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 in stock returns. Resiliency is defined as the quickness of the transitory price recovery from a liquidity shock. Using the Beveridge-Nelson decomposition and the spectral analysis in the frequency domain, we measure resiliency of individual stocks as the speed of the 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 statistically and economically significant abnormal returns. Furthermore, we find that our resiliency measure is complementary to existing liquidity measures to capture a full dimension of liquidity and 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 trading volume or share turnover, which represents how actively market investors trade assets. The other side of the liquidity dimension is trading cost, generally estimated using the Amihud (2002) illiquidity measure or bid–ask spread measures that capture the price impact level that investors should bear when executing market orders. Regarding these two categories, measures of liquidity have been well defined in large numbers in the literature. However, a measure for another side of the liquidity dimension, *resiliency*, has yet to be clearly defined.

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. Bernstein (1987) explains resiliency in terms of order imbalance. He argues 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 or uninformed traders. In this regard, resiliency can be characterized as the speed of price recovery that reverts to its fundamental value from the prior transitory impact driven by an informed trader.

On the basis of these definitions, this study measures resiliency and investigates whether resiliency generates a cross-sectional variation in stock returns. To compute the resiliency, we first 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, as

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[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.

previously discussed.[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 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) also use a 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 trading cost flow using intraday data.

A main distinction of this study is that our resiliency measure is directly derived as the speed of

[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. 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.

a transitory price recovery. By applying spectral analysis in the frequency domain to cyclical stock price components, we obtain the distance and time of the transitory price recovery, which are combined to calculate the speed. Thus we contend that our measure fits better with the literal definition of resiliency than 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 model indicates that the transitory price movement has more than one frequency component that reverts to its fundamental value, which implies that our resiliency measure can capture the speed of the recovery movement over both a long and short-horizon. Regarding the data structure, although many previous studies used intraday microstructure data to compute the resiliency, we use daily stock price data to calculate the monthly resiliency of individual firms, following Amihud (2002).[3]

Our empirical findings show that resiliency is 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 for a higher risk premium to investors. During our sample period of 1965–2013, we find that a 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 Carhart (1997), and the two liquidity factors of Pastor and Staumbaugh (2003) and Charoenrook and Conrad (2005). We also find that our resiliency measure is complementary to existing liquidity measures. The result of the Fama-MacBeth regression on individual stocks shows that our resiliency measure has a significant predictive power on their expected stock returns. It should be noted that resiliency does not reduce the positive predictive power of the Amihud (2002) or Roll (1984) measure on stock returns. The result of a double-sorted portfolio analysis based on the

[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 price impact.

Amihud illiquidity measure and our resiliency measures also shows that resiliency can capture additional risk premiums 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 include the effect of resiliency on an individual firm's stock returns and single/double-sorted portfolio analysis. The last section presents a conclusion.

2. Constructing a resiliency measure

Following 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 which represents the fundamental value of the stock that moves 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 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 η_t and ε_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),

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

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

$$z_t = p_t - q_t \quad (8)$$

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. If a stock has higher speed of reversion, its spectral function will be mainly distributed at a higher frequency level, whereas its spectral function will be distributed at a lower frequency if it has a lower speed of reversion. 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, $\mathrm{Z_k}$ 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 normalized functional form, $\tilde{Z}_k$,[4] as

$$\tilde{Z}_k = \frac{1}{D} Z_k \,, \tag{10}$$

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 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 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,

[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 2π 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.

[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 $k = 1 \sim [D_{i,t}/2]$ on the frequency

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 common 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, 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. Although daily return data are not required to be consecutive, a stock should have 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, this study proceeds to investigate whether the stock resiliency is a systematic risk factor that generates risk premia through the 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

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axis which is matched with the range of $0 \sim \pi$ in the continuous version of the Fourier transform.

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) that are widely adopted measures for capturing price impact and market illiquidity. The 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,

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

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

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

where $\Delta p_d = p_d - p_{d-1}$ for which daily data p_d are available for stock *i* in month *t*. *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 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 on the basis of double sorted portfolios using 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 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

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[7] 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.

value-weighted portfolio market index. For firm size (*Ln_ME*), we use the natural logarithm of a firm's market equity value 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 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 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, and the mean and standard deviation for each variable. In Panel B, we report the pair-wise correlation matrix of the variables.

3. Empirical results

3.1. Cross-sectional analysis with individual stocks

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

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:

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

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 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 a stock return volatility measure, and Model (4) contains trading activity measures using 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, in Panel B, we report 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 previous month 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 negative predicting 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 use 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 ten 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 Carhart (1997), and the liquidity risk factor (LIQ) suggested by Pastor and Stambaugh (2003).[8] In addition to the five factors, we construct the Amihud illiquidity factor (AMI) and include it in our regressions, following Charoenrook and Conrad (2005) and Easley et al. (2010). Then, the resiliency-sorted portfolio excess return, $R_{i,t}$, is regressed on the selected factors as follows:

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

Panel A in Table 3 presents the portfolio characteristics, 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 decile 10. Panel A presents the average value of market capitalization and the average estimate of resiliency. We find that market capitalization decreases monotonically as resiliency increases. This result is consistent with Easley et al. (2010) who show that the information risk is more important for smaller stocks using a measure of a firm's probability of private information-based trade (PIN) and the average PIN decrease monotonically as the average firm size increases. Considering that stocks' price recovery is driven by informed traders, the pattern

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[8] 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.

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 returns and portfolios with higher resiliency have lower average returns. For example, the monthly raw 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 portfolios 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 monthly 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, such that the resiliency-based strategy provides investors with an annualized 7.404 percent. This result 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 the null hypothesis is rejected at the one percent significance level. Panel C reports the results of the equal-weighted case. The equal-weighted 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 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 strongly rejected, as in the case of the value-weighted portfolios. Overall, our empirical findings support the concept that resiliency is systematically priced.

To investigate the risk exposure patterns 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 report the factor loadings in Table 4. 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 dominant factor in explaining the zero-investment portfolio return among the significant four factors with an estimated coefficient of SMB 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 an average firm's market capitalization in decile portfolios decreases monotonically as resiliency increases. However, the average return of the decile portfolio decreases with resiliency, as previously discussed, such that the zero-investment portfolio generates a positive risk premium. This positive risk premium is contrary to the general size effect of small stocks having higher risk premia than large stocks. These results imply that our resiliency measure can capture another dimension of risk that cannot be explained by the size factor.

3.3 Double-sorted portfolios: resiliency and other risk factors

In this section, we apply a double-sorted portfolio strategy to further examine whether resiliency is systematically priced after controlling for other risk factors. As previously discussed, certain variables, such as a firm's market capitalization and trading cost illiquidity, are correlated with resiliency, making 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 a firm's market capitalization as well as resiliency and the Amihud illiquidity. To implement this strategy, we sort all sample firms into tercile groups (bottom 30%, middle 40%, top 30%) on the basis of a firm's market capitalization or Amihud illiquidity, 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 5 presents the returns and alphas of the independently double-sorted portfolios. Panel A shows the value-weighted portfolio of double-sorting between resiliency and a firm's market capitalization.[9] 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 averaged resiliency decile portfolios computed 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 positively significant. The size-controlled zero-investment portfolio gives a risk premium of 0.501 percent and its six-factor alpha is 0.557 percent per month.

Panel B in Table 5 reports the results of the independently double-sorted portfolios between Amihud illiquidity and resiliency. Similar to the results of Panel A, all of 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

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[9] 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 quantitatively and qualitatively similar to those of value weighted case.

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 in stock returns.

Because the strong correlation between two variables might cause the problem that the number of firms in some portfolios is inadequate 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 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 6 presents 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 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 at a one percent level significance. In Panel B, we also report the results of the dependently sorted portfolios with the 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 on the number of optimal lags of the AR 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.[10] 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 spectral domain analysis.

Table 7 shows the returns and alphas of decile portfolios sorted on resiliency which is calculated from the extended ARMA models. The zero-investment spread is 0.425 percent per month with statistical significance and the estimate factor model 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, and also by resiliency and Amihud illiquidity. The estimated results of the independently double-sorted portfolios are reported in Table 8. The 'avg. size' and 'avg. Ami' rows represent the returns of the resiliency decile portfolios averaged across the same control variable levels: size and Amihud illiquidity. The premium of the zero-investment portfolio is 0.457 percent per month for size-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 with Amihud illiquidity-controlled are also distributed within the range from 0.533 to 0.590 percent per month with significance. The estimated results of the dependent double-sorted portfolios are reported in Table 9. The estimated results reported in Table 9

[10] 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.

show a similar pattern to the results of independent 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. Estimated alphas are also statistically and economically significant for both cases.

3.4.2 Sub-period analysis

Table 10 presents the results of the sub-period analysis. We divide the full sample period into two sub-periods: sub-period 1 is from January 1965 to December 1989 and sub-period 2 is from January 1990 to December 2013. The results show that the magnitude of the zero-investment portfolio return of sub-period 2 is substantially higher than that of sub-period 1. The ow-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 significant. The estimated alpha patterns 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. In this regard, we conclude that the effect of resiliency strengthened in the current period for explaining cross-sectional variations in expected stock returns.

4. Conclusion

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

Our empirical findings show that resiliency is a systematic risk factor that generates cross-sectional variations in stock returns. Expected stock returns are a decreasing function of resiliency which implies that stocks with lower resiliency compensate for a higher risk premium. 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 six factors. 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 does not reduce that of 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 measure. These results imply that resiliency can capture an additional dimension of liquidity that is not explained by existing liquidity measures.

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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.

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 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 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 from 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 Asparouhova, Bessembinder, and Kalcheva (2010). Significance at the 10% level is indicated in **bold**. The Newey-West (1987) 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 on the basis of the estimated resiliency and portfolio returns are obtained for 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. 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. The "Low-High" column 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 (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.

	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)
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
Portfolio level analysis – Factor loadings

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios on the basis of the estimated resiliency and portfolio returns are obtained for the subsequent 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 the value-weighted portfolios sorted by resiliency. Panel B reports the factor loadings of the equal-weighted case. The "Low-High" column 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, the momentum factor, the Pastor and Stambaugh liquidity factor and the 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: Six-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: Six-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 on the basis of the estimated resiliency and into three portfolios on the basis of the control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection during the subsequent 12 months. Panel A reports the results of independently double sorting between resiliency and market capitalization. The "Low-High" column denotes the zero-investment's monthly raw returns and alphas. Bottom, middle, and top denote the monthly raw return of the 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 (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 reports the results of independently double sorting between resiliency and the 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										
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 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										
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 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 into three portfolios on the basis of the control variables and then, within each market control variable, grouped into 10 portfolios on the basis of resiliency. The monthly value-weighted returns are estimated from each sorted portfolio for the subsequent 12 months. Panel A reports the results of dependently double sorting between resiliency and market capitalization. The “Low-High” column denotes the zero-investment’s monthly raw returns and alphas. Bottom, middle, and top denote the monthly raw return of the 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 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 reports the results of dependently double sorting between resiliency and the 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										
Three-factor alpha	0.0695	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 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										
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 7
Robustness Check – Sorting by resiliency

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios on the basis of the estimated resiliency, which is computed from the extended ARMA model, and 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 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. The "Low-High" column 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 (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 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)
Three-factor alpha	0.022	-0.044	0.108	0.0311	-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	0.0861	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 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 on the basis of the estimated resiliency, which is computed from the extended ARMA model and into three portfolios on the basis of the control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection during the subsequent 12 months. Panel A reports the results of independently double sorting between resiliency and market capitalization. The "Low-High" column denotes the zero-investment's monthly raw returns and alphas. Bottom, middle, and top denote the monthly raw return of the 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 (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 reports the results of independently double sorting between resiliency and the 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										
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)	(0.00950)	(-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 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										
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 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 on the basis of the estimated resiliency, which is computed from the extended ARMA model and into three portfolios on the basis of the control variables. The monthly value-weighted returns of each portfolio are estimated by taking the intersection during the subsequent 12 months. Panel A reports the results of dependently double sorting between resiliency and market capitalization. The "Low-High" column denotes the zero-investment's monthly raw returns and alphas. Bottom, middle, and top denote 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 (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 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										
Three-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)
Four-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)
Six-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										
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 10
Robustness check - Sub-period analysis

At the end of each year between 1964 and 2012, all available stocks are sorted into 10 portfolios on the basis of estimated resiliency and portfolio returns are obtained for 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. 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 from 1965 to 1989. Panel B reports the monthly raw returns and alphas of the value-weighted decile portfolios from 1990 to 2013. The "Low-High" column 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 (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. 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)
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)