Liquidity skewness premium

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Abstract

Risk-averse investors may dislike decrease of liquidity rather than increase of liquidity, and thus there can be asymmetric preference in variation of liquidity. In addition, investors are likely to avoid extreme illiquidity. This paper examines whether the skewness of an individual firm's liquidity capturing asymmetric distribution of liquidity and extreme illiquidity is priced in the US stock market. Using the skewness of the daily price impact, we find that it is positively priced, and this positive relation is significant up to eight months after controlling for other effects. Moreover, we find our results remain significant with the skewness of alternative liquidity measures, i.e., dollar-volume, and turnover.

Keywords: Liquidity premium; Liquidity skewness; Extreme liquidity risk; Asset pricing

JEL classification: G100, G110, G120

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1. Introduction

A large part of the literature on the pricing effect of illiquidity examines whether the average levels of illiquidity measures are significantly related to the expected stock returns (Acharya and Pedersen, 2005; Amihud, 2002; Amihud et al., 2015; Pastor and Stambaugh, 2003). Amihud and Mendelson (1986) and Amihud (2002) document that investors demand a return premium to compensate for asset illiquidity, and thus, illiquidity will be priced as a firm characteristic. Pastor and Stambaugh (2003) and Korajczyk and Sadka (2008) suggest measures for the systematic liquidity risk and show that their measures are significantly related to the expected stock returns in the US stock markets. Amihud et al. (2015) document that the positive illiquidity return premium exists in 45 countries using Amihud's (2002) illiquidity measure.

Recent studies on liquidity suggest the importance of higher moments of illiquidity in asset pricing. The literature on the higher moments of liquidity can be categorized into two groups. The first group concerns the market-wide liquidity or the joint likelihood of the market crash or crisis and the extreme illiquid event. Wu (2015) focuses on the effect of the market-wide extreme liquidity event and find that the tail distribution of the liquidity risk is significantly related to the expected returns in the US stock markets. The financial crisis in 2007 shows the significant impact of a market-wide extreme liquidity event, and Brunnermeier (2009) and Brunnermeier and Pedersen (2009) suggest a mechanism by which the liquidity can suddenly dry up in a market. Such an extreme illiquidity event rarely occurs, but the 2007 financial crisis shows that this rare event causes dramatic turmoil. Anthonisz and Putnins (2016) extend the model of Acharya and Pedersen (2005) and report that the downside liquidity risk, which is the sensitivity of stock liquidity to negative market returns, has a substantial return premium. In addition, Ruenzi et al. (2018) also provide the comprehensive empirical findings on the downside liquidity risk. They suggest the concept of the extreme downside liquidity risk, and show that it provides a quite large premium and its effects are robust to the other factors. Their results also strongly support the importance of higher moments of liquidity.

The other group pays attention to the firm-specific liquidity (Chordia et al., 2001; Akbas et al., 2011; Menkveld and Wang, 2012). Chordia et al. (2001) explore the idea that investors may care about the risk associated with the fluctuation in liquidity, and so expect that the volatility of trading activity is another firm-characteristic which is significantly associated with the expected return. Akbas et al. (2011) also construct the second moment variables of the individual firm's liquidity, and find the positive relation between the second moment of illiquidity and expected returns. For the higher moment of the firm-specific liquidity, Menkveld and Wang (2012) focus on the extreme liquidity event. They define the '*liquileak* risk' as the probability of finding the security in the illiquid state for more than a week, and find the significant premium on this risk. Overall, those findings suggest the importance of considering the extremely illiquid events in both market-level and firm-level.

In line with those previous studies, this paper investigates the pricing effect of the skewness of the individual firm's liquidity as a firm-characteristic, as well as the mean and volatility of liquidity in the US stock market from July 1962 to June 2014. We believe that the liquidity skewness, in addition to the liquidity level and variance, can be priced due to the following two reasons. First, there is an asymmetric relation between liquidity and expected returns. As Jang et al. (2016) and Anthonisz and Putnins (2016) document in terms of the market-wide liquidity risk, investors care more about downside market-wide liquidity risk than upside liquidity improvement, and so the possibility of the downside liquidity change is incorporated into the price more significantly. We expect that this asymmetric relation exists in terms of individual firms' liquidity as well and the skewness measure captures this asymmetric relation. Second, investors may dislike extreme changes in illiquidity, especially downside extreme changes, more than variance measures can capture. In this case, the skewness of liquidity will be priced after the variance of liquidity is controlled.

Our empirical results can be summarized as follows. First, the skewness of the daily price impact of a stock is positively associated with the expected return of the stock, and its pricing effect remains even after controlling for the effects of the mean and volatility of the daily price impact. These results show that the skewness of illiquidity has additional information that is not contained in the lower moments of illiquidity, and can be interpreted as evidence that investors require compensation for the skewed distribution of liquidity. Next, we investigate the effects of the illiquidity skewness on longer-period future returns. The positive relation between the illiquidity skewness and the returns appears to be significant up to eight months after controlling for other effects. Lastly, we examine the skewness of turnover and dollar-volume and find that they are negatively priced. Though the pricing effect of the skewness of trading activity is much weaker than that of the skewness of the daily price impact, we find marginally significant results in some cases. This relation between the skewness of liquidity measures and the expected return becomes more significant for longer future returns. As we mentioned, the previous research by Chordia et al. (2001) shows that, contrary to their expectation, the volatilities of turnover and dollar-volume are negatively priced. Also, Akbas et al. (2011) find that if the frequency of the data is changed, then this negative effect becomes much weaker. Our results show that when the volatility of turnover (dollar-volume) is constructed by the daily data and its skewness is simultaneously taken into account, then the volatility has a positive relation with the expected returns and is statistically significant in some cases. Thus, we suspect that the negative relation between the volatility of liquidity and expected returns documented by Chordia et al. (2001) may result from the misspecification problem due to the omission of the liquidity skewness.

Our paper is closely related to Wu (2015) in the aspect that both studies focus on the pricing effect of the extreme illiquid event, but differs from it in the aspect that Wu (2015) considers the market-wide extreme illiquid event while we consider the firm-specific (individual firm-level) extreme illiquid event. In Section 3.2, we confirm that an individual firm's illiquidity skewness remains significant even after controlling for other factors or characteristics including the market-wide liquidity of Wu (2015) in the cross-sectional analysis. Our paper is also related to Anthonisz and Putnins (2016) as their model considers the downside liquidity risk. We further investigate the robustness of our liquidity skewness after controlling for their systematic liquidity risk measures in Section 3.2.

Our paper extends the research of Chordia et al. (2001) and Akbas et al. (2011) in the sense that both studies concern the importance of the higher moments of the individual firm's liquidity. Both studies show that the second moment (volatility) of liquidity is significantly priced, and we extend the research to the third moment of liquidity. Our results show that the firm-level skewness of illiquidity is significantly priced in the US market beyond the level and volatility of illiquidity, and should not be ignored. These results remain qualitatively similar when the skewness of turnover or dollar-volume is used instead of the skewness of the Amihud measure. The effects of the skewness of turnover or dollar-volume on the future returns last up to 12 months after controlling for other effects.

The remainder of the paper is organized as follows. Section 2 describes the data, and Section 3 presents the empirical results. Section 3.1 examines the existence of the return premium for the mean, volatility, and skewness of illiquidity using the sorted portfolios, and Section 3.2 examines the pricing effect of those variables by cross-sectional regressions. Section 3.3 presents the effects of the illiquidity skewness on the longer-period future returns, and Section 3.4 investigates the pricing effects of the skewness of trading activity measures, which are other proxies for liquidity. Section 4 is the conclusion.

2. Data and variable construction

We use daily and monthly stock market data from July 1962 to June 2014 for New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) non-financial firms with share codes 10 and 11. In consequence, we obtain 864,806 samples (firms-month observations). The data are provided by the Center for Research in Security Prices (CRSP). We use daily stock returns and trading volume to calculate the daily price impacts following Amihud (2002):

$$Daily\ price\ impact_{i,t} = \frac{|r_{i,t}|}{DVOL_{i,t}} \quad (1)$$

The daily price impact of stock *i* at day *t* is defined as the ratio of the absolute daily return to the dollar volume as in Equation (1). In each month, we compute the mean, coefficient of variation, and skewness of the daily price impact using the past 12-month data for each firm. Specifically, we adopt the mean (*ILLIQ*) as the first moment of illiquidity, and the coefficient of variation (*CVILLIQ*) as the second moment, which indicates the volatility of illiquidity. In the literature about the second moment of (il)liquidity, the coefficient of variation is mainly used instead of the standard deviation (Akbas et al., 2011; Chordia et al., 2001) because the mean and standard deviation show a high correlation. Indeed, our sample shows that the correlation between the mean and standard deviation of the daily price impact is 0.97 on average. Thus, following the literature, we use the coefficient of variation as the second moment of illiquidity. For the third moment, we use the non-parametric skewness measure (*SKILLIQ*) – which is called the median skewness or Pearson's coefficient of skewness – defined by the mean, median, and standard deviation of the daily price impact during the past 12 months as follows:

$$SKILLIQ = (\text{mean - median})/(\text{standard deviation}) \quad (2)$$

As in the relation between the mean and standard deviation, we find that the coefficient of variation is highly correlated with the standard skewness (correlation coefficient = 0.85). If we use the median skewness defined as in Equation (2), however, its correlation with the coefficient of variation is reduced to 0.02.[1] Equation (2) also provides the information about how skewed the price impact is as the standard skewness indicates, thus in this study, we define the median skewness of the daily price impact as in Equation (2). In

[1] If we construct *CVILLIQ* and *SKILLIQ* based on only the past month, the correlation between these two variables is 0.41, while it is 0.02 if the longer historical data (12 months) are used. Our goal is to examine the pricing effects of *CVILLIQ* and *SKILLIQ* separately, and so we mainly use the measures constructed by the past 12 month data. In most of Section 3, however, we examine measures with various lengths of the past data and report the qualitatively similar results regardless of the length of the past data used to construct those liquidity measures.

our paper, we simply denote *CVILLIQ* and *SKILLIQ* as volatility and skewness of illiquidity, rather than the coefficient of variation of illiquidity and the median skewness of illiquidity, respectively, for convenience.

As a proxy for the illiquidity of a firm, we use Amihud's (2002) measure for two reasons. First, it has been extensively used in the literature on stock market liquidity and asset pricing. In the literature, its first moment is mainly used, and thus, our study examining the predictive power of its third moment may be easily compared and extended with the existing literature. Second, according to Goyenko et al. (2009), it measures the price impact of a stock well compared with other price impact measures. As a robustness check, in Section 3.4, we examine other liquidity proxies, i.e., turnover and dollar-volume, and we find that our results are robust to the choice of liquidity measures.

We include firms that have at least 180 days with positive dollar volumes during the past 12 months and that are listed at the end of the previous year. We use monthly CRSP data to compute the past returns and the market capitalization of individual firms, and construct the book-to-market ratios of individual firms using the book values from COMPUSTAT. In each month, we include only firms that have positive book-to-market ratios, market capitalization data at the end of the previous year, and at least the past two-year data in COMPUSTAT to avoid firms that are newly listed.

3. Results

3.1. The moments of the Amihud (2002) illiquidity measure

In this section, we first examine the relations between the expected return of a stock and the first three moments of illiquidity, which are the mean (*ILLIQ*), volatility (*CVILLIQ*), and skewness (*SKILLIQ*) of the daily price impact, respectively. Then, we investigate whether the pricing effect of the firm-level skewness, *SKILLIQ,* can survive even after controlling for *ILLIQ* and *CVILLIQ*.

The existing literature has reported that the mean level of the daily price impact (*ILLIQ*) is significantly priced in the US and international stock markets (Acharya and Pedersen, 2005; Amihud, 2002; Amihud et al., 2015). Recently, Akbas et al. (2011) examine whether the volatility of the daily price impact is priced following the spirit of Chordia et al. (2001), and find that the volatility of the daily price impact is significantly priced in the US stock markets. However, we expect that investors may have different, asymmetric preference over the two types of liquidity changes reflected in the information in the volatility measure, i.e., the increase of liquidity and decrease of liquidity. An investor may dislike the decrease in liquidity much more than the other. The third moment is expected to capture this asymmetric preference, so we extend the literature to the higher moment of illiquidity and verify this issue.

In Table 1, the average one-month holding period returns on decile portfolios sorted by the mean (*ILLIQ*), volatility (*CVILLIQ*), and skewness (*SKILLIQ*) of the daily price impact are reported in Panel A, B, and C, respectively. In this table, portfolio 1 consists of stocks with the lowest values of *ILLIQ*, *CVILLIQ*, or *SKILLIQ*, respectively, while portfolio 10 consists of stocks with the highest values of *ILLIQ*, *CVILLIQ*, or *SKILLIQ*, respectively. In each panel, we compute these three variables based on the past *k* months, for *k* = 1, 3, 6, and 12, and sort stocks by these variables. In each column, we report the number of months (*k*) and the average returns on each set of decile portfolios. For average returns, we compute the equal-weighted portfolio return (EW) and the value-weighted portfolio return (VW), which is the average of returns weighted by the market capitalization of stocks. “Raw” indicates the raw return difference between Portfolio 10 and Portfolio 1, and “4F alpha” indicates the return difference between the abnormal returns or alphas of the two portfolios from the Carhart (1997) four-factor model with the Fama–French (1992) three factors and the momentum factor.

[Insert Table 1]

The overall results in Panel A and B of Table 1 are consistent with the literature. Panel A and B show that the mean and volatility of illiquidity are positively priced, respectively. If we look at the equal-weighted raw returns of *ILLIQ* and *CVILLIQ* decile portfolios, we can see a clear increasing pattern for every *k* in both decile portfolios, and the average raw returns on the 10-1 portfolios in both cases are positive and statistically significant at least at the 10% significance level for every *k*. However, the Carhart alphas of the *ILLIQ* 10-1 portfolio become insignificant for small values of *k*, and significantly positive only for large values of *k*. Thus, only when the illiquidity is calculated using more than the last 3 to 6 months, the firm-level illiquidity is significantly positively priced during our sample period. On the other hand, the *CVILLIQ* 10-1 portfolio remains significant for every *k* even after the risk is adjusted by the Carhart four-factor model. In addition, the magnitude of the Carhart alphas for the *CVILLIQ* 10-1 portfolio is larger than that for the *ILLIQ* 10-1 portfolio. The overall empirical results in Panel A and B of Table 1 show that *CVLLIQ* has a more significant pricing effect than *ILLIQ*, which is consistent with Akbas et al. (2011).

These results indicate that investors demand a higher return when the firm-level illiquidity is high and when the uncertainty of the firm-level illiquidity is high. Since liquidity means investors can obtain cash without much cost in a short time, investors should value the liquidity, and so an illiquid stock should compensate more to investors in return for the inconvenience illiquidity causes. Similarly, if the level of illiquidity changes and if the illiquidity level of a stock is more likely to change than that of the others, investors want to prepare for the adverse change in the level of illiquidity and will demand the compensation for it. From these points of view, it is not a surprise to observe that the 10-1 portfolios based on *ILLIQ* and *CVILLIQ* have positive alphas after controlling for the Carhart four factors.

In terms of the value-weighted returns, both the *ILLIQ* 10-1 portfolio and the *CVILLIQ* 10-1 portfolio show much weaker results compared with the equal-weighted results. Since small firms tend to be more illiquid than large firms, those long-short returns can be much reduced by value-weighting and this decrease in returns is notably large for highly illiquid firms categorized as being in the *ILLIQ* 10 portfolio. In Panel A of Table 1, the value-weighted raw returns for the *ILLIQ* 10-1 portfolios are significant only for the k = 12 case, and the value-weighted Carhart alphas are insignificant for all cases. The significant results for k = 12 seem to be attributed to the smaller decrease in the value-weighted returns in the *ILLIQ* 10 portfolio compared with other ks. The *CVILLIQ* 10 and *ILLIQ* 10 portfolios show similar patterns in their value-weighted returns. The *CVILLIQ* 10 portfolio appears to be largely affected by small firms, similar to the *ILLIQ* 10 portfolio. The returns on the *CVILLIQ* 10 portfolios are highly reduced by value-weighting, and as in the *ILLIQ* 10 portfolio, the returns are largely reduced for smaller k values. Thus, in Panel B of Table 1, the value-weighted raw returns for the *CVILLIQ* 10-1 portfolios are significant only for large ks (k = 6 and 12), but, in terms of the value-weighted Carhart alphas, none of them are significant.

Panel C of Table 1 shows that high *SKILLIQ* portfolios generate higher returns than low *SKILLIQ* portfolios. We can observe an increasing pattern in raw returns for *SKILLIQ*-sorted decile portfolios, and the average raw returns from the *SKILLIQ* 10-1 portfolios are positive and statistically significant at the 5% significance level for every k. This significance survives even after the risk of the 10-1 portfolio is controlled by the Carhart four-factor model. All the alphas are from 0.210% to 0.335%, and are statistically significant at the 5% significance level. Though these values are not as large as the value or momentum premium, they are still economically significant and comparable to those for the *ILLIQ* 10-1 portfolios. In contrast to the value-weighted results for the *ILLIQ* and *CVILLIQ* portfolios, the value-weighted returns from the *SKILLIQ* 10-1 portfolios show significant results. The returns from the *SKILLIQ* 10 portfolio, which is the high illiquidity skewness portfolio, appear to be greatly reduced by value-weighting, but the reduction in returns is much smaller than that from the *ILLIQ* 10 portfolio or the *CVILLIQ* 10 portfolio in Panel A and B of Table 1, respectively. Thus, although the value-weighted raw returns on the 10-1 *SKILLIQ* portfolios tend to be smaller than the equal-weighted raw returns, the differences between the value-weighted returns and the equal-weighted returns are rather small and both are significant for all values of k. The value-weighted

Carhart alphas show weaker results, but they are still significant in most cases. For $k = 1$ and 6, the value-weighted Carhart alphas are significant at the 1% significance level, and for $k = 12$, it is significant at the 10% significant level. The only exception is when $k = 3$.

Overall results in Panel C of Table 1 suggest that there is a significant pricing effect of the skewness of illiquidity. The high skewness of illiquidity of a stock means that (i) the probability of an adverse illiquidity change is higher than the one of a favorable illiquidity change, and (ii) the extent of an extreme adverse change in illiquidity is bigger than the one of an extreme favorable change in illiquidity. Thus, investors will demand a higher return for the stock with a high value of *SKILLIQ*. More importantly, the value-weighted results suggest that though the return differences between the high *ILLIQ* (*CVILLIQ*) and the low *ILLIQ* (*CVILLIQ*) firms can be mainly driven by the small firms, the return differences between the high *SKILLIQ* and the low *SKILLIQ* firms remain strong even for large firms.

Table 2 presents the summary statistics of the characteristics of the *SKILLIQ*-based decile portfolios in Panel A and the time-series average of the cross-sectional correlations among the variables in Panel B. In each month, we sort the sample firms by past 12-month *SKILLIQ* ($k = 12$ case in Table 1) and construct equal-weighted decile portfolios. Portfolio 1 is the portfolio of stocks with the lowest skewness of the illiquidity, and Portfolio 10 is that with the highest skewness of the illiquidity. In addition to the average returns of portfolios, Table 2 also presents the average values of the logarithm of the market capitalization at the end of month t-1 (log*(ME))*, the logarithm of the book-to-market ratio that was constructed following Fama and French (1992) (log*(B/M)*),[2] the market beta based on the past 60 months for firms with at least 12 months of data (*BETA*), the return on month t (*REV*), the turnover of the month t (*TURNM*), which is defined as the one-month trading share volume divided by the number of shares outstanding, and the market

[2] To avoid issues with extreme observations, following Fama and French (1992), the book-to-market ratios are truncated at the 0.5% and 99.5% levels.

price (*Price*) for each portfolio. For comparison, we report the mean, volatility, and skewness of the daily price impact for each portfolio (*ILLIQ*, *CVILLIQ*, and *SKILLIQ*).

[Insert Table 2]

In Panel A of Table 2, most of the characteristics show monotonic patterns, and a high *SKILLIQ* portfolio appears to have the characteristics of highly illiquid firms. For example, firms in a high *SKILLIQ* portfolio tend to have a small market capitalization, a large book-to-market ratio, a high market beta, and a large value of *ILLIQ*. On the other hand, the values of turnover and *CVILLIQ* show slightly U-shaped patterns across the *SKILLIQ* portfolios. Indeed, the correlations – the time-series averages of cross-sectional correlations – reported in Panel B of Table 2 show that though *SKILLIQ* is positively related to both *ILLIQ* and *CVILLIQ*, the correlation between *CVILLIQ* and *SKILLIQ* is as low as 0.023 and the one between *ILLIQ* and *SKILLIQ* is 0.110. These low correlations between *SKILLIQ* and *ILLIQ* or *CVILLIQ* imply that the significant relation between *SKILLIQ* and the return of a stock in Panel C of Table 1 may not be driven by the effects of *ILLIQ* or *CVILLIQ*. In Panel B, all three moments of the illiquidity, *ILLIQ*, *CVILLIQ*, and *SKILLIQ*, are negatively correlated with the firm size (*log(ME)*), but *SKILLIQ* appears to be less correlated with it than *ILLIQ* and *CVILLIQ*. The correlation between *SKILLIQ* and the firm size is -0.316 but the correlation between *ILLIQ* (*CVILLIQ*) and the firm size is -0.354 (-0.544). These results are consistent with the value-weighted results in Table 1 in that the difference between the equal-weighted and value-weighted returns on *SKILLIQ* portfolios is much smaller than that of *ILLIQ* and *CVILLIQ*. The pricing effects of the illiquidity skewness are less affected by the small-firm effects compared with the mean and volatility of the illiquidity.

To clarify whether the relation between *SKILLIQ* and the stock return can be attributed to the relations between stock returns and *ILLIQ* or *CVILLIQ* more clearly, we conduct dependent bivariate sorting analyses below. In each month, we first sort stocks into quintiles by *ILLIQ* (*CVILLIQ*), and then sort stocks in each

ILLIQ (*CVILLIQ*) into quintiles by *SKILLIQ*. Consequently, we construct 25 portfolios with an equal number of stocks in each portfolio. We also construct 25 portfolios by sorting stocks by *SKILLIQ* first, and then *ILLIQ* (*CVILLIQ*).

[Insert Table 3]

In Table 3, Panel A (Panel C) shows the results for the portfolios sorted by *ILLIQ* (*CVILLIQ*) first, and then by *SKILLIQ*. Panel B (Panel D) shows the results for the portfolios sorted by *SKILLIQ* first, and then by *ILLIQ* (*CVILLIQ*). In each panel, we also report the average 5-1 portfolio returns based on one variable after controlling for the other. For example, in Panel A, we construct the *ILLIQ*-controlled *SKILLIQ* 5-1 portfolio returns by averaging the five *SKILLIQ* 5-1 portfolios across five *ILLIQ* categories. Since this *SKILLIQ* 5-1 portfolio contains all the *ILLIQ*-based quintile portfolios with equal numbers, we expect that its return is relatively free from the *ILLIQ*.[3]

In Panel A, the positive relation between *SKILLIQ* and the expected stock returns is significant after controlling for *ILLIQ* in general. Among the five *ILLIQ* groups, all groups show positive raw return differences and three of them are statistically significant at the 10% significance level after controlling for the Carhart four factors. Interestingly, the risk-adjusted returns for the *SKILLIQ* 5-1 portfolios appear to be significant within low *ILLIQ* groups. These results indicate that the skewness of firm-level illiquidity is more important and significant among liquid firms than illiquid firms. Investors may already get enough illiquidity premium for illiquid stocks because they already expect to suffer from a lack of liquidity. For

[3] In Table 3, we report the equal-weighted returns for each portfolio. Though we do not report the value-weighted results in this paper, we find qualitatively similar results for the value-weighted returns. Although the level of significance of the value-weighted returns on *ILLIQ*-controlled *SKILLIQ* 5-1 portfolio and *CVILLIQ*-controlled *SKILLIQ* portfolio 5-1 is lower than that of the equal-weighted returns, they appear to be still significant.

liquid stock, however, investors may require compensation for the possible downside liquidity risk for liquid stocks, even though they do not carry a high liquidity-level premium.

The average raw return and the Carhart alpha from the *ILLIQ*-controlled *SKILLIQ* 5-1 portfolio are significant (*t*-values = 1.90 and 2.79), indicating that the pricing effect of *SKILLIQ* is independent of that of *ILLIQ*. In Panel B, *ILLIQ* shows a much weaker relation with the expected returns. The raw return differences across *ILLIQ* portfolios are significant in some *SKILLIQ* groups, but all of them become insignificant after being adjusted for the risk factors. The raw return on the *SKILLIQ*-controlled *ILLIQ* 5-1 portfolio is positive and significant, but the Carhart alpha becomes insignificant. These results show that the illiquidity-level effect dies out after the skewness of illiquidity and the Carhart four factors are taken into account, which implies that the skewness of illiquidity effect is a more important characteristic that has a significant pricing effect.

Panel C of Table 3 shows that the pricing effect of *SKILLIQ* is significant after controlling for *CVILLIQ*. All the Carhart alphas of the *SKILLIQ* 5-1 portfolios are positive, and two of them are statistically significant. The *CVILLIQ*-controlled *SKILLIQ* 5-1 portfolio also shows a significant raw return (*t*-value = 2.26) and the Carhart alpha (*t*-value = 3.17). Compared with the results in Panel A and C, the pricing effect of *SKILLIQ* seems to be more affected by *CVILLIQ* than *ILLIQ*, but controlling for those variables does not completely diminish the significant relation between *SKILLIQ* and the expected stock returns.

In Panel D, we find that *CVILLIQ* is also significantly associated with the expected returns after controlling for *SKILLIQ*. The raw returns of the *CVILLIQ*-based quintile portfolios show monotonically increasing patterns within each *SKILLIQ* portfolio, and the Carhart alphas of *CVILLIQ*-based 5-1 portfolios are significant for low *SKILLIQ* categories. This shows that the illiquidity volatility premium is more important for the portfolios with more downside illiquid risk. The average raw return of the *SKILLIQ*-controlled *CVILLIQ* 5-1 portfolio is positively significant, and the Carhart alpha remains significant after the four-factor risks are controlled. This means that the premium for *CVILLIQ* exists independently of the *SKILLIQ* premium.

3.2. Cross-sectional analysis with liquidity skewness

In this section, we investigate the firm-level cross-sectional relation between the liquidity skewness and the expected stock returns. In the previous section, we find that *SKILLIQ*, which is the third moment of illiquidity, is significantly priced in the US stock markets and this pricing effect seems to be independent of that of the first and the second moments of illiquidity by the Fama–French-type portfolio analyses. We examine this issue further and more thoroughly by a firm-level cross-sectional regression analysis.

In addition to the three moments of illiquidity, we control for the effects of the firm size, the book-to-market ratio, the market beta, turnover, the past return, and idiosyncratic volatility (*IVOL*) variables since they have been regarded as the variables related to the expected stock returns.[4] To compute idiosyncratic volatility, we use the daily data from the past 12-months and employ the Fama–French Three-factor Model, Carhart Four-factor Model, or Fama-French Five-factor Model (Fama and French, 2015)[5] as in Ang et al. (2006). As dependent variables of the cross-sectional regression, we employ four types of returns on stocks, i.e., raw returns, returns adjusted by the Fama–French Three-factor Model, returns adjusted by the Carhart Four-factor Model, and returns adjusted by the Fama-French Five-factor Model. If the dependent variables are raw returns or returns adjusted by the three-factor model, we employ *IVOL* computed by the three-factor model, and if the dependent variables are returns adjusted by the four-factor model, then we employ *IVOL* computed by the four-factor model. As in Table 1, we compute *ILLIQ*, *CVILLIQ,* and *SKILLIQ* based on

[4] The definitions of the control variables except idiosyncratic volatility are already stated in Section 3.1.
[5] In this paper, we mainly use the Carhart Four-factor Model rather than the Fama-French Five-factor Model because the Carhart model provides longer sample period.

the past k months, for $k = 1$, 3, 6, and 12, to compare the pricing effects of those variables based on the different lengths of the past data.

[Insert Table 4]

In each Panel of Table 4, the dependent variable for models 1 to 4 is raw returns, and the variable for models 5 to 7 are the returns adjusted by the three-, four-, and five-factor models, respectively. First of all, the mean level of illiquidity (*ILLIQ*), which shows a weak relation with the expected return in the portfolio analysis, is significantly priced for all values of k in the cross-sectional regressions with the control variables and does not depend on the set of control variables or the type of the dependent variables. Moreover, the significance and the size of the coefficients of *ILLIQ* increase slightly as k increases. The volatility of illiquidity also shows a significant relation with all types of expected returns in general, at least for some k, but is more significant after controlling for risk factors.

Our main focus in this paper is the pricing effect of *SKILLIQ*. Table 4 shows that the coefficients of *SKILLIQ* are positive and statistically significant in general. The coefficients of *SKILLIQ* become larger as k increases except for $k = 6$, and thus the coefficients of *SKILLIQ* for $k = 12$ (coefficients = 0.905 to 1.244) are almost four times larger than those for $k = 1$ (coefficients = 0.211 to 0.304). The significant positive coefficients of *SKILLIQ* once again confirm that the skewness of illiquidity is well priced in the stock market in addition to the level of illiquidity and the volatility of illiquidity and should not be ignored. Investors take care of any decrease in liquidity and demand compensation for the risk. Considering that the value of one standard deviation for the *SKILLIQ* with $k = 1$ and 12 are 0.15 and 0.06, respectively, an increase in the expected return as a response to a one-standard-deviation change in *SKILLIQ* with $k = 1$ ($k =$

12) ranges from 0.032% to 0.046% (from 0.054% to 0.075%) per month, which is measured from 0.38% to 0.55% (from 0.65% to 0.90%) per year. This is an economically meaningful number.[6]

For a robustness check, we perform four more analyses. First, we divide our sample period into two halves and conduct the cross-sectional analysis in each of subperiods. Recently, Ben-Rephael et al. (2015) document that the liquidity premium in the US stock markets has been reduced as stock liquidity has improved over the recent decades, and thus the liquidity premium exists only in the smallest common stocks. Motivated by these empirical findings, we investigate whether the pricing effect of *SKILLIQ* remains significant even in the recent period. Specifically, on the basis of returns (dependent variable), the first subperiod (1st half) spans the period from July 1963 to December 1988 and the second subperiod (2nd half) spans the period from January 1989 to June 2014. We run Model 6 in Table 4 in each subperiod and report the results in Table 5.

[Insert Table 5]

First of all, consistent with Ben-Raphael et al. (2015), Table 5 shows that the illiquidity premium (coefficients on *ILLIQ*) is decreased in the recent period. Though these coefficients remain significant in the 2nd half-period, our results show that their values are substantially reduced. For example, in case of k = 1, the coefficient on *ILLIQ* is reduced from 0.066 in the 1st half-period to 0.021 in the 2nd half-period. Next, with regard to coefficients of *SKILLIQ*, they become larger as k increases as in Table 4. In case of k = 12, the coefficients on *SKILLIQ* appear to be significant at the 5% and 10% significance levels in the 1st and 2nd half-periods, respectively. Moreover, in case of k = 6, the 2nd half shows even more significant results than the 1st half. In other words, the price impact of the illiquidity skewness appears to be significant in the

[6] As the liquidity effect can be closely associated with the short-term return reversal, we skip month t and examine the returns on month t+1 for the portfolio analysis in Table 1 and the cross-sectional analysis in Table 4, but we find that the results are qualitatively the same.

recent period (2nd half) if the measure is constructed from the longer history. However, we also find some results that are consistent with Ben-Rephael et al. (2015). In case of k = 1 and 3, our results show that the liquidity skewness premium is more dominant in the 1st half-period and becomes much weaker in the 2nd half-period. Specifically, the coefficients on *SKILLIIQ* are highly significant (t-statistics = 3.23 and 3.24) only in the 1st half-period as opposed to the recent period. Overall, however, we find that their values in Table 5 are comparable to the values in Table 4 while their significance is reduced. For example, in case of k = 12, Table 4 shows that the coefficient on *SKILLIQ* is 1.244 while these on the 1st and 2nd subperiods are 1.154 and 1.334, respectively. As the values of coefficients on *SKILLIQ* are comparable in both full-sample and subsample, the decrease in significance seems to be mainly due to the reduction in the sample size. Though the subsample results in Table 5 are weaker than the full-sample results in Table 4, considering the reduction in sample size and significant results in case of k = 6 and 12 where we confirm especially strong price impact of *SKILLIQ* in the previous analysis, it seems to be difficult to deny that the pricing effect of the liquidity skewness is diminished in the recent period.

Second, we examine whether our findings are robust to the systematic liquidity risks. Our measure can be simply regarded as a proxy for a downside liquidity risk, and thus comparison with the systematic liquidity measures should be conducted. In the literature on the liquidity risk, one of the representative liquidity models is the one suggested by Acharya and Pederson (2005). They provide the liquidity-adjusted CAPM (L-CAPM), in which liquidity is incorporated into the pricing kernel. We compare the pricing effect of our skewness measure with that of Acharya and Pedersen's (2005) three liquidity betas. Acharya and Pedersen (2005) construct four betas based on the L-CAPM. In specific, the first one is the market beta as CAPM (β_1), the second one captures the covariance between the asset's illiquidity and the market illiquidity (β_2), the third one captures the covariance between a security's return and the market liquidity (β_3), and the last one captures the covariance between a security's illiquidity and the market return (β_4). Among these four betas, all except the first one can be considered as the liquidity risk. Moreover, we consider the extended liquidity-adjusted model suggested by Anthonisz and Putnins (2016). They extend the L-CAPM to additionally consider the downside liquidity risk. Their model, the liquidity-adjusted downside CAPM (LD-CAPM), allows asymmetric effects of the liquidity risk, and thus we may expect that their model is more closely associated with our analysis. Anthonisz and Putnins (2016) construct four gammas ($\gamma_1, \gamma_2, \gamma_3$, and γ_4) in a similar way, but computed in the negative subspace where the innovation in market liquidity cost exceeds the market excess return.

We estimate each firm's four betas and four gammas in each month, and conduct the cross-sectional analysis with our skewness measures.[7] We first check the correlation between the betas and *SKILLIQ*. In case of $k = 12$, we find that the correlations with β_2, β_3, and β_4 are 0.0058, 0.0007, and 0.0060, respectively. Moreover, we find that the correlations with γ_2, γ_3, and γ_4 are 0.0289, 0.0508, and 0.0151, respectively. Though the risks estimated from the LD-CAPM show slightly larger correlations with *SKILLIQ*, still *SKILLIQ* is rarely correlated with the systematic liquidity risks of either the L-CAPM or the LD-CAPM. For other choices of k, the results appear to be consistent, and *ILLIQ* and *CVILLIQ* also show low correlations with them. These low correlations with the estimates of the L-CAPM and LD-CAPM indeed are not so surprising because these estimates are based on the innovation on the daily liquidity cost while our illiquidity variables based on Amihud (2002), such as *ILLIQ*, *CVILLIQ*, and *SKILLIQ*, are based on the total level of daily price impact, not the innovation of it. In fact, our measure can be different from the risk factors derived from the L-CAPM and LD-CAPM as they intend to measure the systematic liquidity risk. As we document, the betas and gammas are computed based on innovations in illiquidity while our measure is based on the total illiquidity level. Acharya and Pedersen (2005) also include the mean level of illiquidity

[7] In estimating Acharya and Pedersen's (2005) betas, we follow the methodology of Anthonisz and Putnins (2016). Anthonisz and Putnins (2016) estimate four betas using daily observations in rolling six-month windows. In measuring illiquidity cost, they employ an AR model on the daily time-series of individual stocks and then use only innovation term in computing betas. Moreover, the market and individual stock returns are also measured in terms of the excess returns. We expect that their methodology can be more appropriate for capturing the time-varying liquidity risks and comparable to our measures that are also time-varying.

to capture the effect of illiquidity as a firm-characteristic in addition to four betas. As our study is intended to capture the pricing effect of liquidity skewness as a firm-characteristic, we measure illiquidity by the total level of the price impact, not by the innovation term, and this approach is also consistent with previous studies on liquidity as a firm-characteristic. Consequently, we may expect that the firm's illiquidity variables (such as *ILLIQ*, *CVILLIQ*, and *SKILLIQ*) as firm-characteristics affecting expected returns is different from these systematic liquidity risks, and thus their effects cannot be ignored. For the cross-sectional regression model, we add the four betas to the regression model 6 in Table 4. We report the results for k = 1, 3, 6, and 12 in Table 6.

[Insert Table 6]

The results in Panel A of Table 6 are consistent with the correlations among the variables. In Panel A, for all cases of ks, the coefficients on *SKILLIQ* are positive and significant (coefficients = 0.2381 to 1.2541, t-values = 2.00 to 2.62) while the systematic liquidity risks (β_2, β_3, and β_4) are positive but insignificant. Compared to the results in the model 6 of Table 4, the coefficients on *SKILLIQ* seem to be rarely affected by these systematic liquidity risks. Moreover, the coefficients on *ILLIQ* and *CVILLIQ* are significant even after controlling for the systematic liquidity risks. These results suggest the importance of the firm's liquidity and the robustness of the pricing effect of *SKILLIQ* as well as *ILLIQ* and *CVILLIQ* even after controlling for the systematic liquidity risk factors.

The overall results with the LD-CAPM in Panel B of Table 6 seem to be consistent with the results with the L-CAPM. Among four gammas estimated from the LD-CAPM, the fourth component which indicates the covariance between a security's illiquidity and the market return appears to be significant in all cases (t-statistics = 1.99 to 2.75), but the pricing effect of *SKILLIQ* seems to be rarely affected by these gammas with only one exception (k = 6). Overall, except the case of k = 6 in Panel B, *SKILLIQ* shows significant effects even after controlling for the systematic liquidity risks of the L-CAPM or LD-CAPM.

As the third robustness check, we investigate whether the pricing effect of the skewness measure is robust to Wu's (2015) liquidity risk measure. To compare with the pricing effect of Wu's (2015) market-wide liquidity tail risk, we verify the pricing effect of *SKILLIQ* after controlling for Wu's tail risk. For the regression models 4, 5, and 6 in Table 4, we additionally include Wu's tail risk.[8] The value and significance of the coefficients on *SKILLIQ* are both reduced by including the tail risk, but they remain significant. For example, in case of k = 12, the t-values of the coefficients on *SKILLIQ* ranges from 2.15 to 2.55 while in Table 4 they range from 2.42 to 2.57. As in Table 4, we find the rather weak results in case of k = 6, but for the model 6 with the tail risk, the coefficient on *SKILLIQ* is still significant at the 10% significance level (t-value = 1.72). More importantly, in all cases, we find no significant pricing effect of the market-wide tail risk. These results support our hypothesis that the firm-level liquidity skewness is important.

Lastly, we investigate whether our results are driven by few outliers in our data set. Following Amihud (2002) and Amihud et al. (2015) we additionally exclude stocks whose price is lower than five dollars, and then eliminate stocks whose *ILLIQ* is at the highest 1% tail of the distribution in each month. As the literature suggests there might be a bias caused by the outlier of the estimated Amihud's illiquidity measure and noise in stocks with low prices, we examine whether our results are robust after controlling for these effects. Using the filtered data, we find that our results are robust to these possible errors. For example, from the model 6 in Table 4 with the filtered data, we find that the coefficients of *SKILLIQ* are significant for all ks with only exception (k = 6). In case of k = 12, the t-statistics of coefficients of *CVILLIQ* and *SKILLIQ* are 2.66 and 2.10, respectively, indicating that both are significant at the 5% significance level, while that of *ILLIQ* is only 1.16.

[8] In specific, following Wu (2015), we first construct the market-wide tail risk variable, and then run the time-series regression in each month to estimate the coefficient on the variable. For the cross-sectional analysis, we include this estimated coefficient on the tail risk variable. For the construction method of the variable and the estimation of the coefficient, see Section II of Wu (2015).

To summarize, our cross-sectional regression results show that the third moment of illiquidity is significantly priced in addition to the first and second moments of illiquidity. The pricing effects of the skewness of illiquidity are significant regardless of the risk-adjustment, the choice of the length of the past period used to calculate the skewness, and the set of control variables. Our results show robust evidence for the pricing effect of the illiquidity skewness.

3.3. The skewness effects for longer-period returns

In this section, we investigate the effects of the illiquidity skewness on longer-period future returns. In examining the effects of some risk factors or firm-characteristics on the expected returns, the majority of studies focus on the next one-month return as a proxy for the expected return. If the skewness of illiquidity persists, then long-term holding-period returns may be related to the skewness measure used in the previous sections. However, as Cochrane and Piazzesi's (2005) factor shows in the bond market, their factor affects only one-year or long-period returns, not one-month returns, and so the effects of illiquidity on long-period returns may be different from those on one-month returns. Considering that investors have different investment horizons, it is worthwhile to investigate how different the relation between the expected return and illiquidity measures might depend on the length of the holding period, and how robust the relation is out to the length of the investment horizon.

We examine the effects of the moments of illiquidity measured at month t on the cumulative returns from month t+1 to month $t+m$ (m = 2, 3, 4, … , 12). In the previous section, we focus on the relation between the illiquidity variables at month t and the one-month returns that are the returns at month t+1 (m = 1), and in this section, we extend it to longer periods. We run the same firm-level cross-sectional regressions as in section 3.2 except for the dependent variables. We examine the cumulative returns, which can be obtained by holding the stocks for m months from month t, where we measure the cumulative returns in terms of raw returns and risk-adjusted abnormal returns. The abnormal returns are adjusted by Carhart's Four-factor Model, and for computing the cumulative abnormal returns we sum up each month's abnormal return during the holding period following Cooper et al. (2004).

[Insert Table 7]

Table 7 reports the results from the cross-sectional regressions of returns with different investment horizons against illiquidity measures and other control variables. Panel A and B of Table 7 use the cumulative raw returns and the risk-adjusted returns from month t+1 to month t+m as the dependent variable, respectively. The empirical results reported in Table 7 document that the effects of illiquidity skewness exist for longer periods as well as the one-month holding period. In terms of raw returns, in Panel A, the coefficients of *SKILLIQ* are significant at the 10% significance level up to nine months (m = 9). In terms of risk-adjusted returns, in Panel B, though the effects of *SKILLIQ* seem to be slightly reduced, they are still significant up to eight months (m = 8). Though we do not report here, we also examined the return on each month t+m rather than the cumulative return until month t+m for m = 1, 2, … , 12 and find that the t+m month returns are significant up to m = 5. These results show that the significant effects of *SKILLIQ* on the cumulative returns for longer periods are not solely driven by the effects on the first-month return. Compared with the effects of the lower moments of illiquidity, the effects of the illiquidity skewness (*SKILLIQ*) appear to be significant for longer periods than those for *CVILLIQ* but shorter than those for *ILLIQ*.

Table 7 also shows the effects of the level and volatility of illiquidity on stock returns with various investment horizons through the coefficients of *ILLIQ* and *CVILLIQ*. The coefficients of *ILLIQ* are highly significant for all values of m (t-value = 5.28 to 5.67 in Panel A, 6.08 to 7.35 in Panel B). We expect that these results are driven by the persistent nature of *ILLIQ*. Though not reported here, we find that the probability that a firm in the lowest (highest) *ILLIQ* decile belongs to the lowest (highest) *ILLIQ* decile in the next month is 85% (79%), and the coefficients of *ILLIQ* for the month t+m returns are significant for all m. These features may contribute to the strong and long-lasting effects of *ILLIQ* on the returns up to one year. The volatility of illiquidity (*CVILLIQ*) shows significant results only in the short-term returns to three months (m = 2) at the 10% significance level for raw returns in Panel A of Table 7, but the effects of *CVILLIQ* appear to be significant up to nine months (m = 10) at the 10% significance level for the risk-adjusted returns in Panel B.

To summarize, our results show that illiquidity effects on the future stock returns are not limited to the next month but last longer. The positive relation between the illiquidity skewness and stock returns appears to be significant up to eight months after controlling for other effects. The mean level of illiquidity shows significant results for all investment horizons up to 12 months, and the volatility of illiquidity shows significant results up to nine months after controlling for other effects.

3.4. Skewness of trading activity measures

In this section, we examine the pricing effect of the third moment of liquidity with different measures, i.e., turnover and dollar volume. Liquidity has several dimensions, and so the literature has suggested various proxies for measuring each of these dimensions. For instance, the Amihud illiquidity measure, which we mainly use in this paper, captures the price impact of trades and is associated with the trading cost. It indicates that the price of an illiquid stock can be impacted more by the occurrence of a trade. On the other hand, there are other liquidity measures that capture the size of trading costs in a different way or other dimensions of liquidity, such as the frequency of trades. Among them, turnover and trading volume are the representative liquidity measures that capture how the stock is actively traded in the market (Chordia et al., 2001). In the literature on liquidity, there are various liquidity measures, but turnover and trading volume are especially appropriate alternatives in our study. To construct the skewness measure, as *SKILLIQ*, we first compute the level of liquidity or illiquidity in daily frequency. Then, based on the distribution of this daily liquidity values, we derive the skewness of it in each month. As turnover and trading volume are the ones that can be computed in daily frequency like Amihud's (2002) daily price impact and their monthly averages are generally used as a liquidity measure, our approach is applicable to these measures.

In this paper, we hypothesize that the skewness of the price impact is priced in the stock market because there can be an asymmetric preference of investors on the change of liquidity and investors may fear an extreme illiquid event. In terms of trading activity, we also expect a liquidity skewness premium as investors may fear the depletion of trading on a stock in the market, and thus, they will require compensation for this risk. The literature has documented the importance of the volatility of turnover and trading volume as the volatility of the price impact. Chordia et al. (2001) and Akbas et al. (2011) document that the volatility (coefficient of variation) of monthly turnover and dollar-volume are negatively priced in the US stock markets.

As in the previous sections, we define the second moment of turnover (dollar-volume) as the coefficient of variation of the daily turnover (dollar-volume), and the third moment of turnover (dollar-volume) as the standardized difference between its mean and median values as in Equation (2), because of the high correlation between the coefficient of variation and the standard skewness measure. Unlike Chordia et al. (2001), we construct these variables based on the daily data instead of the monthly data. As Akbas et al. (2011) show, using daily data can be advantageous in capturing the short-term variability in liquidity and allows for the possibility that liquidity may change between months. Hence, as we compute the higher moments of price impacts in the previous sections, we use daily turnover and dollar-volume to compute the higher moments of these variables.

We denote the average, coefficient of variation, and skewness of the daily turnover (dollar-volume) as *TURN* (*DVOL*), *CVTURN* (*CVDVOL*), and *SKTURN* (*SKDVOL*), respectively. Moreover, as in Table 4, we compute these variables based on the past *k* months, for *k* = 1, 3, 6, and 12, to compare the pricing effects of these variables based on the different lengths of the past data, and employ three types of returns, i.e., raw returns and two risk-adjusted returns as in the previous section.

[Insert Table 8]

[Insert Table 9]

In each Panel of Table 8 and Table 9, the dependent variables for models 1 to 4 are raw returns, and the variable for models 5 to 7 are the returns adjusted by the three-, four-, and five-factor models, respectively. Table 8 and Table 9 show that the skewness of both turnover and dollar-volume is more weakly priced than that of the daily price impact. Both measures are significantly priced only for small values of *k*. Specifically, in Table 8, *SKTURN* shows negative and significant coefficients at the 10% significance level if it is computed based on the past one month (*k* = 1), but it becomes insignificant if longer periods of past data are used. In Table 9, *SKDVOL* appears to be significant for *k* = 1 and 3. For *k* = 1, raw returns show a significant relation with *SKDVOL* but the coefficient of *SKDVOL* becomes insignificant if other risks are controlled. The negative coefficients of *SKTURN* and *SKDVOL* are consistent with the positive coefficients of *SKILLIQ* because the large value of turnover or dollar-volume indicates that the stock is liquid while the large value of the price impact indicates that the stock is illiquid. We also find that the skewness of turnover and dollar-volume shows more significant effects on the expected stock returns than the volatility of them.

Another interesting observation is that the negative pricing effects of the volatility of turnover and dollar-volume become positive in general if the returns are adjusted by the Fama and French model or the Carhart model. In Table 8, models 5 and 6 show that the coefficients of *CVTURN* are positive and significant except for those in Panel D. In Table 9, the coefficients of *CVDVOL* are also positive in model 5 and 6 in Panel C and D. These results are in contrast to the findings of Chordia et al. (2001). There may be two reasons for the differences. Akbas et al. (2011) report that the negative effects of *CVTURN* and *CVDVOL* become insignificant if the daily data are used instead of the monthly data, but no positive effect is reported. Akbas et al. (2011) insist that the daily data allow for the possibility that liquidity may change within a month, and we expect that this advantage can be substantial in measuring the volatility and skewness of liquidity. Second, the negative effects documented in Chordia et al. (2001) may be due to the fact that the skewness is not controlled for in their model specification. Since the skewness of liquidity is positively related to the volatility of liquidity, though small, and since the skewness of liquidity has a negative relation with the expected returns, the effects of volatility will appear to be negative if the negative effect of the skewness dominates the positive effect of volatility and the skewness term is omitted in the model specification. Indeed, we can observe the negative relations between *CVTURN* (*CVDVOL*) and returns in Panels A and B of Tables 8 and 9 when *SKTURN* (*SKDVOL*) is omitted in the regression specifications.

Next, as in Section 3.3, we examine the effects of the turnover and dollar-volume variables on the longer future returns.[9] We examine the effects of the moments of turnover and dollar-volume measured at month t on the cumulative returns from month t+1 to month $t+m$ (m = 2, 3, 4, …, 12), where the cumulative returns are measured in terms of raw returns as well as risk-adjusted abnormal returns.

[Insert Table 10]

In Table 10, Panel A and B examine the effects of the turnover variables, while Panel C and D examine the effects of the dollar-volume variables. Panel A and C are for the raw returns and Panel B and D are for the risk-adjusted returns. Both turnover and dollar-volume cases show similar patterns, but dollar-volume shows more significant results in general. First of all, the skewness variables (*SKTURN* and *SKDVOL*) are negatively related to the raw cumulative returns for all m, but they tend to be insignificant for small m. In

[9] In the analysis of the illiquidity variables, we mainly use the variables constructed by the past 12 month data (k = 12). In Table 8 and 9, however, we find significant results for k = 1, and we conduct the analysis with the variables constructed by the past one month data (k = 1).

Panel A (Panel C), the coefficients of *SKTURN* (*SKDVOL*) are significant for m = 5, 10, and 11 (from m = 3 to 12, with one exception m = 8). Thus, in terms of raw returns, the negative relation between the skewness of liquidity (*SKTURN* and *SKDVOL*) and the expected return shows up more clearly in the longer-term returns. However, if we examine the risk-adjusted returns, the skewness effects are significant in most of the cases. In Panel B, the negative relation between the skewness and the future returns appears to be significant in all cases except m = 1 and 2. In Panel D, we find significant relations for all m at the 1% significance level except that *SKDVOL* is significant at the 10% significance level in the case of m = 1. Moreover, in Panel B, we find positive and significant results for *CVTURN* and in Panel D, we find the same results for *CVDVOL* from m = 6.

In Panel A and B of Table 10, the mean level of turnover (*TURN*) shows a significant relation with both raw returns and risk-adjusted returns for all m, except m = 2 in Panel A, but in Panel C and D of Table 10, the mean level of dollar-volume (*DVOL*) shows insignificant results in most of the cases. Though both variables are proxies for trading activity, the mean levels of these variables show mixed results. In the cases of volatilities of turnover (*CVTURN*) and dollar-volume (*CVDVOL*), they are insignificant in terms of the raw returns, while they become more significant if the risk factors are controlled.

In summary, we find that the skewness of trading activity is significantly and negatively priced in the US stock markets when we use turnover and dollar-volume as the liquidity measures. Though the pricing effect of the skewness of trading activity seems to be much weaker than that of the skewness of the daily price impact, we find marginally significant results in some cases (for small k and when returns are controlled for the risk factors) and this relation between the skewness of liquidity measures and the expected return becomes more significant for the longer future returns.

4. Conclusion

According to the literature, it is known that the mean and volatility of the firm-level liquidity affect the expected return on stocks. In this paper, we examine whether the skewness of the firm-level liquidity has any additional information regarding the expected returns of stocks. Because the high skewness of illiquidity of a stock means that the stock is more likely to face an adverse illiquidity shock than a favorable illiquidity shock compared with the others with less skewness of illiquidity, investors will prefer the stock less to the others. Thus, investors will demand a higher return for the stock with a high value of the skewness of illiquidity. We mainly use the Amihud (2002) illiquidity measure to measure the firm-level liquidity of a stock, and turnover and dollar-volume of trades for the robustness check.

Our empirical results show the followings:

(1) The skewness of the daily price impact of a stock is positively associated with the expected return of the stock and its pricing effect remains even after controlling for the effects of the mean and volatility of the daily price impact. These results show that the skewness of illiquidity has additional information that is not contained in the lower moments of illiquidity, and can be interpreted as evidence that investors require compensation for bearing the risk of decreasing liquidity.

(2) The skewness of firm-level illiquidity is more important and significant among liquid firms than illiquid firms. Investors may require compensation for the possible downside liquidity risk for liquid stocks, which do not carry a high liquidity-level premium, while investors may already get enough illiquidity premium for illiquid stocks because they already expect to suffer from a lack of liquidity.

(3) The positive relation between the illiquidity skewness and stock returns appears to be significant up to eight months after controlling for other effects.

(4) The positive relation between the illiquidity skewness and stock returns holds even when the skewness of turnover or dollar-volume is used instead of the skewness of the Amihud measure, and

the effects of the skewness of turnover or dollar-volume on future returns last up to 12 months after controlling for other effects.

In general, our results show that the skewness of the firm-level liquidity is one of the important firm-characteristic which explains the cross-sectional expected returns across stocks.

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Table 1. Returns on illiquidity decile portfolios

This table shows the one-month holding returns on *ILLIQ*, *CVILLIQ*, and *SKILLIQ* decile portfolios in Panel A, B, and C, respectively. We compute *ILLIQ*, *CVILLIQ*, and *SKILLIQ* based on the past *k* months for *k* = 1, 3, 6, and 12. In each column, we report the number of months (*k*) and the percentage returns on each set of decile portfolios. For average returns, we compute the equal-weighted portfolio return (EW) and the value-weighted portfolio return (VW), which is the average of returns weighted by the market capitalization of stocks. Raw indicates the raw return difference between portfolio 10 and portfolio 1, and 4F alpha indicates the return difference between them after being adjusted by the Carhart four-factor model. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses.

Panel A. *ILLIQ* portfolios								
	Number of months (*k*)							
Decile	1		3		6		12	
	EW	VW	EW	VW	EW	VW	EW	VW
1	0.961	0.857	0.937	0.851	0.944	0.855	0.931	0.852
2	1.095	1.045	1.050	1.020	1.043	1.010	1.056	1.023
3	1.146	1.026	1.184	1.116	1.173	1.097	1.148	1.078
4	1.230	1.115	1.162	1.080	1.150	1.105	1.155	1.110
5	1.260	1.142	1.278	1.187	1.231	1.168	1.180	1.173
6	1.316	1.138	1.264	1.154	1.251	1.141	1.232	1.139
7	1.324	1.182	1.296	1.217	1.280	1.244	1.286	1.276
8	1.375	1.230	1.426	1.393	1.390	1.411	1.335	1.374
9	1.267	1.070	1.267	1.146	1.312	1.290	1.380	1.455
10	1.420	0.936	1.529	1.076	1.620	1.185	1.692	1.334
10-1								
Raw	0.458	0.080	0.591	0.224	0.676	0.330	0.761	0.482
	(1.74)	(0.34)	(2.23)	(0.94)	(2.56)	(1.38)	(2.90)	(1.98)
4F alpha	0.248	-0.264	0.351	-0.135	0.390	-0.079	0.401	-0.002
	(1.34)	(-1.79)	(1.89)	(-0.88)	(2.10)	(-0.52)	(2.20)	(-0.02)
Panel B. *CVILLIQ* portfolios								

Decile	Number of months							
	1		3		6		12	
	EW	VW	EW	VW	EW	VW	EW	VW
1	1.018	0.878	1.037	0.873	1.005	0.880	0.921	0.837
2	1.078	0.819	1.105	0.881	1.102	0.875	1.028	0.851
3	1.157	0.986	1.113	0.902	1.114	0.943	1.177	1.047
4	1.151	0.852	1.118	0.939	1.182	0.983	1.153	1.048
5	1.207	0.995	1.289	1.108	1.193	0.981	1.257	1.042
6	1.325	1.025	1.245	1.070	1.299	1.137	1.196	1.129
7	1.290	1.028	1.281	1.093	1.197	1.121	1.349	1.207
8	1.346	1.033	1.330	1.074	1.380	1.095	1.354	1.268
9	1.352	1.061	1.331	1.149	1.334	1.137	1.336	1.208
10	1.470	1.070	1.547	1.062	1.589	1.227	1.625	1.193
10-1								
Raw	0.451	0.192	0.511	0.188	0.584	0.348	0.704	0.356
	(3.03)	(1.45)	(3.08)	(1.32)	(3.25)	(2.24)	(3.42)	(1.89)
4F alpha	0.490	0.108	0.453	0.102	0.472	0.166	0.482	-0.023
	(3.85)	(1.01)	(3.31)	(0.90)	(3.24)	(1.29)	(3.27)	(-0.15)

Panel C. *SKILLIQ* portfolios

Decile	Number of months (k)							
	1		3		6		12	
	EW	VW	EW	VW	EW	VW	EW	VW
1	1.057	0.805	1.108	0.898	1.083	0.840	1.090	0.852
2	1.209	0.905	1.158	0.875	1.171	0.907	1.101	0.859
3	1.222	0.892	1.171	0.933	1.218	0.858	1.105	0.906
4	1.189	0.975	1.149	0.867	1.194	0.971	1.172	0.921
5	1.287	1.032	1.203	0.923	1.219	0.935	1.217	1.040

6	1.225	0.924	1.245	0.960	1.279	1.056	1.247	1.000
7	1.230	1.063	1.282	1.005	1.230	0.901	1.267	1.068
8	1.252	0.905	1.358	0.968	1.304	1.053	1.307	1.017
9	1.308	0.931	1.298	1.097	1.284	1.139	1.375	1.172
10	1.416	1.078	1.423	1.169	1.413	1.187	1.514	1.257
10-1								
Raw	0.359	0.273	0.315	0.271	0.329	0.347	0.425	0.405
	(3.92)	(2.72)	(2.89)	(2.55)	(2.87)	(3.28)	(2.71)	(2.63)
4F alpha	0.335	0.250	0.216	0.118	0.210	0.214	0.280	0.213
	(3.96)	(2.41)	(2.26)	(1.16)	(2.17)	(2.22)	(2.26)	(1.69)

Table 2. Descriptive statistics

This table shows the summary statistics for decile portfolios of stocks sorted by the skewness (*SKILLIQ*) of the daily price impact (Panel A) and the time-series average of cross-sectional correlations (Panel B). This table presents the equal-weighted percentage return on the next month (*RET(t+1)*), the logarithm of the market capitalization (*log(ME)*), the logarithm of the book-to-market ratio (*log(B/M)),* the market beta (*BETA*), the previous month return (*Ret(t-1)*), turnover (*TURNM*), and the market price (*Price*). *ILLIQ*, *CVILLIQ*, and *SKILLIQ* show the mean, coefficient of variation, and skewness of daily illiquidity during the past 12 months, respectively. The sample period is from July 1962 to June 2014.

Panel A. Decile portfolios sorted by *SKILLIQ*

	RET(t+1)	*log(ME)*	*log(B/M)*	*BETA*	*Price*	*Ret(t-1)*	*TURNM*	*ILLIQ*	*CVILLIQ*	*SKILLIQ*
1	1.090	13.472	-0.503	1.062	31.454	0.955	8.633	1.372	1.551	0.182
2	1.101	13.151	-0.493	1.100	30.648	1.062	8.535	1.003	1.324	0.230
3	1.105	12.932	-0.481	1.123	29.471	1.130	8.417	0.961	1.306	0.252
4	1.172	12.743	-0.462	1.132	28.614	1.173	8.223	1.103	1.316	0.268
5	1.217	12.598	-0.459	1.142	28.058	1.164	7.977	1.129	1.321	0.283
6	1.247	12.449	-0.442	1.150	26.875	1.299	7.775	1.216	1.336	0.296
7	1.267	12.277	-0.424	1.157	25.599	1.312	7.627	1.455	1.351	0.310
8	1.307	12.091	-0.397	1.174	24.503	1.466	7.549	1.671	1.378	0.325
9	1.375	11.863	-0.367	1.184	22.738	1.516	7.399	2.241	1.408	0.345
10	1.514	11.407	-0.296	1.204	18.631	1.895	8.212	4.692	1.493	0.387

Panel B. Correlations

	ILLIQ	*CVILLIQ*	*SKILLIQ*	*RET(t+1)*	*log(ME)*	*log(B/M)*	*BETA*	*Price*	*Ret(t-1)*	*TURNM*
ILLIQ	1	0.327	0.110	0.010	-0.354	0.099	0.030	-0.177	0.017	-0.060
CVILLIQ		1	0.023	0.004	-0.544	0.139	0.078	-0.306	0.012	-0.057
SKILLIQ			1	0.006	-0.316	0.073	0.069	-0.122	0.017	-0.006
RET(t+1)				1	-0.002	0.022	-0.011	0.001	-0.035	-0.007
log(ME)					1	-0.261	-0.166	0.562	-0.015	0.044
log(B/M)						1	-0.096	-0.199	0.024	-0.058

BETA	1	-0.134	-0.008	0.221
Price		1	0.063	0.039
Ret(t-1)			1	0.137
TURNM				1

Table 3. Dependently sorted portfolios

This table shows the monthly returns on 25 dependently sorted portfolios. The sample period is from July 1962 to June 2014. Panel A (Panel C) shows the results of portfolios sorted by *ILLIQ* (*CVILLIQ*) first, and then by *SKILLIQ*. Panel B (Panel D) shows the results of portfolios sorted by *SKILLIQ* first, and then by *ILLIQ* (*CVILLIQ*). The variables, *ILLIQ*, *CVILLIQ*, and *SKILLIQ* are constructed from the past 12 month data. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses.

Panel A. *ILLIQ* first, then *SKILLIQ*

		SKILLIQ								
		1	2	3	4	5	5-1 (Raw)		5-1 (4F)	
ILLIQ	1	0.913	0.908	0.950	1.099	1.099	0.187	(2.12)	0.175	(1.97)
	2	0.998	1.165	1.141	1.225	1.229	0.231	(2.02)	0.362	(3.25)
	3	1.164	1.127	1.168	1.291	1.281	0.117	(0.94)	0.243	(2.05)
	4	1.290	1.285	1.302	1.358	1.315	0.025	(0.17)	0.199	(1.38)
	5	1.410	1.517	1.541	1.514	1.700	0.290	(1.68)	0.215	(1.23)
	5-1 (Raw)	0.497	0.609	0.591	0.415	0.601				
		(2.09)	(2.67)	(2.59)	(1.87)	(2.39)				
	5-1 (4F)	0.212	0.369	0.288	0.064	0.252				
		(1.21)	(2.16)	(1.70)	(0.40)	(1.28)				
				ILLIQ-controlled *SKILLIQ* 5-1 portfolio			0.170	(1.90)	0.239	(2.79)

Panel B. *SKILLIQ* first, then *ILLIQ*

		ILLIQ								
		1	2	3	4	5	5-1 (Raw)		5-1 (4F)	
SKILLIQ	1	0.881	0.934	1.050	1.231	1.381	0.500	(2.23)	0.218	(1.42)
	2	0.969	1.147	1.055	1.321	1.198	0.229	(1.11)	-0.019	(-0.13)
	3	1.003	1.185	1.243	1.210	1.519	0.516	(2.41)	0.239	(1.49)
	4	1.176	1.164	1.274	1.311	1.511	0.334	(1.57)	0.013	(0.08)
	5	1.264	1.294	1.376	1.480	1.811	0.547	(2.17)	0.250	(1.12)
	5-1 (Raw)	0.383	0.360	0.326	0.249	0.430				

		(2.94)	(2.36)	(1.98)	(1.35)	(2.27)		
	5-1 (4F)	0.273	0.240	0.196	0.222	0.306		
		(2.63)	(1.97)	(1.46)	(1.35)	(1.63)		
		SKILLIQ-controlled *ILLIQ* 5-1 portfolio					0.425 (2.18)	0.140 (1.05)
Panel C. *CVILLIQ* first, then *SKILLIQ*								
		SKILLIQ						
		1	2	3	4	5	5-1 (Raw)	5-1 (4F)
CVILLIQ	1	0.916	0.956	0.906	0.985	1.110	0.195 (2.20)	0.120 (1.12)
	2	1.125	1.217	1.165	1.124	1.193	0.068 (0.78)	0.226 (2.63)
	3	1.179	1.128	1.209	1.336	1.279	0.100 (0.93)	0.055 (0.57)
	4	1.253	1.248	1.367	1.407	1.482	0.229 (1.79)	0.199 (1.94)
	5	1.386	1.291	1.421	1.585	1.719	0.333 (1.58)	0.205 (1.38)
	5-1 (Raw)	0.470	0.335	0.515	0.600	0.609		
		(2.51)	(1.87)	(2.71)	(2.79)	(2.35)		
	5-1 (4F)	0.159	0.124	0.538	0.172	0.244		
		(1.19)	(1.04)	(3.55)	(1.35)	(1.49)		
		CVILLIQ-controlled *SKILLIQ* 5-1 portfolio					0.185 (2.26)	0.161 (3.17)
Panel D. *SKILLQ* first, then *CVILLIQ*								
		CVILLIQ						
		1	2	3	4	5	5-1 (Raw)	5-1 (4F)
SKILLIQ	1	0.851	0.995	1.084	1.159	1.388	0.537 (2.73)	0.420 (2.74)
	2	0.944	1.076	1.207	1.174	1.290	0.346 (1.95)	0.245 (1.72)
	3	1.079	1.172	1.201	1.169	1.540	0.461 (2.52)	0.300 (2.02)
	4	1.177	1.206	1.294	1.320	1.437	0.260 (1.41)	0.095 (0.60)
	5	1.247	1.330	1.396	1.507	1.746	0.499 (2.37)	0.285 (1.54)
	5-1 (Raw)	0.396	0.335	0.311	0.348	0.358		
		(3.01)	(2.47)	(2.07)	(1.96)	(1.76)		
	5-1 (4F)	0.351	0.180	0.185	0.306	0.216		

	(3.28)	(1.60)	(1.49)	(1.95)	(1.10)				
		SKILLIQ-controlled *CVILLIQ* 5-1 portfolio				0.420	(2.63)	0.269	(2.32)

Table 4. Cross-sectional regressions with Amihud's illiquidity measure

This table presents the results of the cross-sectional regressions. *ILLIQ*, *CVILLIQ*, and *SKILLIQ* indicate the mean, coefficient of variation, and skewness of the daily price impact during the past *k* months (*k* = 1, 3, 6, and 12), respectively. In models 1 to 4, dependent variables are individual firms' raw returns, and in models 5, 6, and 7, the dependent variables are the returns adjusted by Fama and French's (1992) three-factor model, Carhart's (1997) four-factor model, and Fama and French's (2015) five-factor model. log*(ME)*, log*(B/M)*, *BETA*, *REV*, *TURNM*, *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, monthly turnover from the past month, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Fama and French three-factor model for models 1 to 5, the Carhart four-factor model for model 6, and the Fama and French five-factor model for model 7. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

	Panel A. *k* = 1							Panel B. *k* = 3						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.317	3.035	3.169	2.991	1.483	1.344	1.445	3.385	2.959	3.169	2.796	1.223	1.082	1.202
	(6.69)	(5.61)	(6.25)	(5.49)	(4.12)	(3.72)	(4.04)	(6.80)	(5.24)	(6.30)	(4.96)	(3.31)	(2.95)	(3.24)
log*(ME)*	-0.131	-0.120	-0.126	-0.119	-0.088	-0.076	-0.090	-0.133	-0.116	-0.128	-0.112	-0.077	-0.064	-0.079
	(-4.12)	(-3.68)	(-3.92)	(-3.62)	(-3.88)	(-3.36)	(-3.97)	(-4.17)	(-3.40)	(-3.99)	(-3.29)	(-3.30)	(-2.80)	(-3.39)
log*(B/M)*	0.213	0.212	0.214	0.213	0.140	0.203	0.132	0.208	0.203	0.209	0.204	0.130	0.193	0.122
	(3.33)	(3.32)	(3.33)	(3.33)	(3.15)	(4.50)	(2.94)	(3.25)	(3.19)	(3.26)	(3.21)	(2.95)	(4.30)	(2.75)
TURNM	2.042	2.173	2.089	2.166	1.678	1.489	2.048	2.222	2.326	2.197	2.297	1.854	1.674	2.213
	(3.05)	(3.32)	(3.14)	(3.32)	(2.33)	(2.11)	(2.81)	(3.34)	(3.58)	(3.32)	(3.55)	(2.62)	(2.41)	(3.10)
REV	-0.048	-0.047	-0.048	-0.047	-0.050	-0.051	-0.052	-0.048	-0.048	-0.048	-0.049	-0.051	-0.052	-0.054
	(-9.99)	(-9.93)	(-9.99)	(-9.93)	(-10.62)	(-10.86)	(-10.98)	(-10.11)	(-10.19)	(-10.15)	(-10.21)	(-10.95)	(-11.20)	(-11.24)
IVOL	-0.224	-0.222	-0.224	-0.222	-0.300	-0.272	-0.266	-0.250	-0.254	-0.249	-0.253	-0.340	-0.313	-0.302
	(-3.07)	(-3.05)	(-3.07)	(-3.05)	(-5.03)	(-4.51)	(-4.71)	(-3.40)	(-3.44)	(-3.39)	(-3.42)	(-5.61)	(-5.12)	(-5.25)
ILLIQ	0.038	0.037	0.038	0.038	0.043	0.043	0.041	0.046	0.043	0.045	0.042	0.051	0.053	0.048
	(2.95)	(2.99)	(2.94)	(2.98)	(2.87)	(2.96)	(2.74)	(3.76)	(3.66)	(3.69)	(3.61)	(3.78)	(3.92)	(3.55)
CVILLIQ		0.130		0.100	0.240	0.250	0.002		0.170		0.160	0.290	0.300	0.003

		(1.74)		(1.35)	(3.24)	(3.40)	(3.07)		(2.22)		(2.04)	(4.11)	(4.35)	(3.73)
SKILLIQ			0.304	0.216	0.243	0.249	0.211			0.493	0.429	0.533	0.548	0.470
			(2.89)	(2.09)	(2.32)	(2.41)	(2.01)			(2.63)	(2.26)	(2.68)	(2.71)	(2.38)
R^2 (%)	6.40	6.61	6.49	6.69	4.46	4.35	4.29	6.46	6.72	6.58	6.83	4.60	4.50	4.44
	Panel C. k = 6							Panel D. k = 12						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.400	3.016	3.236	2.759	1.238	1.091	1.239	3.514	3.173	3.145	2.520	1.160	0.966	1.192
	(6.85)	(5.50)	(6.25)	(4.77)	(3.12)	(2.79)	(3.12)	(7.11)	(6.16)	(6.41)	(4.69)	(2.88)	(2.39)	(2.92)
log(ME)	-0.133	-0.115	-0.127	-0.107	-0.074	-0.061	-0.076	-0.137	-0.122	-0.129	-0.104	-0.077	-0.063	-0.080
	(-4.15)	(-3.45)	(-3.93)	(-3.12)	(-3.11)	(-2.63)	(-3.22)	(-4.28)	(-3.76)	(-4.10)	(-3.25)	(-3.45)	(-2.84)	(-3.52)
log(B/M)	0.202	0.195	0.201	0.193	0.119	0.181	0.112	0.190	0.185	0.190	0.184	0.110	0.172	0.104
	(3.16)	(3.05)	(3.16)	(3.04)	(2.72)	(4.08)	(2.54)	(2.98)	(2.90)	(3.01)	(2.91)	(2.54)	(3.90)	(2.37)
TURNM	2.394	2.462	2.353	2.434	2.009	1.825	2.354	2.620	2.688	2.594	2.668	2.249	2.067	2.619
	(3.56)	(3.73)	(3.51)	(3.69)	(2.80)	(2.59)	(3.26)	(3.88)	(4.06)	(3.85)	(4.03)	(3.13)	(2.94)	(3.63)
REV	-0.049	-0.049	-0.049	-0.049	-0.052	-0.053	-0.054	-0.049	-0.049	-0.049	-0.049	-0.052	-0.053	-0.054
	(-10.23)	(-10.32)	(-10.25)	(-10.35)	(-11.10)	(-11.35)	(-11.37)	(-10.28)	(-10.35)	(-10.27)	(-10.38)	(-11.11)	(-11.36)	(-11.37)
IVOL	-0.269	-0.277	-0.268	-0.276	-0.372	-0.346	-0.331	-0.310	-0.333	-0.310	-0.336	-0.431	-0.407	-0.388
	(-3.63)	(-3.71)	(-3.61)	(-3.69)	(-6.05)	(-5.61)	(-5.68)	(-4.15)	(-4.42)	(-4.17)	(-4.50)	(-7.01)	(-6.59)	(-6.63)
ILLIQ	0.056	0.053	0.056	0.053	0.059	0.061	0.056	0.069	0.067	0.069	0.068	0.070	0.072	0.066
	(4.32)	(4.24)	(4.30)	(4.22)	(4.37)	(4.53)	(4.12)	(5.47)	(5.45)	(5.55)	(5.53)	(5.99)	(6.26)	(5.67)
CVILLIQ		0.130		0.150	0.260	0.270	0.002		0.140		0.180	0.250	0.270	0.002
		(1.85)		(2.12)	(3.74)	(3.98)	(3.26)		(2.52)		(3.15)	(3.84)	(4.11)	(3.35)
SKILLIQ			0.337	0.416	0.539	0.559	0.429			0.905	1.243	1.152	1.244	0.986
			(1.21)	(1.46)	(1.92)	(2.02)	(1.48)			(1.94)	(2.49)	(2.42)	(2.57)	(2.11)
R^2 (%)	6.43	6.69	6.56	6.81	4.61	4.50	4.45	6.44	6.67	6.61	6.84	4.69	4.58	4.52

Table 5. Cross-sectional regressions in two subperiods

This table presents the results of the cross-sectional regressions in two subpeirods. On the basis of returns (dependent variable), the first subperiod (1st half) spans the period from July 1963 to December 1988 and the second subperiod (2nd half) spans the period from January 1989 to June 2014. *ILLIQ*, *CVILLIQ*, and *SKILLIQ* indicate the mean, coefficient of variation, and skewness of the daily price impact during the past *k* months (*k* = 1, 3, 6, and 12), respectively. The dependent variables are the returns adjusted by Carhart's (1997) four-factor model. log*(ME)*, log*(B/M)*, *BETA*, *REV*, *TURNM*, *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, monthly turnover from the past month, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Carhart four-factor model. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression.

	k = 1		*k* = 3		*k* = 6		*k* = 12	
	1st half	2nd half	1st half	2nd half	1st half	2nd half	1st half	2nd half
Intercept	1.407	1.281	1.261	0.904	1.583	0.600	1.550	0.382
	(2.69)	(2.56)	(2.42)	(1.75)	(2.98)	(1.05)	(2.85)	(0.65)
log(ME)	-0.084	-0.068	-0.078	-0.050	-0.086	-0.036	-0.092	-0.033
	(-2.58)	(-2.17)	(-2.45)	(-1.53)	(-2.71)	(-1.07)	(-2.87)	(-1.10)
log(B/M)	0.286	0.121	0.273	0.112	0.255	0.107	0.241	0.102
	(4.65)	(1.86)	(4.50)	(1.74)	(4.26)	(1.66)	(4.13)	(1.57)
TURNM	-0.076	-0.025	-0.077	-0.027	-0.078	-0.027	-0.079	-0.027
	(-12.13)	(-4.56)	(-12.45)	(-4.82)	(-12.60)	(-4.92)	(-12.79)	(-4.85)
REV	2.946	0.032	3.094	0.254	3.353	0.298	3.667	0.467
	(2.27)	(0.06)	(2.44)	(0.49)	(2.62)	(0.56)	(2.87)	(0.89)
IVOL	-0.328	-0.216	-0.376	-0.251	-0.423	-0.268	-0.491	-0.323
	(-3.42)	(-2.97)	(-3.83)	(-3.44)	(-4.35)	(-3.60)	(-4.98)	(-4.41)
ILLIQ	0.066	0.021	0.075	0.030	0.082	0.041	0.080	0.063
	(2.38)	(2.22)	(3.10)	(2.73)	(3.43)	(3.30)	(4.23)	(4.92)
CVILLIQ	0.003	0.002	0.003	0.003	0.002	0.003	0.002	0.003
	(3.78)	(1.81)	(3.24)	(3.03)	(2.32)	(3.29)	(2.12)	(3.72)

SKILLIQ	0.443	0.055	0.869	0.227	0.418	0.701	1.154	1.334
	(3.23)	(0.36)	(3.24)	(0.76)	(1.03)	(1.86)	(2.01)	(1.71)
R^2 (%)	4.60	4.10	4.76	4.23	4.81	4.19	4.86	4.29

Table 6. Cross-sectional regressions with systematic liquidity risks

This table presents the results of the cross-sectional regressions with systematic liquidity risks estimated by the L-CAPM (Panel A) and LD-CAPM (Panel B). Acharya and Pedersen (2005) construct four betas; The first one is the market beta as CAPM (β_1), the second one captures the covariance between the asset's illiquidity and the market illiquidity (β_2), the third one captures the covariance between a security's return and the market liquidity (β_3), and the last one captures the covariance between a security's illiquidity and the market return (β_4). Anthonisz and Putnins (2016) construct four gammas ($\gamma_1, \gamma_2, \gamma_3$, and γ_4) in a similar way, but computed in the negative subspace where the innovation in market liquidity cost exceeds the market excess return. *ILLIQ*, *CVILLIQ*, and *SKILLIQ* indicate the mean, coefficient of variation, and skewness of the daily price impact during the past *k* months (*k* = 1, 3, 6, and 12), respectively. To compute *IVOL*, we use the past 12 month data and employ the Carhart four-factor model. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

Panel A. L-CAPM				
	k=1	*k*=3	*k*=6	*k*=12
Intercept	1.329	1.066	1.054	0.925
	(3.66)	(2.89)	(2.68)	(2.29)
log*(ME)*	-0.075	-0.063	-0.059	-0.061
	(-3.34)	(-2.77)	(-2.55)	(-2.77)
log*(B/M)*	0.204	0.193	0.181	0.172
	(4.52)	(4.32)	(4.08)	(3.91)
TURNM	1.460	1.647	1.821	2.052
	(2.05)	(2.35)	(2.57)	(2.91)
REV	-0.0503	-0.052	-0.0523	-0.0525
	(-10.83)	(-11.15)	(-11.28)	(-11.32)
IVOL	-0.272	-0.312	-0.346	-0.407
	(-4.52)	(-5.12)	(-5.66)	(-6.62)
ILLIQ	0.038	0.047	0.056	0.067
	(2.86)	(3.85)	(4.54)	(6.37)
CVILLIQ	0.003	0.003	0.003	0.003
	(3.71)	(4.64)	(4.29)	(4.29)
SKILLIQ	0.238	0.530	0.553	1.254
	(2.30)	(2.62)	(2.00)	(2.56)
β_1	0.002	0.001	0.001	0.001
	(0.55)	(0.32)	(0.28)	(0.37)
β_2	-0.004	-0.004	-0.004	-0.004
	(-1.52)	(-1.50)	(-1.41)	(-1.32)

β_3	-0.003	-0.002	-0.002	-0.003
	(-0.89)	(-0.62)	(-0.54)	(-0.66)
β_4	0.004	0.004	0.004	0.004
	(1.55)	(1.56)	(1.46)	(1.34)
R^2 (%)	5.04	5.16	5.18	5.26

Panel B. LD-CAPM

	k=1	*k*=3	*k*=6	*k*=12
Intercept	1.614	1.261	1.075	0.632
	(4.45)	(3.33)	(2.85)	(1.48)
log*(ME)*	-0.076	-0.054	-0.035	-0.020
	(-3.68)	(-2.53)	(-1.68)	(-0.95)
log*(B/M)*	0.162	0.157	0.148	0.140
	(3.93)	(3.83)	(3.63)	(3.51)
TURNM	1.183	1.533	1.821	1.994
	(1.88)	(2.45)	(2.83)	(3.12)
REV	-0.036	-0.037	-0.037	-0.038
	(-8.82)	(-8.92)	(-9.04)	(-9.26)
IVOL	-0.377	-0.405	-0.432	-0.477
	(-6.46)	(-6.98)	(-7.44)	(-8.21)
ILLIQ	-0.261	0.021	0.319	0.271
	(-1.10)	(0.08)	(1.19)	(1.51)
CVILLIQ	0.001	0.001	0.001	0.002
	(1.94)	(1.38)	(1.29)	(1.92)
SKILLIQ	0.224	0.497	0.252	0.985
	(2.29)	(2.80)	(0.95)	(2.46)
γ_1	0.0003	0.0004	0.0005	0.00035
	(0.42)	(0.61)	(0.73)	(0.55)
γ_2	-0.0002	-0.0008	-0.0014	-0.0007
	(-0.17)	(-0.49)	(-0.86)	(-0.53)
γ_3	-0.045	-0.043	-0.044	-0.048
	(-0.75)	(-0.73)	(-0.75)	(-0.82)
γ_4	0.390	0.363	0.387	0.254
	(2.75)	(2.43)	(2.66)	(1.99)
R^2 (%)	4.72	4.81	4.88	5.06

Table 7. Cross-sectional regressions for longer holding returns

This table presents the results of the cross-sectional regressions. We examine the effects of the moments of illiquidity measured at month *t* on the cumulative returns from month *t*+1 to month *t*+*m* (*m* = 2, 3, 4, … , 12). Panel A is for the raw returns and Panel B is for the risk-adjusted returns. log*(ME)*, log*(B/M)*, *BETA*, *REV*, *TURNM*, *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, monthly turnover from the past month, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Carhart four-factor model. The variables, *ILLIQ*, *CVILLIQ*, and *SKILLIQ* are constructed from the past 12 month data. Newey–West (1987) adjusted *t*-statistics (with the number of months 2*m*+1) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

Panel A. Raw returns											
	m = 2	*m* = 3	*m* = 4	*m* = 5	*m* = 6	*m* = 7	*m* = 8	*m* = 9	*m* = 10	*m* = 11	*m* = 12
Intercept	4.728	7.115	9.546	11.793	14.161	16.783	19.461	22.343	25.737	29.429	33.383
	(4.50)	(4.44)	(4.37)	(4.18)	(4.00)	(3.90)	(3.84)	(3.78)	(3.81)	(3.88)	(3.94)
log*(ME)*	-0.189	-0.283	-0.382	-0.470	-0.561	-0.665	-0.767	-0.885	-1.030	-1.190	-1.371
	(-3.01)	(-2.92)	(-2.82)	(-2.62)	(-2.46)	(-2.37)	(-2.28)	(-2.24)	(-2.26)	(-2.30)	(-2.35)
log*(B/M)*	0.421	0.673	0.941	1.237	1.540	1.832	2.084	2.324	2.536	2.722	2.888
	(3.45)	(3.76)	(4.00)	(4.22)	(4.42)	(4.57)	(4.64)	(4.64)	(4.59)	(4.47)	(4.33)
TURNM	1.429	-0.453	-3.126	-5.587	-7.572	-9.065	-11.087	-13.644	-16.308	-18.498	-21.137
	(1.34)	(-0.32)	(-1.71)	(-2.47)	(-2.76)	(-2.83)	(-2.90)	(-3.08)	(-3.13)	(-3.18)	(-3.29)
REV	-0.044	-0.028	-0.020	-0.013	-0.002	0.005	0.012	0.029	0.035	0.048	0.059
	(-6.82)	(-3.50)	(-2.19)	(-1.10)	(-0.15)	(0.29)	(0.63)	(1.41)	(1.55)	(2.01)	(2.35)
IVOL	-0.508	-0.643	-0.711	-0.778	-0.852	-0.911	-0.992	-1.047	-1.168	-1.271	-1.327
	(-3.45)	(-2.88)	(-2.34)	(-1.98)	(-1.77)	(-1.61)	(-1.53)	(-1.42)	(-1.43)	(-1.40)	(-1.31)
ILLIQ	0.123	0.194	0.266	0.355	0.457	0.563	0.683	0.797	0.964	1.152	1.328
	(5.28)	(5.37)	(5.38)	(5.46)	(5.46)	(5.49)	(5.43)	(5.50)	(5.46)	(5.67)	(5.52)
CVILLIQ	0.290	0.340	0.330	0.370	0.410	0.460	0.570	0.610	0.600	0.590	0.620
	(2.59)	(2.13)	(1.63)	(1.51)	(1.42)	(1.37)	(1.47)	(1.40)	(1.27)	(1.12)	(1.05)
SKILLIQ	2.346	3.213	4.069	4.777	5.239	5.377	5.148	5.232	5.125	4.816	4.249

	(2.44)	(2.32)	(2.32)	(2.31)	(2.23)	(2.11)	(1.88)	(1.78)	(1.59)	(1.31)	(1.02)
R^2 (%)	7.74	8.16	8.33	8.48	8.55	8.67	8.80	8.83	8.85	8.90	8.91
Panel B. 4F alpha											
	m = 2	*m* = 3	*m* = 4	*m* = 5	*m* = 6	*m* = 7	*m* = 8	*m* = 9	*m* = 10	*m* = 11	*m* = 12
Intercept	1.458	2.006	2.344	2.591	2.930	3.526	4.227	4.883	5.708	6.968	8.446
	(1.87)	(1.70)	(1.49)	(1.34)	(1.27)	(1.34)	(1.44)	(1.51)	(1.61)	(1.82)	(2.06)
log*(ME)*	-0.098	-0.129	-0.149	-0.163	-0.176	-0.201	-0.224	-0.250	-0.284	-0.339	-0.409
	(-2.33)	(-2.04)	(-1.73)	(-1.51)	(-1.34)	(-1.30)	(-1.27)	(-1.26)	(-1.30)	(-1.42)	(-1.59)
log*(B/M)*	0.355	0.557	0.777	1.007	1.233	1.457	1.630	1.801	1.957	2.088	2.201
	(4.39)	(4.94)	(5.50)	(5.91)	(6.20)	(6.40)	(6.43)	(6.52)	(6.65)	(6.67)	(6.63)
TURNM	-0.170	-3.013	-6.747	-9.812	-12.414	-14.914	-17.749	-20.334	-23.546	-26.373	-29.229
	(-0.14)	(-1.91)	(-3.37)	(-3.94)	(-4.17)	(-4.47)	(-4.71)	(-4.80)	(-5.02)	(-5.14)	(-5.21)
REV	-0.047	-0.033	-0.027	-0.022	-0.013	-0.005	0.001	0.010	0.017	0.029	0.038
	(-7.60)	(-4.53)	(-3.31)	(-2.20)	(-1.05)	(-0.34)	(0.05)	(0.58)	(0.92)	(1.56)	(1.90)
IVOL	-0.626	-0.803	-0.914	-1.034	-1.170	-1.275	-1.389	-1.475	-1.565	-1.652	-1.723
	(-4.99)	(-4.16)	(-3.43)	(-3.00)	(-2.73)	(-2.47)	(-2.29)	(-2.14)	(-2.01)	(-1.89)	(-1.79)
ILLIQ	0.137	0.218	0.300	0.406	0.521	0.631	0.746	0.867	0.995	1.152	1.304
	(6.08)	(6.39)	(6.77)	(7.31)	(7.35)	(7.23)	(7.02)	(6.97)	(6.89)	(6.80)	(6.64)
CVILLIQ	0.470	0.590	0.660	0.720	0.820	0.900	0.980	1.030	1.070	1.050	1.080
	(3.50)	(2.89)	(2.41)	(2.14)	(2.08)	(1.98)	(1.88)	(1.79)	(1.70)	(1.52)	(1.43)
SKILLIQ	2.303	3.020	3.839	4.675	4.927	4.906	4.589	4.369	4.068	3.464	2.462
	(2.59)	(2.36)	(2.38)	(2.44)	(2.27)	(2.01)	(1.68)	(1.44)	(1.21)	(0.94)	(0.60)
R^2 (%)	5.03	5.29	5.47	5.66	5.82	6.00	6.19	6.33	6.49	6.65	6.75

Table 8. Cross-sectional regressions with *TURNOVER* measures

This table presents the results of the cross-sectional regressions. *TURN*, *CVTURN*, and *SKTURN* indicate the mean, coefficient of variation, and skewness of the daily turnover during the past *k* months (*k* = 1, 3, 6, and 12), respectively. In models 1 to 4, dependent variables are individual firms' raw returns, and in models 5, 6, and 7 , the dependent variables are the returns adjusted by Fama and French's (1992) three-factor model, Carhart's (1997) four-factor model, and Fama and French's (2015) five-factor model. log*(ME)*, log*(B/M)*, *BETA*, *REV*, and *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Fama and French three-factor model for models 1 to 5, the Carhart four-factor model for model 6, and the Fama and French five-factor model for model 7. The coefficients of *CVTURN* are multiplied by 10^2. Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

	Panel A. *k* = 1							Panel B. *k* = 3						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.291	3.286	3.360	3.316	1.843	1.730	1.796	3.174	3.152	3.224	3.188	1.588	1.498	1.544
	(6.65)	(5.93)	(6.63)	(5.96)	(5.04)	(4.78)	(4.84)	(6.37)	(5.73)	(6.21)	(5.55)	(4.21)	(3.96)	(4.03)
log*(ME)*	-0.134	-0.134	-0.136	-0.134	-0.103	-0.092	-0.104	-0.123	-0.122	-0.123	-0.122	-0.085	-0.075	-0.086
	(-4.22)	(-3.95)	(-4.25)	(-3.96)	(-4.34)	(-3.93)	(-4.32)	(-3.85)	(-3.59)	(-3.82)	(-3.55)	(-3.53)	(-3.13)	(-3.53)
log*(B/M)*	0.220	0.219	0.220	0.220	0.149	0.213	0.141	0.216	0.217	0.216	0.217	0.146	0.209	0.138
	(3.41)	(3.41)	(3.42)	(3.42)	(3.33)	(4.70)	(3.12)	(3.37)	(3.40)	(3.37)	(3.40)	(3.26)	(4.62)	(3.06)
REV	-0.048	-0.048	-0.048	-0.048	-0.051	-0.051	-0.053	-0.048	-0.047	-0.047	-0.047	-0.050	-0.051	-0.053
	(-10.18)	(-10.09)	(-10.14)	(-10.06)	(-10.78)	(-11.02)	(-11.12)	(-10.17)	(-10.15)	(-10.15)	(-10.14)	(-10.89)	(-11.17)	(-11.17)
IVOL	-0.181	-0.178	-0.180	-0.177	-0.236	-0.207	-0.207	-0.152	-0.147	-0.151	-0.146	-0.204	-0.175	-0.175
	(-2.55)	(-2.51)	(-2.54)	(-2.50)	(-3.95)	(-3.42)	(-3.61)	(-2.16)	(-2.08)	(-2.15)	(-2.08)	(-3.38)	(-2.86)	(-3.03)
TURN	0.337	0.341	0.340	0.344	0.183	0.135	0.276	-0.100	-0.108	-0.106	-0.114	-0.306	-0.370	-0.215
	(2.36)	(2.36)	(2.39)	(2.38)	(1.12)	(0.84)	(1.68)	(-0.59)	(-0.64)	(-0.63)	(-0.68)	(-1.71)	(-2.10)	(-1.22)
CVTURN		-0.029		-0.004	0.110	0.110	0.087		-0.014		-0.012	0.090	0.088	0.080
		(-0.39)		(-0.06)	(1.74)	(1.80)	(1.40)		(-0.24)		(-0.21)	(1.89)	(1.86)	(1.68)
SKTURN			-0.197	-0.201	-0.168	-0.179	-0.159			-0.166	-0.129	0.069	0.053	0.035

			(-1.78)	(-1.95)	(-1.60)	(-1.70)	(-1.49)			(-0.85)	(-0.67)	(0.34)	(0.27)	(0.17)
R^2 (%)	5.86	6.06	5.94	6.13	3.93	3.83	3.78	5.94	6.15	6.02	6.23	3.97	3.87	3.81

	Panel C. k = 6							Panel D. k = 12						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.139	3.062	3.259	3.178	1.533	1.444	1.479	3.093	3.097	3.095	3.100	1.445	1.368	1.402
	(6.24)	(5.57)	(6.35)	(5.47)	(4.06)	(3.86)	(3.86)	(6.14)	(5.61)	(6.20)	(5.26)	(3.76)	(3.67)	(3.59)
log(ME)	-0.119	-0.115	-0.123	-0.119	-0.079	-0.069	-0.081	-0.114	-0.114	-0.115	-0.115	-0.074	-0.064	-0.076
	(-3.69)	(-3.38)	(-3.79)	(-3.45)	(-3.32)	(-2.92)	(-3.35)	(-3.53)	(-3.32)	(-3.59)	(-3.31)	(-3.05)	(-2.73)	(-3.13)
log(B/M)	0.211	0.213	0.211	0.212	0.141	0.203	0.133	0.206	0.205	0.205	0.203	0.132	0.194	0.125
	(3.32)	(3.36)	(3.32)	(3.35)	(3.17)	(4.53)	(2.98)	(3.26)	(3.25)	(3.25)	(3.24)	(3.01)	(4.35)	(2.82)
REV	-0.048	-0.047	-0.048	-0.048	-0.051	-0.051	-0.053	-0.048	-0.048	-0.048	-0.048	-0.051	-0.052	-0.053
	(-10.21)	(-10.22)	(-10.21)	(-10.23)	(-10.96)	(-11.23)	(-11.24)	(-10.29)	(-10.29)	(-10.30)	(-10.33)	(-11.06)	(-11.34)	(-11.32)
IVOL	-0.142	-0.139	-0.141	-0.138	-0.197	-0.167	-0.170	-0.136	-0.132	-0.137	-0.133	-0.193	-0.162	-0.166
	(-2.05)	(-2.00)	(-2.05)	(-1.99)	(-3.28)	(-2.73)	(-2.94)	(-1.99)	(-1.89)	(-2.01)	(-1.90)	(-3.16)	(-2.61)	(-2.82)
TURN	-0.323	-0.328	-0.328	-0.335	-0.521	-0.618	-0.439	-0.448	-0.457	-0.458	-0.466	-0.679	-0.795	-0.591
	(-1.74)	(-1.78)	(-1.77)	(-1.82)	(-2.76)	(-3.30)	(-2.35)	(-2.17)	(-2.23)	(-2.25)	(-2.31)	(-3.49)	(-4.08)	(-3.01)
CVTURN		0.022		0.020	0.120	0.110	0.110		-0.021		-0.018	0.086	0.078	0.084
		(0.46)		(0.40)	(2.73)	(2.62)	(2.61)		(-0.40)		(-0.32)	(1.64)	(1.53)	(1.63)
SKTURN			-0.287	-0.262	-0.015	-0.021	-0.013			0.038	0.031	0.206	0.205	0.200
			(-1.12)	(-0.96)	(-0.06)	(-0.08)	(-0.04)			(0.11)	(0.08)	(0.52)	(0.51)	(0.49)
R^2 (%)	5.98	6.18	6.08	6.29	4.01	3.90	3.85	6.01	6.21	6.12	6.34	4.05	3.95	3.90

Table 9. Cross-sectional regressions with the *DVOL* measure

This table presents the results of the cross-sectional regressions. *DVOL*, *CVDVOL*, and *SKDVOL* indicate the mean, coefficient of variation, and skewness of the daily turnover during the past *k* months (*k* = 1, 3, 6, and 12), respectively. In models 1 to 4, dependent variables are individual firms' raw returns, and in models 5, 6, and 7 , the dependent variables are the returns adjusted by Fama and French's (1992) three-factor model, Carhart's (1997) four-factor model, and Fama and French's (2015) five-factor model. log*(ME)*, log*(B/M)*, *BETA*, *REV*, and *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Fama and French three-factor model for models 1 to 5, the Carhart four-factor model for model 6, and the Fama and French five-factor model for model 7. The coefficients of *DVOL* (*CVDVOL*) are multiplied by 10^6 (10^2). Newey–West (1987) adjusted *t*-statistics (with the number of lags 3) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

	Panel A. *k* = 1							Panel B. *k* = 3						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.425	3.474	3.481	3.495	2.511	2.332	2.346	3.325	3.411	3.487	3.555	2.466	2.305	2.289
	(6.72)	(6.19)	(6.69)	(6.21)	(5.79)	(5.37)	(5.42)	(6.51)	(6.12)	(6.72)	(6.27)	(5.70)	(5.23)	(5.28)
log*(ME)*	-0.143	-0.146	-0.144	-0.145	-0.152	-0.135	-0.143	-0.134	-0.139	-0.138	-0.143	-0.145	-0.129	-0.135
	(-4.19)	(-4.08)	(-4.20)	(-4.07)	(-5.09)	(-4.53)	(-4.83)	(-3.93)	(-3.89)	(-4.03)	(-3.97)	(-4.84)	(-4.26)	(-4.54)
log*(B/M)*	0.212	0.211	0.213	0.212	0.141	0.205	0.133	0.212	0.212	0.211	0.211	0.141	0.205	0.133
	(3.28)	(3.27)	(3.29)	(3.28)	(3.18)	(4.57)	(2.96)	(3.27)	(3.29)	(3.27)	(3.28)	(3.19)	(4.57)	(2.98)
REV	-0.049	-0.048	-0.048	-0.048	-0.051	-0.052	-0.054	-0.048	-0.048	-0.048	-0.048	-0.052	-0.052	-0.054
	(-10.23)	(-10.18)	(-10.20)	(-10.16)	(-11.03)	(-11.32)	(-11.27)	(-10.19)	(-10.22)	(-10.15)	(-10.19)	(-11.05)	(-11.35)	(-11.30)
IVOL	-0.185	-0.182	-0.184	-0.180	-0.266	-0.237	-0.228	-0.181	-0.177	-0.179	-0.176	-0.264	-0.235	-0.225
	(-2.68)	(-2.63)	(-2.65)	(-2.61)	(-4.72)	(-4.17)	(-4.26)	(-2.62)	(-2.56)	(-2.60)	(-2.54)	(-4.69)	(-4.14)	(-4.21)
DVOL	0.058	0.056	0.057	0.056	0.074	0.069	0.061	0.037	0.037	0.036	0.036	0.056	0.049	0.040
	(2.32)	(2.31)	(2.31)	(2.32)	(3.19)	(2.95)	(2.81)	(1.40)	(1.41)	(1.35)	(1.36)	(2.28)	(1.97)	(1.84)
CVDVOL		-0.051		-0.031	0.053	0.058	0.038		-0.049		-0.046	0.044	0.043	0.035
		(-0.69)		(-0.41)	(0.85)	(0.94)	(0.60)		(-0.83)		(-0.77)	(0.87)	(0.84)	(0.69)
SKDVOL			-0.189	-0.174	-0.163	-0.176	-0.160			-0.437	-0.404	-0.249	-0.280	-0.268

			(-1.73)	(-1.64)	(-1.50)	(-1.62)	(-1.45)			(-2.34)	(-2.15)	(-1.29)	(-1.48)	(-1.36)
R^2 (%)	5.50	5.67	5.57	5.74	3.67	3.59	3.52	5.50	5.70	5.59	5.79	3.71	3.62	3.55

	Panel C. k = 6							Panel D. k = 12						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Intercept	3.271	3.227	3.275	3.230	2.110	1.973	1.911	3.238	3.191	3.115	2.997	1.958	1.833	1.753
	(6.40)	(5.79)	(6.41)	(5.67)	(4.84)	(4.51)	(4.34)	(6.33)	(5.59)	(6.33)	(5.12)	(4.19)	(4.00)	(3.72)
log(ME)	-0.130	-0.128	-0.131	-0.130	-0.130	-0.115	-0.119	-0.127	-0.126	-0.125	-0.122	-0.123	-0.109	-0.112
	(-3.80)	(-3.59)	(-3.85)	(-3.65)	(-4.41)	(-3.88)	(-4.06)	(-3.72)	(-3.44)	(-3.70)	(-3.33)	(-4.02)	(-3.58)	(-3.67)
log(B/M)	0.212	0.213	0.211	0.210	0.142	0.205	0.134	0.213	0.211	0.211	0.207	0.139	0.203	0.131
	(3.27)	(3.30)	(3.26)	(3.27)	(3.20)	(4.59)	(2.99)	(3.29)	(3.27)	(3.27)	(3.23)	(3.15)	(4.56)	(2.93)
REV	-0.048	-0.048	-0.048	-0.049	-0.052	-0.053	-0.054	-0.048	-0.048	-0.048	-0.049	-0.052	-0.053	-0.054
	(-10.17)	(-10.27)	(-10.20)	(-10.32)	(-11.18)	(-11.47)	(-11.45)	(-10.15)	(-10.29)	(-10.17)	(-10.35)	(-11.21)	(-11.49)	(-11.46)
IVOL	-0.177	-0.177	-0.179	-0.178	-0.268	-0.239	-0.231	-0.175	-0.174	-0.178	-0.178	-0.269	-0.239	-0.231
	(-2.59)	(-2.54)	(-2.62)	(-2.57)	(-4.75)	(-4.19)	(-4.30)	(-2.56)	(-2.47)	(-2.62)	(-2.55)	(-4.64)	(-4.08)	(-4.20)
DVOL	0.024	0.025	0.023	0.023	0.045	0.036	0.028	0.016	0.016	0.013	0.014	0.036	0.028	0.020
	(0.87)	(0.90)	(0.82)	(0.86)	(1.74)	(1.39)	(1.23)	(0.58)	(0.59)	(0.49)	(0.55)	(1.41)	(1.05)	(0.84)
CVDVOL		0.016		0.019	0.110	0.100	0.110		0.008		0.026	0.120	0.100	0.110
		(0.31)		(0.35)	(2.32)	(2.19)	(2.20)		(0.15)		(0.43)	(2.04)	(1.92)	(2.03)
SKDVOL			0.022	0.034	0.183	0.139	0.208			0.376	0.481	0.353	0.321	0.380
			(0.07)	(0.11)	(0.59)	(0.47)	(0.66)			(0.93)	(1.04)	(0.81)	(0.74)	(0.84)
R^2 (%)	5.50	5.72	5.62	5.85	3.75	3.66	3.60	5.50	5.72	5.67	5.91	3.82	3.73	3.67

Table 10. Cross-sectional regressions for longer holding returns with the *TURNOVER* and *DVOL* measures

This table presents the results of the cross-sectional regressions. We examine the effects of the moments of turnover and dollar-volume measured at month *t* on the cumulative returns from month *t*+1 to month *t*+*m* (*m* = 2, 3, 4, … , 12). Panel A and B examine the effects of turnover variables and Panel C and D examine the effects of dollar-volume variables. Panel A and C are for the raw returns and Panel B and D are for the risk-adjusted returns. The coefficients of *DVOL* are multiplied by 10^6. log*(ME)*, log*(B/M)*, *BETA*, *REV*, *TURNM*, *IVOL* indicate the logarithm of the market capitalization, the logarithm of the book-to-market ratio, the market beta, the previous month return, monthly turnover from the past month, and idiosyncratic volatility, respectively. To compute *IVOL*, we use the past 12 month data and employ the Carhart four-factor model. Newey–West (1987) adjusted *t*-statistics (with the number of months 2*m*+1) are reported in parentheses. R^2 indicates the time-series average of the adjusted *R*-squared value of the regression. The sample period is from July 1962 to June 2014.

Panel A. Raw returns											
	m = 2	*m* = 3	*m* = 4	*m* = 5	*m* = 6	*m* = 7	*m* = 8	*m* = 9	*m* = 10	*m* = 11	*m* = 12
Intercept	6.061	8.812	11.489	13.887	16.251	18.825	21.604	24.269	27.557	30.904	34.734
	(5.60)	(5.56)	(5.28)	(4.91)	(4.56)	(4.33)	(4.16)	(4.01)	(3.99)	(3.98)	(4.03)
log*(ME)*	-0.237	-0.345	-0.452	-0.544	-0.638	-0.746	-0.865	-0.981	-1.131	-1.288	-1.478
	(-3.54)	(-3.43)	(-3.22)	(-2.95)	(-2.74)	(-2.61)	(-2.52)	(-2.44)	(-2.45)	(-2.46)	(-2.52)
log*(B/M)*	0.484	0.763	1.059	1.378	1.710	2.034	2.312	2.583	2.835	3.057	3.242
	(3.92)	(4.22)	(4.48)	(4.69)	(4.90)	(5.08)	(5.15)	(5.15)	(5.11)	(5.00)	(4.84)
REV	-0.041	-0.025	-0.016	-0.007	0.006	0.014	0.022	0.039	0.048	0.061	0.074
	(-6.37)	(-3.00)	(-1.63)	(-0.55)	(0.38)	(0.81)	(1.12)	(1.84)	(1.96)	(2.41)	(2.76)
IVOL	-0.233	-0.263	-0.229	-0.187	-0.134	-0.078	-0.054	-0.001	0.016	0.057	0.102
	(-1.63)	(-1.19)	(-0.75)	(-0.48)	(-0.28)	(-0.14)	(-0.08)	(0.00)	(0.02)	(0.06)	(0.10)
TURN	-0.089	-0.596	-1.311	-1.978	-2.569	-3.056	-3.664	-4.386	-5.167	-5.846	-6.572
	(-0.38)	(-1.96)	(-3.20)	(-3.84)	(-4.08)	(-4.15)	(-4.17)	(-4.21)	(-4.20)	(-4.22)	(-4.29)
CVTURN	-0.045	-0.014	-0.014	0.060	0.160	0.260	0.340	0.460	0.510	0.590	0.580
	(-0.37)	(-0.10)	(-0.08)	(0.28)	(0.59)	(0.83)	(1.01)	(1.23)	(1.22)	(1.29)	(1.17)
SKTURN	-0.152	-0.213	-0.348	-0.514	-0.508	-0.609	-0.629	-0.531	-0.799	-0.880	-0.817
	(-1.12)	(-1.16)	(-1.58)	(-1.79)	(-1.49)	(-1.56)	(-1.56)	(-1.12)	(-1.78)	(-1.73)	(-1.48)

R^2 (%)	7.29	7.69	7.81	7.97	7.99	8.05	8.12	8.15	8.13	8.14	8.14

Panel B. 4F alpha

	m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9	m = 10	m = 11	m = 12
Intercept	2.700	3.485	3.907	4.159	4.292	4.638	5.053	5.454	6.059	6.769	7.732
	(3.75)	(3.32)	(2.79)	(2.32)	(1.96)	(1.80)	(1.68)	(1.62)	(1.62)	(1.65)	(1.75)
log*(ME)*	-0.145	-0.187	-0.210	-0.223	-0.233	-0.253	-0.275	-0.299	-0.333	-0.376	-0.438
	(-3.17)	(-2.81)	(-2.34)	(-1.95)	(-1.68)	(-1.55)	(-1.45)	(-1.40)	(-1.41)	(-1.45)	(-1.56)
log*(B/M)*	0.432	0.666	0.917	1.178	1.435	1.694	1.899	2.099	2.281	2.444	2.578
	(5.17)	(5.71)	(6.32)	(6.74)	(7.07)	(7.31)	(7.38)	(7.46)	(7.59)	(7.67)	(7.66)
REV	-0.044	-0.029	-0.022	-0.014	-0.003	0.007	0.013	0.023	0.032	0.044	0.055
	(-7.06)	(-3.77)	(-2.43)	(-1.29)	(-0.23)	(0.48)	(0.82)	(1.26)	(1.63)	(2.17)	(2.48)
IVOL	-0.258	-0.272	-0.241	-0.208	-0.178	-0.140	-0.134	-0.106	-0.074	-0.034	-0.005
	(-2.13)	(-1.48)	(-0.97)	(-0.65)	(-0.45)	(-0.30)	(-0.25)	(-0.17)	(-0.11)	(-0.04)	(-0.01)
TURN	-0.573	-1.384	-2.394	-3.247	-4.052	-4.768	-5.562	-6.302	-7.180	-7.959	-8.723
	(-1.97)	(-3.50)	(-4.57)	(-4.88)	(-5.05)	(-5.28)	(-5.53)	(-5.64)	(-5.89)	(-6.05)	(-6.16)
CVTURN	0.210	0.330	0.510	0.710	0.930	1.100	1.310	1.460	1.550	1.690	1.780
	(2.03)	(2.34)	(2.63)	(2.85)	(3.28)	(3.23)	(3.38)	(3.20)	(3.07)	(3.13)	(3.05)
SKTURN	-0.175	-0.301	-0.378	-0.556	-0.532	-0.635	-0.730	-0.739	-0.932	-1.128	-1.154
	(-1.29)	(-1.61)	(-1.79)	(-2.21)	(-1.83)	(-1.89)	(-2.16)	(-1.89)	(-2.20)	(-2.50)	(-2.38)
R^2 (%)	4.40	4.58	4.70	4.87	4.98	5.11	5.25	5.36	5.47	5.57	5.67

Panel C. Raw returns

	m = 2	m = 3	m = 4	m = 5	m = 6	m = 7	m = 8	m = 9	m = 10	m = 11	m = 12
Intercept	6.562	9.622	12.715	15.430	18.078	20.940	24.139	27.289	31.151	35.154	39.670
	(5.99)	(5.95)	(5.77)	(5.42)	(5.04)	(4.79)	(4.62)	(4.47)	(4.47)	(4.46)	(4.55)
log*(ME)*	-0.270	-0.400	-0.538	-0.653	-0.771	-0.901	-1.051	-1.204	-1.398	-1.606	-1.845
	(-3.86)	(-3.79)	(-3.70)	(-3.45)	(-3.22)	(-3.07)	(-3.00)	(-2.93)	(-2.97)	(-2.99)	(-3.08)

log*(B/M)*	0.475	0.754	1.051	1.372	1.706	2.029	2.313	2.588	2.844	3.072	3.262
	(3.84)	(4.17)	(4.43)	(4.64)	(4.85)	(5.02)	(5.09)	(5.11)	(5.07)	(4.98)	(4.83)
REV	-0.045	-0.031	-0.025	-0.020	-0.011	-0.004	0.001	0.017	0.022	0.034	0.043
	(-6.91)	(-3.81)	(-2.69)	(-1.70)	(-0.74)	(-0.22)	(0.05)	(0.80)	(0.95)	(1.38)	(1.68)
IVOL	-0.281	-0.361	-0.388	-0.400	-0.402	-0.401	-0.438	-0.456	-0.515	-0.548	-0.583
	(-2.03)	(-1.69)	(-1.32)	(-1.05)	(-0.87)	(-0.73)	(-0.69)	(-0.64)	(-0.66)	(-0.64)	(-0.61)
DVOL	0.083	0.101	0.123	0.143	0.168	0.188	0.208	0.241	0.274	0.300	0.311
	(1.69)	(1.28)	(1.13)	(1.02)	(0.95)	(0.89)	(0.85)	(0.85)	(0.85)	(0.84)	(0.80)
CVDVOL	-0.100	-0.100	-0.200	-0.200	-0.080	0.009	0.052	0.160	0.180	0.230	0.170
	(-1.04)	(-0.82)	(-0.94)	(-0.68)	(-0.30)	(0.03)	(0.16)	(0.43)	(0.45)	(0.55)	(0.38)
SKDVOL	-0.162	-0.303	-0.434	-0.646	-0.645	-0.730	-0.759	-0.705	-0.988	-1.094	-1.082
	(-1.13)	(-1.48)	(-1.65)	(-2.16)	(-1.75)	(-1.73)	(-1.84)	(-1.50)	(-2.14)	(-2.09)	(-1.97)
R^2 (%)	6.87	7.3%	7.43	7.59	7.62	7.6%	7.76	7.77	7.74	7.73	7.73
Panel D. 4F alpha											
	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$	$m = 7$	$m = 8$	$m = 9$	$m = 10$	$m = 11$	$m = 12$
Intercept	4.074	5.552	6.700	7.605	8.250	9.120	10.250	11.297	12.586	14.062	15.779
	(4.78)	(4.50)	(4.13)	(3.75)	(3.33)	(3.17)	(3.08)	(3.03)	(3.04)	(3.07)	(3.19)
log*(ME)*	-0.244	-0.339	-0.415	-0.477	-0.528	-0.588	-0.665	-0.737	-0.824	-0.924	-1.040
	(-4.24)	(-4.05)	(-3.79)	(-3.52)	(-3.22)	(-3.09)	(-3.03)	(-3.00)	(-3.02)	(-3.08)	(-3.21)
log*(B/M)*	0.425	0.662	0.915	1.179	1.440	1.703	1.914	2.118	2.303	2.469	2.604
	(5.12)	(5.72)	(6.36)	(6.81)	(7.13)	(7.38)	(7.46)	(7.52)	(7.64)	(7.71)	(7.69)
REV	-0.049	-0.038	-0.034	-0.031	-0.023	-0.015	-0.011	-0.004	0.002	0.012	0.019
	(-7.91)	(-5.03)	(-4.13)	(-3.12)	(-1.95)	(-1.15)	(-0.78)	(-0.27)	(0.11)	(0.66)	(1.00)
IVOL	-0.360	-0.451	-0.509	-0.550	-0.588	-0.620	-0.692	-0.741	-0.789	-0.828	-0.881
	(-3.12)	(-2.54)	(-2.09)	(-1.74)	(-1.51)	(-1.32)	(-1.26)	(-1.19)	(-1.12)	(-1.06)	(-1.02)
DVOL	0.104	0.126	0.141	0.163	0.172	0.179	0.190	0.211	0.230	0.240	0.239
	(2.33)	(1.81)	(1.51)	(1.35)	(1.14)	(0.99)	(0.90)	(0.87)	(0.85)	(0.81)	(0.74)

CVDVOL	0.062	0.130	0.230	0.380	0.560	0.720	0.880	1.000	1.070	1.160	1.190
	(0.62)	(0.98)	(1.30)	(1.64)	(2.18)	(2.36)	(2.54)	(2.46)	(2.38)	(2.45)	(2.33)
SKDVOL	-0.250	-0.415	-0.563	-0.790	-0.755	-0.912	-0.996	-1.118	-1.393	-1.641	-1.728
	(-1.78)	(-2.19)	(-2.50)	(-3.23)	(-2.55)	(-2.67)	(-2.78)	(-2.76)	(-3.18)	(-3.40)	(-3.31)
R^2 (%)	4.12	4.25	4.32	4.43	4.48	4.56	4.65	4.72	4.77	4.83	4.90