in decile 10. Panel A presents the average value of market capitalization and the average estimate of resiliency. We find that the market capitalization decreases monotonically as resiliency increases. This result is consistent with Aslan et al. (20007) and Easley et al. (2010), where the authors show that information risk is more important for smaller stocks using a measure of a firm's probability of private information-based trade (PIN). Considering that stocks' price recovery is driven by informed trader, the pattern of resiliency measure with market capitalization is expectedly similar to that of PIN.

In panel B, we report the value-weighted portfolio case. In accordance with our hypothesis, portfolios with lower resiliency have higher average monthly return and portfolios with higher resiliency have lower average return. For example, the monthly raw return of decile 1 is 0.934 percent per month and decile 10 is 0.454 percent per month respectively. The average return of decile portfolio decreases almost monotonically with resiliency. We also construct zero-investment portfolio which is long in lowest resiliency portfolio (decile 1) and short in highest resiliency portfolio (decile

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8 Fama-French 3 factors and Momentum factor are obtained from Kenneth French's website and 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.

10). This zero-investment portfolio has the average monthly return of 0.479 percent per month with statistical and economical significance. This result shows that resiliency-based trading strategy can give an excess return of 5.748 percent per year to investors.

It is also shown that abnormal returns decrease almost monotonically with resiliency. Alphas from the selected six-factor model are distributed from 0.0779 percent in decile 1 to -0.539 percent in decile 10. Zero-investment portfolio has also significant alphas. The Fama-French 3 factor alpha is 0.627 percent per month and the four and six factor alpha is, respectively, 0.613 and 0.617. Interestingly, including liquidity factors (LIQ, AMI) rarely affect the magnitude of zero-investment portfolio's alpha, so that resiliency-based strategy gives investors annualized 7.404 percent. This results supports our hypothesis that resiliency is another critical component of liquidity risk. We also test the hypothesis that the all alphas are jointly equal to zero, using the test of Gibbons, Ross, and Shanken (1989, hereafter GRS F-test). The results of the GRS F-test show that null hypothesis is rejected at 1 percent significance level. Panel C reports the results of equal-weighted case. The equal-weighted portfolio returns and alphas show analogous with the results of the value-weighted portfolios. Zero-investment portfolio's monthly returns and alphas are slightly lower than those of the value-weighted case but still statistically and economically significant. The Fama-French alpha is 0.471 percent per month and the six-factor alpha is 0.436 percent per month. We perform the GRF F-test again and the null hypothesis is also strongly rejected as in the case of the value-weighted portfolios. Overall, our empirical findings support that the resiliency is systematically priced.

To investigate the patterns of risk exposures of the resiliency-sorted portfolios, we report factor loadings on the time series regression. We regress excess returns of resiliency decile portfolios and the zero-investment portfolio on the selected six factors. Table 4 shows that the effect of resiliency is in the opposite direction to the well-known size effect. For the case of value-weighted zero-investment portfolio in panel A, SMB is a dominant factor for explaining the zero-investment portfolio return series among the significant four factors with estimated coefficient of -0.992, and the corresponding t-value is -18.40. Negative and significant factor loading on SMB implies that zero-investment portfolio behaves like large firm that is consistent to the results in panel A of table 3 which present that average firm's market capitalization in decile portfolios decreases monotonically as resiliency increases. However the average return of decile portfolio decreased with resiliency as we discussed above, so that zero-investment portfolio generates the positive risk premium which is contrary to the common size effect that small stocks have risk premium compared to large stocks in general. Therefore, these opposite patterns enhance the estimated abnormal return with respect to existing factor models. In panel B, we report similar results for the case of equal-weighted portfolios with estimated factor loading of -0.625, and the corresponding t-values is -18.53 on SMB.

3.3 Double-sorted portfolios: resiliency and other risk factors

In this section, we examine whether resiliency is systematically priced after controlling for other risk factors, by applying double-sorted portfolio strategy. As we discussed above, some variables are correlated with resiliency such as firm's market capitalization and trading cost illiquidity, thus it is possible that the resiliency risk premium partially affected by them. To control for the influence of these variables, we implement portfolio analysis of a double-sorting between resiliency and firm's market capitalization as well as resiliency and Amihud illiquidity measure. To implement this strategy, at the end of each year, we sort all sample firms into tercile groups (bottom 30%, middle 40%, top 30%) based on firm's market capitalization or Amihud illiquidity measure, and then independently sort same firms into 10 groups based on resiliency.

Table 5 presents returns and alphas of independently double-sorted portfolios. Panel A shows the value-weighted portfolio of double-sorting between resiliency and firm's market capitalization.[9] The first to third rows ("Size") report the monthly raw returns of size-controlled resiliency decile

[9] Asparouhova et al. (2013) show that estimated alphas of the equal-weighted portfolios are biased due to 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 quantitatively and qualitatively similar to those of value weighted case.

portfolios. The fourth row ("Avg.size") reports returns of the resiliency decile portfolios averaged across of the three firm's market capitalization portfolios. The bottom three rows report alphas of averaged resiliency decile portfolios computed with respect to Fama-French 3 factors, MOM, and two liquidity factors, LIQ, AMI. "Low-High" column represents the returns and alphas of zero-investment portfolios that buy lowest resiliency portfolio and sell highest resiliency portfolio. It is shown that all alphas of zero-investment portfolios are positively significant. The size-controlled zero-investment portfolio gives a risk premium of 0.501 percent a month and its 6 factor alpha is 0.557 percent per month.

Panel B in Table 5 reports independently double-sorting results between Amihud illiquidity measure and resiliency. Similar to the results of panel A, all of the alphas of 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 6 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 also complementary to those of the existing trading cost measure in portfolio analysis. The average return of the portfolio with lowest resiliency and top ranked group of Amihud illiquidity is 1.373 percent per month and highest resiliency (portfolio with the most illiquid stocks in terms of resiliency and Amihud illiquidity) and bottom ranked group of Amihuid illiquidity is 0.254 percent per month (portfolio with the most liquid stocks in terms of resiliency and Amihud illiquidity). 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.

As the strong correlation between two variables might cause a problem that the number of firms in some portfolios is not enough to eliminate individual firm's idiosyncratic risk, we also sort sample firms dependently again. First, we sort all sample firms into tercile groups (bottom 30%, middle 40%, top 30%) on the basis of firm's market capitalization or Amihud illiquidity measure at the end of the each year. We then sort sample firms within each market capitalization or Amihud illiquidity measure group into decile portfolios based on resiliency. Table 6 present the results. Panel A in Table 6 shows the results of dependently double-sorted portfolios based on firm's market capitalization and resiliency. As is similar to the results of independent sorting case, the averaged 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 with 1% level significance. We also report dependent sorting results of Amihud illiquidity measure and resiliency in panel B. The averaged risk premium of the amihud illiquidity-controlled zero-investment portfolio is 0.429 per month and all the alphas are positively significant. Overall, we can conclude that the pricing capability of our resiliency measure is still valid after controlling 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 with AR(1) process. To capture different autoregressive effects of each firm, we lessen the model restriction so that the stationary component can has one to three lagged terms of autoregressive model rather than only one lagged term. To decide the number of lagged terms of AR model for stationary component, we use Bayesian Information Criterion. At the end of each month, we estimate the coefficients of ARMA(1,1), ARMA(2,2) and ARMA(3,3) model using each firm's all available historical return series which denotes that AR(1), AR(2), AR(3) model in stationary component, respectively. [10] We then apply BIC rules to these three estimated model parameters to detect most appropriate number of AR lagged terms. Once proper coefficients of ARMA

[10] As we mentioned in section 2.1, a non-stationary series contains random walk process and AR process can be transformed to ARMA model.

model are estimated, the level of each firm's resiliency is calculated in a same way introduced in section 2 using B-N decomposition and spectral domain analysis.

Table 7 shows the returns and alphas of decile portfolios sorted on resiliency which is calculated from extended ARMA models. The zero-investment spread is 0.425 percent per month with statistical significance and the estimate factor model alphas are distributed with the range of 0.556 to 0.585 percent per month. We also test double-sorted portfolios based on resiliency and firm's size, resiliency and Amihud measure. The estimated results of independent double-sorted portfolios are reported in Table 8. The row of 'avg. size' and 'avg. Ami' represents the returns of the resiliency decile portfolios averaged across the same levels of control variables: size and Amihud measure. The premium of zero-investment portfolio is 0.457 percent per month for size-controlled double sorts and 0.501 percent per month for Amihud measure-controlled double sorts, respectively. Estimated alphas of zero-investment portfolio with size controlled are statistically and economically significant with the range of 0.457 to 0.517 percent per month. Alphas of zero-investment portfolio with Amihud controlled are also distributed with the range of 0.533 to 0.590 percent per month with significance. The estimated results of dependent double-sorted portfolios are reported in Table 9. The estimated results reported in Table 9 also shows similar pattern to the results of independent double-sorted portfolios.

3.4.2 Sub-period Analysis

Table 10 present the results of the sub-period analysis. We divide the full sample period into two sub-periods: the sub-period 1 is January 1965 to 1989 December and the sub-period 2 is January 1990 to December 2013. The results show that the magnitude of zero-investment portfolio return of the sub-period 2 is substantially higher than that of the sub-period 1. Low-High return premium of the sub-period 2 is 0.619 percent per month with statistical significance while that of sub-period 1 is 0.346 percent per month which is not significant. The patterns of estimated alphas are also similar to those of zero-investment portfolio returns. The alphas are distributed at the range of 0.753 percent to

0.844 percent per month in sub-period 2 while 0.468 percent to 0.624 percent in sub-period 1. In this regard, we can conclude that the effect of resiliency has strengthened in current period for explaining cross-sectional variation of expected stock returns.

4. Conclusion

This paper investigates whether resiliency is a systematic risk factor for asset pricing. We define resiliency as quickness of price recovery from a liquidity shock. From this definition, our study focuses on measuring resiliency and investigating its effect on stock returns. To compute resiliency, first, we decompose stock price into fundament value and transitory price component. We then transform transitory price into spectral functional form in frequency domain to calculate the speed of transitory price recovery. The level of resiliency of individual firm can be obtained by dividing magnitude component by its cycle in frequency domain.

Our empirical findings show that resiliency plays a systematic risk factor that generates the cross-sectional variations of stock returns. Expected stock returns are a decreasing function of resiliency which implies that stocks with lower resiliency compensate a higher risk premium. During our sample period for the years 1965-2013, we find that a zero-investment portfolio that long in low resiliency stocks and short in high resiliency stocks earns a statistically and economically significant abnormal return with respect to six factors. Furthermore, we find that the effect of our resiliency measure on the expected stock returns is complementary to those of existing trading cost measure. A significantly negative predicting power of resiliency on the expected stock returns does not reduce the predicting power of trading cost measure on the stock returns. In addition, we show that resiliency generate additional cross-sectional variation of stock returns in addition to that of Amihud illiquidity measure. These results imply that resiliency can capture a new dimension of liquidity which is not explained by existing liquidity measure.

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Table 1
Descriptive statistics

Panel A reports the summary statistics of the explanatory variables. *Beta* denotes post-ranking market beta estimated using Fama and French (1992) method. *Ln_ME*, *LN_BM* denotes the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively,. Resiliency denotes the speed of 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* 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, 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 pair-wise correlation matrix between the explanatory variables in our sample. The samples cover the period from January 1965 to December 2013.

Panel A : Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Percentile				
				5th	25th	50th	75th	95th
Beta	1,224,754	1.098	0.330	0.646	0.837	1.080	1.319	1.734
Ln_ME	1,224,754	12.658	1.896	9.763	11.272	12.570	13.906	15.948
Ln_BM	1,224,754	-7.283	1.046	-8.820	-7.827	-7.285	-6.800	-5.893
Resiliency	1,224,754	0.020	0.023	0.002	0.006	0.012	0.025	0.065
Roll	1,224,693	0.006	0.026	-0.033	-0.011	0.009	0.021	0.047
Amihud	1,134,610	0.686	2.521	0.000	0.004	0.038	0.335	3.180
TrdVol	1,214,077	102.209	614.489	0.193	1.695	9.619	51.579	404.777
TURN	1,213,940	5.569	13.586	0.302	1.113	2.724	6.431	19.038
Vol	990,239	0.117	0.060	0.052	0.077	0.104	0.141	0.224

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 the cross-section of expected stock returns.

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 usual Fama-MacBeth (1973) methodology. *Beta* denotes post-ranking market beta estimated using Fama and French (1992) method. *Ln_ME*, *LN_BM* denotes the natural logarithm of the market capitalization, and the natural logarithm of the book-to-market equity ratio, respectively. *Resiliency* denotes the speed of 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* 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, 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 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 Fama-MacBeth (1973) methodology by weighted least squares suggested by Asparouhvova, Bessembinder, and Kalcheva (2010). Significance at 10% level indicated in **bold**. The Newey-West t-statistics are given in parentheses. The samples cover the period from January 1965 to December 2013.

Panel A. Fama-Macbeth regression

	(1)	(2)	(3)	(4)	(5)	(6)
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

Panel B. Fama-Macbeth regression by weighted least squares

	(1)	(2)	(3)	(4)	(5)	(6)
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 10 portfolios based on estimated resiliency and portfolio returns are obtained over next 12 months. Resiliency denotes the speed of 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. At least 24-month return observations are required to be included in the sample. Panel A presents the decile portfolio's averaged market capitalization and estimated resiliency. Panel B reports the monthly raw returns and alphas of the value-weighted decile portfolios and Panel C reports the equal weighted case. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 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 Characteristics										
Market cap	26.52	25.65	20.41	16.45	12.75	10.28	8.30	6.78	3.60	2.15	
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)
3 Factor	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)
4 Factor	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)
6 Factor	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)
3 Factor	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)
4 Factor	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)
6 Factor	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
Portfolio level analysis – Factor loadings

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios based on estimated resiliency and portfolio returns are obtained over next 12 months. Resiliency denotes the speed of 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. At least 24-month return observations are required to be included in the sample. Panel A presents the factor loadings of value-weighted portfolios sorted by resiliency. Panel B reports factor loadings of equal-weighted case. Column "Low-High" denotes the zero-investment's factor loadings. The factor loadings are estimated as coefficients from the regressions of excess portfolio returns on six factors including the Fama-French factor, momentum factor, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor. The t-statistics are in parentheses.

	Decile Portfolio										
	1(Low)	2	3	4	5	6	7	8	9	10(High)	Low-High
	A. Value-weighted Portfolio factor loading: 6 factor model case										
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

	Decile Portfolio										
	1(Low)	2	3	4	5	6	7	8	9	10(High)	Low-High
	B. Equal-weighted Portfolio factor loading: 6 factor model case										
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 5

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 10 portfolios based on estimated resiliency and 3 portfolios based on control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection over next 12 months. Panel A reports the results of independently double sorting between resiliency and market capitalization. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. Bottom, middle and top denotes the monthly raw return of controlled resiliency decile portfolios. Avg. Portfolio denotes the average returns of the resiliency decile portfolios, averaged across the control variable. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 Factor alpha). Panel B reports the results of independently double sorting between resiliency and Amihud illiquidity measure. 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 returns										
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										
3 Factor alpha	0.0699	0.0452	0.0225	-0.0150	-0.0686	-0.0699	-0.0858	-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)
4 Factor alpha	0.121	0.0911	0.0757	0.0690	0.0138	0.0346	0.0120	-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)
6 Factor alpha	0.125	0.0980	0.0752	0.0714	0.0164	0.0352	0.0147	-0.102	-0.0997	-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 Amihud illiquidity measure										
Ami (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)
Ami (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)
Ami (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. Ami	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)
	B-2. Double sorting with Amihud illiquidity measure										
3 Factor alpha	0.104	0.0712	0.0742	0.00800	0.0404	0.0173	-0.00663	-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)
4 Factor alpha	0.133	0.0961	0.124	0.0429	0.0940	0.0701	0.0482	-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)
6 Factor alpha	0.132	0.0957	0.117	0.0393	0.0883	0.0646	0.0448	-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 6

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 3 portfolios based on control variables and then, within each market control variable group into 10 portfolios based on resiliency The monthly value-weighted returns are estimated from each sorted portfolio over next 12 months. Panel A reports the results of dependently double sorting between resiliency and market capitalization. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. Bottom, middle and top denotes the monthly raw return of controlled resiliency decile portfolios. Avg. Portfolio denotes the average returns of the resiliency decile portfolios, averaged across the control variable. The alphas are estimated as intercepts from the regressions of controlled excess portfolio returns on the Fama-French factor returns (3 Factor alpha), on the Fama-French with momentum factor returns (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 Factor alpha). Panel B reports the results of dependently double sorting between resiliency and Amihud illiquidity measure. 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 returns										
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										
3 Factor alpha	0.0695	0.0231	-0.0328	0.0299	0.0214	-0.105	-0.0492	-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)
4 Factor alpha	0.116	0.0758	0.0202	0.0979	0.104	-0.0258	0.0303	-0.0674	-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)
6 Factor alpha	0.118	0.0828	0.0253	0.0984	0.103	-0.0243	0.0331	-0.0600	-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 Amihud illiquidity measure : Portfolio returns										
Ami (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)
Ami (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)
Ami (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. Ami	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)
	B-2. Double sorting with Amihud illiquidity measure : Alpha										
3 Factor alpha	0.0940	0.0991	0.0463	0.0874	0.0415	-0.0418	-0.0383	-0.0116	-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)
4 Factor alpha	0.124	0.101	0.0785	0.126	0.0748	-0.0241	0.0166	0.00619	-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)
6 Factor alpha	0.123	0.101	0.0703	0.118	0.0727	-0.0270	0.0137	0.00209	-0.123	-0.357	0.480
	(2.180)	(1.886)	(1.272)	(2.411)	(1.463)	(-0.577)	(0.309)	(0.0414)	(-2.333)	(-4.653)	(5.057)

Table 7
Robustness Check – Sorting by resiliency

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios based on estimated resiliency which is computed from extended ARMA model and portfolio returns are obtained over next 12 months. Resiliency denotes the speed of 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. At least 24-month return observations are required to be included in the sample. Panel A presents the decile portfolio's averaged market capitalization and estimated resiliency. Panel B reports the monthly raw returns and alphas of the value-weighted decile portfolios and Panel C reports the equal weighted case. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 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 Characteristics										
Market cap	21.45	20.74	21.52	19.14	15.40	12.24	9.97	6.62	3.74	2.29	
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)
3 Factor	0.0221	-0.0435	0.108	0.0311	-0.0330	-0.0347	-0.0965	-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)
4 Factor	0.0951	-0.0122	0.126	0.0861	0.0286	0.0144	0.0259	-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)
6 Factor	0.0963	-0.00790	0.121	0.0836	0.0250	0.0117	0.0309	-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 8

Robustness Check – Independently double sorting by resiliency and control variables

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios based on estimated resiliency which is computed from extended ARMA model and 3 portfolios based on control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection over next 12 months. Panel A reports the results of independently double sorting between resiliency and market capitalization. Column “Low-High” denotes the zero-investment’s monthly raw returns and alphas. Bottom, middle and top denotes the monthly raw return of controlled resiliency decile portfolios. Avg. Portfolio denotes the average returns of the resiliency decile portfolios, averaged across the control variable. The alphas are estimated as intercepts from the regressions of controlled excess portfolio returns on the Fama-French factor returns (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 Factor alpha). Panel B reports the results of independently double sorting between resiliency and Amihud illiquidity measure. 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 returns										
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										
3 Factor alpha	0.0794	0.0475	0.0384	0.000476	-0.0684	-0.0370	-0.0969	-0.160	-0.271	-0.438	0.517
	(1.584)	(0.982)	(0.770)	(0.00950)	(-1.398)	(-0.771)	(-1.983)	(-2.987)	(-4.583)	(-5.013)	(5.234)
4 Factor alpha	0.114	0.0985	0.0990	0.0754	0.00584	0.0558	0.00239	-0.0725	-0.159	-0.348	0.462
	(2.252)	(2.036)	(1.995)	(1.539)	(0.122)	(1.227)	(0.0521)	(-1.397)	(-2.830)	(-3.977)	(4.601)
6 Factor alpha	0.116	0.0984	0.0985	0.0782	0.00812	0.0544	0.00308	-0.0665	-0.154	-0.341	0.457
	(2.342)	(2.094)	(2.032)	(1.665)	(0.175)	(1.224)	(0.0684)	(-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 Amihud illiquidity measure : Portfolio returns										
Ami (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)
Ami (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)
Ami (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. Ami	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)
	B-2. Double sorting with Amihud illiquidity measure : Alpha										
3 Factor alpha	0.0883	0.0937	0.0878	0.0252	0.0308	0.0192	-0.0483	-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)
4 Factor alpha	0.126	0.119	0.119	0.0444	0.0759	0.0666	0.00199	-0.0697	-0.112	-0.406	0.533
	(1.976)	(2.007)	(1.972)	(0.808)	(1.435)	(1.313)	(0.0399)	(-1.247)	(-1.807)	(-4.665)	(4.965)
6 Factor alpha	0.126	0.117	0.114	0.0400	0.0722	0.0590	-0.00235	-0.0711	-0.112	-0.410	0.536
	(2.062)	(1.991)	(1.921)	(0.761)	(1.419)	(1.217)	(-0.0482)	(-1.294)	(-1.819)	(-4.700)	(5.120)

Table 9

Robustness Check – Dependently double sorting by resiliency and control variables

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios based on estimated resiliency which is computed from extended ARMA model and 3 portfolios based on control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection over next 12 months. Panel A reports the results of dependently double sorting between resiliency and market capitalization. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. Bottom, middle and top denotes the monthly raw return of controlled resiliency decile portfolios. Avg. Portfolio denotes the average returns of the resiliency decile portfolios, averaged across the control variable. The alphas are estimated as intercepts from the regressions of controlled excess portfolio returns on the Fama-French factor returns (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 Factor alpha). Panel B reports the results of dependently double sorting between resiliency and Amihud illiquidity measure. 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 returns										
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										
3 Factor alpha	0.0798	0.0453	0.0171	0.000535	-0.0131	-0.111	-0.0438	-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)
4 Factor alpha	0.111	0.0981	0.0750	0.0735	0.0645	-0.0294	0.0262	-0.0487	-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)
6 Factor alpha	0.111	0.0990	0.0759	0.0730	0.0633	-0.0254	0.0295	-0.0471	-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 Amihud illiquidity measure : Portfolio returns										
Ami (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)
Ami (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)
Ami (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. Ami	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)
	B-2. Double sorting with Amihud illiquidity measure : Alpha										
3 Factor alpha	0.0757	0.0900	0.0435	0.121	0.0356	-0.0497	-0.0312	-0.0172	-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)
4 Factor alpha	0.109	0.106	0.0641	0.137	0.0744	-0.0303	-0.000148	0.0144	-0.106	-0.342	0.451
	(1.811)	(1.944)	(1.144)	(2.765)	(1.377)	(-0.638)	(-0.00320)	(0.293)	(-1.959)	(-4.536)	(4.710)
6 Factor alpha	0.109	0.104	0.0543	0.131	0.0719	-0.0324	-0.00328	0.00930	-0.111	-0.344	0.452
	(1.886)	(1.976)	(1.004)	(2.711)	(1.399)	(-0.711)	(-0.0730)	(0.192)	(-2.047)	(-4.543)	(4.818)

Table 10

Robustness check - Sub-period Analysis

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios based on estimated resiliency and portfolio returns are obtained over next 12 months. Resiliency denotes the speed of 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. At least 24-month return observations are required to be included in the sample. Panel A presents monthly raw returns and alphas of the value-weighted decile portfolios during 1965 to 1989. Panel B reports the monthly raw returns and alphas of the value-weighted decile portfolios during 1990 to 2013. Column "Low-High" denotes the zero-investment's monthly raw returns and alphas. The alphas are estimated as intercepts from the regressions of excess portfolio returns on the Fama-French factor (3 Factor alpha), on the Fama-French with momentum factor (4 Factor alpha), on the 4 Factor model with two liquidity factors, Pastor and Stambaugh liquidity factor and Amihud illiquidity factor (6 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. January 1965-December 1989										
Raw 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)
3 Factor	-0.0588	0.0659	0.0486	0.0915	0.0627	-0.00407	-0.0618	-0.235	-0.335	-0.527	0.468
	(-0.607)	(0.870)	(0.803)	(1.478)	(0.985)	(-0.0542)	(-0.694)	(-2.719)	(-3.632)	(-4.374)	(2.942)
4 Factor	0.0866	0.116	0.0747	0.155	0.0990	0.0663	0.00215	-0.188	-0.259	-0.489	0.576
	(0.904)	(1.487)	(1.191)	(2.455)	(1.506)	(0.863)	(0.0234)	(-2.106)	(-2.742)	(-3.909)	(3.510)
6 Factor	0.110	0.148	0.0532	0.163	0.0919	0.0648	0.00283	-0.168	-0.261	-0.514	0.624
	(1.140)	(1.891)	(0.847)	(2.560)	(1.389)	(0.846)	(0.0305)	(-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)
3 Factor	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)
4 Factor	0.131	-0.0582	0.0729	0.0536	-0.0640	-0.0750	-0.0990	-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)
6 Factor	0.117	-0.0507	0.0724	0.0411	-0.0857	-0.0908	-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)