Flight to Liquidity and the Cross-Section of Stock Returns

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ABSTRACT

We design an intuitive yet simple measure of market liquidity (*TC*) to capture "flight to liquidity" aspect of the liquidity risk. *TC* is constructed as the ratio of total trade volume of stocks in the top trading volume quintile to that in the bottom. Its variation captures the liquidity shift between the most liquid (highest quality) and the least liquid (lowest quality) stocks, intensified during the flight to liquidity. Among the liquidity risk factors, one constructed from *TC* (*TC* factor) is the most effective in yielding evidence consistent with the predictions of popular models of flight to liquidity. *TC* is a priced state variable whose pricing impact is beyond those of existing liquidity measures. Annualized return spread between top and bottom quintiles of *TC* factor loading sorted portfolios is about 5%.

JEL: G11, G12
Keywords: Trading volume; liquidity; asset pricing; flight to liquidity; flight to quality

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I. Introduction

"Flight to liquidity" refers to the episodes in which a large shock to market liquidity induces traders shift towards high quality and liquid stocks, making low quality and illiquid stocks extremely illiquid. In this study, we construct trading volume concentration (*TC*) as an intuitive yet simple measure of market liquidity aiming at capturing "flight to liquidity" risk. *TC* is constructed as the ratio of total trade volume of stocks in the top trade volume quintile to that in the bottom, thus its variation captures the liquidity shift between the most liquid (highest quality) and the least liquid (lowest quality) stocks, intensified during the flight to liquidity[1] We find that stocks with high *TC*-based liquidity risk ex-ante suffered from the most negative return in the months of flights ex-post; However, they also have higher expected return in the overall sample period even after controlling for existing liquidity risk measures, indicating that flight to liquidity risk is priced and its price impact is beyond those captured by existing risk measures.

Brunnermeier and Pedersen (2009) links market liquidity to funding liquidity. In their model, speculative traders play the role of market makers who provide liquidity and immediacy, but they also face funding constraints and obtain financing from financiers by posting margins and pledging the securities as collateral. When a significantly negative shock hits the market, stock prices decline considerably and speculators hit their margin constraints and are forced to liquidate, which impairs their ability to provide liquidity. The worsen market liquidity, in turn, raises financiers' risk of capital provision and induces them to raise margins on speculators' accounts; the reduced funding liquidity, in turn, furthers reduce speculators' ability to provide liquidity, and hence a liquidity spiral. Furthermore, as this happens, the deterioration of speculators' capital induces them to shift liquidity provision away from illiquid stocks toward liquid stocks as the former is more capital-expensive

[1] "Flight to liquidity" and "flight to quality" are generally refer to similar phenomena in practices and in most literature. Though Beber, Brandt, and Kavajecz (2009) distinctly refer "flight to quality" and "flight to liquidity" as investors rebalancing portfolios toward low credit risk and liquid securities respectively in bond market, there is less distinction in equity market. Hence, we use the two terms interchangeably in this paper.

due to higher margins, which widens the liquidity differential between liquid and illiquid stocks even more and results in flight to liquidity. Note that the distinguishing feature of the flight to liquidity episode — the intensified liquidity shifting from illiquid stocks to liquid stocks would be captured as increasing *TC*.[2]

The argument of flight to liquidity can also be made from the demand side of market liquidity. Vayanos (2004) presents an asset pricing model where investors have to liquidate when asset prices fall below a lower bound. This liquidation risk can lead to flight to liquidity when illiquid assets become riskier and investors become more risk averse during volatile times (such as financial crises). Næs, Skjeltorp, and Ødegaard (2011), using a unique stock market ownership data for Norway, find that changes in stock market liquidity coincide with changes in investors' portfolio composition. Particularly, they find that investors shift their stock portfolios from smaller and less liquid stocks into larger and more liquid stocks when market becomes illiquid. While investors' portfolio choices cannot be observed directly, trading volume concentration in the cross-section of stock market provides a good proxy. As suggested by Longstaff (2009), when market is illiquid, featured by a "blackout" risk of illiquid assets, liquid assets become the "only game in town" and investors trade more on them. Trading more on larger and more liquid stocks manifests as high *TC* in the end.

As discussed above, one key feature of *TC* is that it captures the liquidity shift from illiquid to liquid stocks. Most, if not all, of the existing market-wide liquidity measures focus only on the average. That is, they are constructed by averaging the liquidity measures across all individual stocks and hence, cannot capture the liquidity shift among these stocks.[3] For example, Amihud's (2002) market illiquidity is the cross-sectional average of individual stock's illiquidity measure. A

[2] Flight-to-liquidity phenomena is most likely to trigger within asset market rather than across asset markets due to capital immobility and market segmentation as featured by, for example, Mitchell, Pedersen, and Pulvino (2007), Duffie (2010) and He and Xiong (2013).

[3] To our best knowledge, no existing measure considers the liquidity shift among individual stocks in gauging market-wide liquidity risk. For example, Amihud (2002), Pastor and Stambaugh (2003), Liu (2006), Sadka (2006), and Brennan, Huh, and Subrahmanyam (2013) use the equally (or value) weighted average of their proprietary liquidity measures for individual stocks to construct the market-wide liquidity measures. Readers are referred to Pastor and Stambaugh (2003, p.657) for detail discussion of the construction of aggregate stock market liquidity measures used in literature from averaging across sample stocks.

larger Amihud (2002) market illiquidity do not necessarily mean investors will move from high liquidity stocks to low liquidity stocks; it could just mean the Amihud illiquidity measure of all stocks in the market become larger, which misses the notion of flight to liquidity. Similarly, although a large aggregate trade volume is often associated with liquid market, high aggregate trading volume is also observed in a market where flight to liquidity is taking place. The former situation leads to smaller trading volume concentration while the latter leads to high trading volume concentration when trading moves from low volume stocks to high volume ones. Consistent with this observation, we find that more than 60% of *TC* is indeed unexplained by other existing liquidity risk measures. Moreover, we will show later that stocks with high sensitivity to *TC*-based liquidity risk factor have different firm characteristics and behave differently from stocks with high sensitivity to existing liquidity risk factors in the literature.[4]

Other than relying on its intuitive appeal, we further demonstrate that *TC* is effective in capturing the predictions from prominent models of flight to liquidity. Consistent with Brunnermeier and Pedersen (2009), we find that a decreased funding liquidity (an increase in TED spread) reduces market liquidity (an increase in *TC*) more than other prominent market liquidity measures that include Amihud (2002), Pastor and Stambaugh (2003), Liu (2006), Sadka (2006), and Brennan et al. (2013).

Brunnermeier and Pedersen (2009) suggest that high volatility stocks are most costly to

[4] The phenomenon of flight to liquidity in the cross section of stock market also has been emphasized in Acharya and Pedersen (2005) who find that illiquid stocks also tend to have high liquidity risk, suggesting that illiquid stocks becomes even less liquid in times of down markets or generally illiquidity markets. Acharya and Pedersen (2005) develop a unified theoretical model (i.e., liquidity-adjusted CAPM) to explain the pricing effect of liquidity and liquidity risk. There are three liquidity risks in their model. In addition to the return sensitivity to market liquidity, the co-movement of stock liquidity with market return and market liquidity are also components of liquidity risk. Among the three liquidity betas considered in their model, they find that the most important source of liquidity risk is from the co-movement of stock liquidity with market return (i.e., their β^4). Furthermore, their empirical tests show that this risk premium with respect to this liquidity beta, which is largely ignore in previous literature is the largest. However, due to the problem of collinearity among liquidity level and their three liquidity betas, they can only find weak empirical support for the notion. Our *TC* measure of flight to liquidity risk is different from theirs in that our *TC*-beta is in a U-shaped relationship with Amihud's illiquid level. This U-shaped relationship enables us to mitigate collinearity problem they face in their β^4 and to capture flight to liquidity risk that is least contaminated by the level of liquidity. Indeed, our results also suggest that the risk arising from the concern of liquidity in down market or when market is extremely illiquid (i.e., the flight to quality risk) is an important component of liquidity risk. Our results also confirm that this aspect of liquidity risk goes beyond the traditional liquidity risk (i.e., the return sensitivity to the average market liquidity) and probably is more important in the pricing of liquidity risk.

provide liquidity as they require larger margins. Liquidation risk, the main driver of flight to liquidity in Vayanos (2004), is also higher for more volatile stocks. Both models predict volatile stocks would have a larger flight to liquidity risk. This implies the price impact differential between high and low volatility stocks from a liquidity shock would be greatest when the shock come from a liquidity measure like *TC* that is best able to capturing the liquidity shift between illiquid (volatile) stocks and liquid (less volatile) stocks during the flights. Indeed, we find that liquidity shocks in *TC* explain the cross-sectional price impact across volatility portfolios better than shocks to existing liquidity risk measures.

After showing *TC* to be the most effective market-wide liquidity measure in capturing flight to liquidity, we move on to investigate whether *TC* is a priced state variable and whether its price impact goes beyond those of existing liquidity risk measures. Affirmative outcome from these investigations would strongly suggest flight to liquidity is a priced risk. The existence of commonality of liquidity (i.e., liquidity of individual asset co-moves with market-wide liquidity) is first documented by Chordia, Roll and Subrahmanyam (2000). This discovery may have facilitated Pastor and Stambaugh (2003) to recognize the possibility that market liquidity can be a priced state variable--- a notion subsequently adopted by Acahraya and Pedersen (2005) and Sadka (2006) among others. Following these works, we construct a *TC*-based liquidity risk factor (ΔTC) as innovations of *TC* from a VAR model that also controls for the Fama–French three factors and for an exogenous time trend indicator.[5] We estimate the liquidity risk of a stock (*TC-beta*) as the factor loading of ΔTC based on the Fama-French (1993) three-factor model augmented with ΔTC, and then test if stocks with higher (lower) *TC-beta* have higher (lower) expected returns. As we construct our liquidity risk factor (ΔTC) by taking the negative value of *TC* innovations, a high ΔTC indicates a high market liquidity state. We find a significant liquidity risk premium in the cross-section of stock returns. In portfolio tests, the average value-weighted stock return in the

[5] The time-series pattern of *TC* demonstrates a long-term uptrend and is autocorrelated. This time-series pattern coincides with recent evolution of trading activity in U.S. stock market, which has increased over the past few decades as discussed, among others, in French (2008) and Chordia, Roll and Subrahmanyam (2011). To be comparable with other liquidity measures, we also use a simple AR (2) with time trend model to filter out the time trend and autocorrelation components in the time series. The results from employing this model are qualitatively unchanged.

highest *TC-beta* quintile significantly outperforms that in the lowest *TC-beta* quintile by about 5% annually. The return premium remains significantly positive after risk-adjusting by the CAPM and the Fama−French (1993) three- and four-factor models.

We also perform Two Stage Cross Sectional Regression (2SCSR) tests on individual stocks similar in spirit to Core, Guay and Verdi (2008) and Hirshleifer and Jiang (2010), and find a significantly positive coefficient on *TC-beta*, indicating again that *TC*-based liquidity risk factor is a priced factor. The coefficient remains significant after controlling for other liquidity risk measures and firm characteristics. Our tests that perform a horse race also show that the power of *TC-beta* to explain returns appears to dominate other existing liquidity betas. These results indicate that *TC* is indeed a priced state variable and that the pricing impact of *TC*-based liquidity risk goes beyond those of existing liquidity risk measures, which, in turn, strongly suggests that flight to liquidity risk is an important component of liquidity risk.

To verify that the higher expected return earned by *TC-beta* stocks indeed reflect the risk premium of (compensation to) flight to liquidity, we examine if stocks with large *TC-beta* ex-ante experience the greatest price decline during the flight months, as captured by large drops in ΔTC. We find stocks in the highest *TC-beta* quintile on average experience a more negative monthly return of 0.76% compared to stocks in the lowest *TC-beta* quintile during flight months. More importantly, *TC-beta* dominates other liquidity-betas in explaining the negative return impacts in the cross section of stocks during the flight periods just as it does in explaining the expected return in the overall sample period.

We contribute to the liquidity risk literature by introducing a new liquidity measure designed specifically to capture flight to liquidity. Existing liquidity risk measures (e.g., Amihud 2002, Pastor and Stambaugh 2003, Archaya and Pedersen (2005), Sadka 2006) are constructed as innovation to the level of *average* marker-wide liquidities, which are ineffective in capturing the liquidity shift from liquid stocks to illiquid stocks during the flights. In contrast, a large (small) *TC* literally describes a state variable in which the flights and the liquidity shift are (not) taking place. We provide strong empirical support for Brunnermeier and Pedersen (2009) and Vayonos (2004), which predict tight links among funding liquidity, volatility and market liquidity that can lead to flight to liquidity under certain conditions. The fact that we find these links are tightest when *TC* is employed as the market liquidity measure are consistent with (1) *TC* is a good measure of flight to liquidity and (2) Brunnermeier and Pedersen (2009) and Vayonos (2004) are good models of fight to liquidity.

We also contribute to flight to liquidity literature by investigating if the risk of flight to liquidity is priced. Using data on Euro-area government bond markets, Beber et al. (2009) find that credit quality matters for bond valuations but in the time of market stress, investors chase liquidity such that the most illiquid bonds would have the highest yield spread. Other than the market difference, this paper differs from Beber et al. (2009) in two important aspects. First, Beber et al. (2009) study the pricing impact of the level of ex-post liquidity, we study the impact of ex-ante liquidity risk where *TC-beta* was estimated with 60-months rolling window leading up to the formation month. Second, their results are about the contemporaneous relationship between return and liquidity. While we also investigate the contemporaneous impact of *TC-beta* during the liquidity crisis periods, our focus is mainly on the impact of ex-ante liquidity risk on expected return. We find that high *TC-beta* stocks suffered from the most negative return in the months of flights, they also have the higher expected return in normal time, indicating that *TC-beta* risk is priced. Furthermore, the price impact of *TC-beta*, the liquidity risk measure motivated specifically to measure the flight to liquidity, dominate the price impact of other liquidity risk measures in both type of tests strongly suggest the risk of flight to liquidity is priced.

The rest of the paper is organized as follows. Section II describes the properties of *TC* and the construction of our *TC*-based liquidity factor. Section III provides evidence to support that *TC* is better than others in capturing the flight to liquidity aspect of liquidity risk. Section IV conducts the asset pricing tests of *TC* in the cross-section of stock returns. Section V concludes this paper.

II. Properties of Trading Volume Concentration

A. Data and Sample Selection

Our empirical tests use a sample that includes NYSE/AMEX stocks over the period from January 1967 to December 2013.[6] We restrict our sample to those stocks with CRSP share codes 10 or 11. Data on stock prices and volumes are obtained from CRSP daily or monthly stock files. To construct the monthly time series of trading volume concentration, we first generate monthly dollar volume for individual stocks ($DVOL$) by aggregating their daily dollar volume over a given month, where daily dollar volume is calculated by multiplying the number of shares traded by the stock's price per share on a specified day. In addition, we require other relevant variables on firm characteristics, such as market capitalization (ME); book-to-market ratio (BM)[7]; cumulative return from *t*−7 to *t*−12 month ($RET_{(-12,-7)}$)[8]; share turnover ($TURN$); idiosyncratic volatility (IV), defined as the standard deviation of return residuals estimated by regressing individual stocks' daily excess returns on the Fama−French three factors in a given month; Amihud's (2002) return-to-volume illiquidity measure (RV); Brennan et al.'s (2013) turnover-version down (negative returns) half-Amihud liquidity measure (RV^-); and Liu's (2006) $LM1$ and $LM12$ illiquidity measures.

To estimate the factor-adjusted returns associated with liquidity risk, we require traditional four factors such as market factor (MKT), size factor (SMB), value factor (HML), and momentum factor (MOM), which are obtained from French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Besides, to test the effect of funding liquidity, we also require data on the TED spread, as defined by the difference between the 3-month LIBOR Eurodollar rate and the 3-month T-bill rate (1986−2013), which is collected from Federal Reserve Bank of St. Louis.

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[6] We exclude NASDAQ stocks in constructing the trading volume concentration because of different trading protocols across exchanges (e.g., Atkins and Dyl (1997), Chordia et al. (2007), and Chordia et al. (2011)). Also, data on NASDAQ stock returns and volume are available from CRSP only beginning January 1983.

[7] When adopting book value of equity to measure book-to-market ratio (BM), as suggested by Hirshleifer, Hou, Teoh, and Zhang (2004), we assume a minimum 4-month gap between the fiscal year end and the actual report release month. Data on book value of equity is collected from Compustat, with a sample excluding negative-BM stocks.

[8] Novy-Marx (2012) suggests that momentum effect is mainly driven by stocks' performance 12 to 7 months prior to portfolio formation, we thus use $RET_{(-12,-7)}$ to capture momentum effect.

B. Metrics of Trading Volume Concentration (TC) and *TC-based Liquidity Factor*

To study the properties of trading volume concentration, we begin by investigating the cross section of trading-volume distribution over time. At the end of each month, we sort all NYSE/AMEX stocks into dollar-volume quintiles (denoted as High, Q4, Q3, Q2, and Low) based on their NYSE breakpoints of monthly dollar volume. To show the concentration of cross-sectional trading volume, we calculate the trading-volume density (denoted as TD) as the sum of dollar volumes of stocks in each quintile divided by aggregating dollar volumes of all sample stocks. Hence, the sum of trading-volume density (%) across all five quintiles is equal to 100% in each month. The cross-sectional distribution of trading volume is highly concentrated on the dollar-volume quintile High and this concentration has increased gradually over the sample period. During January 1963 to December 2013. As shown in Table I, the average trading-volume density for the quintile High is 75.9%. Over time, the trading-volume density for the quintile High is 67% in January 1963 and has increased to 77% in December 2013.[9] On the other hand, the remaining four quintiles (Q4, Q3, Q2, and Low) together only account for a small portion of aggregate trading volume.

【Table I Insert Here】

Since we propose that trading volume concentration captures the tendency of "flight to liquidity/quality" effect in the stock market, our metrics should easily and directly measure the relative volume contribution from liquid (and/or high quality) versus illiquid (and/or low quality) stocks. Table I shows that the dollar-volume quintile High (Low) is generally comprised of stocks with large (small) size, high (low) liquid and low (high) idiosyncratic volatility. The average market capitalization (ME) for quintile High is \$12.76 billion and monotonically decreases to \$0.09 billion

[9] We also plot the time series of the dollar-volume and market-capitalization contributions for stocks that experienced the largest (top 30, 100, 200 and 300) annual dollar volume for each year. The time-series patterns of these smaller subsets of top trading volume stocks also replicate that of dollar-volume quintile High. This provides an additional and even stronger evidence of high and increasing trading volume concentration since this approach focuses on top ends of cross-sectional distributions and is independent of the method of grouping (For example, DeAngelo, DeAngelo, and Skinner (2004) apply this approach to show the high and increasing dividend concentration and earning consolidation).

for quintile Low. Amihud's (2002) illiquidity measure (RV) monotonically increases from 0.01 for quintile High to 12.91 for quintile Low. The idiosyncratic return volatility (IV) monotonically increases from 1.75% for quintile High to 3.26% for quintile Low. Hence, we construct our metrics of trading volume concentration (TC) as the natural log of the ratio of the dollar volume density of quintile High relative to that of quintile Low:

$$TC_t = \ln\left(\frac{TDH_t}{TDL_t}\right) \tag{1}$$

where TDH_t (TDL_t) is the trading-volume density of quintile High (Low) in month *t*.

The logarithm rescales to the trading-volume density is not trivial. It preserves the time-series properties while captures more intuitively the nature of liquidity risk. Though the trading-volume density for quintile Low (TDL) is small, it is also important in detecting the dynamics of market liquidity. Næs et al. (2011) show that investors' portfolio choice is correlated with market liquidity, especially for the smallest firms. Longstaff (2009) also shows that distortion in agent's consumption plans arising from illiquid assets in the market has an equilibrium asset pricing effect even in the absence of transaction costs or other explicit liquidity costs.

【Figure 1 Insert Here】

The top panel of Figure 1 plots the monthly time series of TC over the period from January 1967 to December 2013. We observe that peaks in TC generally correspond to the occurrence of major market crises, such as market crashes in 1987, internet bubble burst in 2001, and financial crisis in 2008. This anecdotal observation suggests that TC captures the flight to liquidity effect as predicted by the recent literature. That is, the flight to liquidity effect occurs when market declines, becomes illiquid, or becomes more volatile. For example, Brunnermeier and Pedersen (2009) predict that market liquidity is subject to "flight to liquidity" and co-moves with market returns. The models of Gromb and Vayanos (2002) and Garleanu and Pedersen (2007) also predict that higher market volatility is related to less available risk-bearing capacity, which implies a lower liquidity. Hameed, Kang, and Viswanathan (2010) provide empirical evidence on that negative market returns decrease stock liquidity.

To capture the liquidity risk associated with TC, we need to estimate innovations in TC. Similar to Chen and Petkova (2012), we construct our TC-based liquidity risk factor by estimating a first-order VAR model that includes the Fama−French three factors and TC. An exogenous variable, time trend indicator, is also included into the model.[10] Specifically, we estimate the first-order VAR model using data available up to month *t*:

$$\begin{bmatrix} MKT_t \\ SMB_t \\ HML_t \\ TC_t \end{bmatrix} = A \begin{bmatrix} MKT_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \\ TC_{t-1} \end{bmatrix} + B[t] + e_t \qquad (2)$$

where e_t represents a vector of innovations for each variable in the state vector. At each month *t*, we extract innovations in TC from the residuals ($\hat{e}_t$). As high TC reveals high tendency to flight to liquidity and proxies for worse market liquidity state, we define our TC-based liquidity risk factor (ΔTC) as the reverse of the innovations in TC to follow the convention that high (low) value of ΔTC indicates a high (low) market liquidity state. The first observation for ΔTC is for January 1972 since we require the estimation of Eq. (2) to contain at least 60 months. As shown in the bottom panel of Figure 1, several periods with extremely low levels of ΔTC coincide with the occurrence of major market crises, suggesting ΔTC exhibits potential ability in capturing flight to liquidity risk.

C. Comparison with Other Liquidity Risk Measures

To show that our TC-based liquidity risk factor captures different aspect of liquidity risk, we compare it with several other existing liquidity factors that are commonly used in the literature. The liquidity measures we consider are aggregate dollar volume, Amihud's (2002) illiquidity measure, Brennan et al.'s (2013) turnover-version negative half-Amihud illiquidity measure, Liu's (2006) turnover-adjusted number of zero trade measure, Pastor and Stambaugh's (2003) price impact measure, and Sadka's (2006) variable-permanent price impact measure. We summarize how these

[10] As shown in the top panel of Figure 1, the time-series pattern in TC exhibits certain degree of time trend and autocorrelations, which motivates us to estimate a first-order VAR model with an exogenous time-trend indicator.

liquidity factors are designed as follows.

First, to show that the liquidity risk information contained in our TC-based liquidity factor is different from that in aggregate trading volume, we consider aggregate dollar trading volume as a pseudo liquidity measure for comparison. Aggregate trading volume in a given month ($ADVOL_t$) is calculated by averaging individual stocks' monthly dollar volume traded ($DVOL_{i,t}$) over all sample stocks listed on NYSE/AMEX. Using the similar VAR model by replacing TC with $ADVOL$ in Eq. (2), we construct a liquidity factor associated with aggregate trading volume, as denoted by $\Delta ADVOL$.

Second, Amihud (2002) provides a simple illiquidity measure in attempt to capture the price impact aspect of liquidity. We take the time-average of daily return-to-volume ratio over one month to construct stock *i*'s Amihud (2002) illiquidity measure in month *t* ($RV_{i,t}$):

$$RV_{i,t} = \frac{1}{N}\sum_{d=1}^{N}\frac{|R_{i,d,t}|}{DVOL_{i,d,t}} \tag{3}$$

where $|R_{i,d,t}|$ is stock *i*'s absolute daily return on day d in month *t* and $DVOL_{i,d,t}$ is stock *i*'s dollar trading volume (in \$ millions) on day d in month *t*. N is the number of trading days over month *t*.[11] $RV_{i,t}$ measures illiquidity because high price impact is related to low liquidity. We then take a simple average across all common stocks listed on NYSE/AMEX to generate market-wide Amihud's (2002) illiquidity level ($Amihud_t$) and construct a liquidity factor associated with $Amihud$, as denoted by $\Delta Amihud$, using the similar VAR model by replacing TC with $Amihud$ in Eq. (2). A recent paper by Brennan et al. (2013) further decomposes the turnover-version Amihud's (2002) illiquidity measure into components that correspond to positive and negative return days and find that only the down-market component, negative half-Amihud illiquidity measure, is priced. Thus, we also construct a market-wide negative half-Amihud illiquidity measure ($Amihud_t^-$).

Third, Pastor and Stambaugh (2003) also propose a price impact measure by focusing on a dimension related to temporary price changes accompanying order flows. The estimates of the

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[11] We form $RV_{i,t}$ using a sample of NYSE/AMEX common stocks with at least 15 trading days per month.

liquidity measure for stock *i* in month *t* can be generated from the following regression model:

$$R^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} R_{i,d,t} + Gamma_{i,t} sign\left(R^e_{i,d,t}\right) \times DVOL_{i,d,t} + \epsilon_{i,d+1,t} \tag{4}$$

where $R^e_{i,d,t}$ is stock *i*'s excess daily return (in excess of CRSP value-weighted market return) on day *d* in month *t*. $Gamma_{i,t}$ is designed to catch the price reverse from the previous day's order flow shock. By taking a cross-sectional average of $Gamma_{i,t}$ across NYSE/AMEX stocks in a given month and scaling a series of total dollar value, Pastor and Stambaugh (2003) construct a liquidity factor (we denote it as ΔPS) based on a AR (1) model, which can be obtained from Wharton Research Data Services (WRDS).

Fourth, Liu (2006) introduces a new illiquidity measure associated with the number of zero trading volumes and argue that it performs well in capturing multi-dimensions of liquidity such as trading speed, quantity, and cost. Liu (2006) defines the standardized turnover-adjusted number of zero daily trading volume over the prior 1 month ($LM1_{i,t}$) for stock *i* in month *t* as:

$$LM1_{i,t} = [\#1_{i,t} + \frac{1/\,TURN1_{i,t}}{480{,}000}] \times \frac{21}{NoTD1_{i,t}} \tag{5}$$

where $\#1$ is the number of zero daily volumes in prior 1 month. $TURN1$ is share turnover over the prior 1 month. $NoTD1$ is the total number of trading days in the market over the prior 1 month. Once $LM1_{i,t}$ is constructed, the aggregate change in market liquidity at the end of month *t* can be calculated as: $DALM1_t = \frac{1}{obs_t}\sum_{i=1}^{obs_t}(LM1_{i,t} - LM1_{i,t-1})$, where obs_t is the number of eligible NYSE/AMEX common stocks at the end of month *t*. We then denote ΔLiu as a liquidity factor by estimating the residuals in $DALM1_t$ based on the AR (1) specification with a drift using data available up to month *t*.

Finally, using intra-day transaction data (TAQ), Sadka (2006) decomposes firm-level liquidity into variable and fixed price-impact effects and finds that the variation of the market-wide variable component (LIQ^λ_t), not the fixed component, is priced in the cross-section of momentum and PEAD portfolios. We denote LIQ^λ_t as $\Delta Sadka$ in this paper and collect the data on $\Delta Sadka$, covering the period from April 1983 to December 2012, from Sadka's website (https://www2.bc.edu/ronnie-sadka/).

【Table II Insert Here】

Table II reports descriptive statistics on ΔTC and its correlations with other risk factors and other liquidity factors, which include $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$. As shown in Panel A of Table II, by construction, the mean and median of ΔTC both close to 0 and the magnitudes of maximum and minimum are roughly equal. It suggests that ΔTC is stationary and symmetrically distributed. Similarly, the descriptive statistics shown in Panel A also suggest that the time series of other liquidity factors we considered are stationary and symmetrically distributed. As shown in Panel B, ΔTC is positively correlated with market excess return (MKT) at 0.09 during the period from January 1972 to December 2013, suggesting that negative shocks to TC (increases in illiquidity) coincide with declines in the market. Also, ΔTC is positively correlated with size premium (SMB) at 0.16. However, ΔTC appears to be uncorrelated with HML and MOM.

Panel B of Table II further shows the correlations among ΔTC and other liquidity factors. As we expect that the time-series variation in TC captures market-wide liquidity risk, ΔTC is significantly correlated with other existing liquidity factors. Correlations between ΔTC and $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$ are −0.15, −0.13, −0.54, 0.15, and 0.20, respectively. Interestingly, a positive correlation between $\Delta ADVOL$ and $\Delta Amihud$ (0.23) and a negative correlation between $\Delta ADVOL$ and $\Delta Amihud^{-}$ (−0.17) appear to reflect that innovations in aggregate trading volume are ambiguous in capturing dynamics of market liquidity risk. In addition, we find that almost all the correlations between each pair are statistically significant. The overall correlation matrix confirms that ΔTC captures the dynamic of market-wide liquidity and supports Korajczyk and Sadka (2008) that there exists common information regarding market liquidity risk across liquidity measures.

Nevertheless, the correlation structure above implies that these liquidity factors are somewhat similar but far from identical in how they vary over time. Following Hu, Pan, and Wang (2013), we run a set of time-series regressions of ΔTC on other liquidity factors. Panel C of Table II reports the results. The first row includes $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, and ΔPS as explanatory variables over the whole period from January 1972 to December 2013, and shows that the adjusted R^2 of this regression is 0.38. The second row includes $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$ as explanatory variables over the period from April 1983 to December 2012, and reveals that the adjusted R^2 is 0.30. Overall, other liquidity factors jointly explain only 38% (or less) of the time variation of ΔTC, and more than 60% of the time variation of ΔTC is unexplained by these existing liquidity factors. These results suggest that TC-based liquidity factor, ΔTC, contains additional information regarding liquidity risk that is distinguished from other liquidity risk factors.

The overall evidence above suggests that ΔTC is correlated with but different from other existing liquidity factors and thus it captures the market-wide liquidity risk through the investors' "flight to liquidity" tendency, which is missed in existing liquidity risk measures. That is, ΔTC is a novel measure in capturing the episodes that when market liquidity risk is high, investors tend to migrate from small and illiquid stocks to large and liquid stocks, resulting in the unexpected increase in trading volume concentration and verse vice.

III. Evidence on Flight to Liquidity

So far, we have relied on the intuitive notion that variation in TC captures the movement of trading between the most liquid and the least liquid stocks as a justification for TC being good at capturing the flight to quality aspect of market-wide liquidity risk. In this section, we provide justification from evidence predicted by widely accepted models on flight to liquidity such as Vayanos (2004) and Brunnermeier and Pedersen (2009).

A. Funding Liquidity and Market Liquidity

Brunnermeier and Pedersen (2009) suggest that some negative shocks to the collateral of market makers would affect their capability to provide liquidity, especially for illiquid stocks, which may lead to flight to liquidity. Their model predicts that speculator's capital (funding liquidity) and market volatility affect market liquidity. To empirically test this prediction, we run a time-series regression of our TC-based liquidity factor (ΔTC) on changes in a funding liquidity measure. For comparison, we also consider various other liquidity factors (i.e., $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$) as dependent variables. Following Brunnermeier, Nagel, and Pedersen (2008) and Frazzini and Pedersen (2014), we use TED spread as a proxy for funding liquidity. We also control for several variables that may affect market liquidity (e.g., Brennan, Chordia, Subrahmanyam, and Tong (2012)): market returns ($R_{m,t}$), measured by monthly returns on the value-weighted CRSP NYSE/AMEX/NASDAQ index in month *t*; market volatility (VIX_t), measured by the daily CBOE VIX option implied volatility index averaged over month *t*; change in the ratio of the number of stocks with a positive return to that with a negative return in month *t* ($\Delta Up/Down_t$); change in default yield premium in month *t* (ΔDEF_t); change in term yield premium in month *t* ($\Delta TERM_t$); and the January dummy variable, JAN_t, to capture the January effect that may seasonally affect the market liquidity conditions. The time-series regression for the period from January 1986 to December 2012 is set as follows:[12]

$$\Delta Liq_t = \gamma_0 + \gamma_1 \Delta TED_t + \gamma_2 R_{m,t} + \gamma_3 VIX_t + \gamma_4 \Delta Up/Down_t$$

$$+\gamma_5 \Delta DEF_t + \gamma_6 \Delta TERM_t + \gamma_7 JAN_t + \epsilon_t \tag{6}$$

where ΔLiq_t are various liquidity factors (i.e., $\Delta TC, \Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$). ΔTED_t is change in TED spread in month *t*. To compare the sensitivities of various liquidity factors to funding liquidity, we standardize each of dependent variables to have an equal mean of zero and an equal standard deviation of one when estimating Eq. (6).

【Table III Insert Here】

[12] We choose this period because data on TED spread is available since 1986. Also, since $\Delta Sadka$ is considered as a comparable candidate and its sample period is available end at December 2012, the analysis here covers the period from January 1986 to December 2012.

Table III reports the results. The first column shows that the coefficient on ΔTED for the dependent variable ΔTC is −0.33, statistically significant with a t-statistic of −2.09. Consistent with Brunnermeier and Pedersen's (2009) prediction, this result suggests that a decrease in funding liquidity (an increase in TED spread) makes market makers harder to provide liquidity and to shift to high quality stocks, hence reducing market liquidity. In addition, the coefficient on market volatility (VIX_m) is −0.02, again statistically significant (t-statistic = −3.04), suggesting a more volatile market tends to reduce market liquidity. By considering innovation in aggregate trading volume ($\Delta ADVOL$) as a pseudo liquidity proxy, the second column shows that the coefficient on ΔTED for the dependent variable $\Delta DVOL$ is 0.31, significant with a t-statistic of 2.01. The positive coefficient shows that a tightened funding liquidity actually increases aggregate trading volume. As discussed below, this is consistent with Pastor and Stambaugh (2003) and Longstaff (2009). Moving from third to last column, however, we find that the regression coefficients on ΔTED for other liquidity factors as the dependent variables are insignificant or marginally significant.

Aggregate trading volume (or market turnover) is a commonly used proxy for market liquidity since it is generally positively correlated with market liquidity in liquid market conditions. However, its ability in capturing market liquidity risk becomes problematic when market is illiquid. Pastor and Stambaugh (2003) show that trading volume or turnover is useful in explaining the cross-sectional difference in liquidity but seems not to capture the time variation in aggregate liquidity, because aggregate trading volume tend to be higher not only in liquid market, but also in illiquid market. Particularly, they show that the time-series correlation between their market liquidity measure and aggregate dollar volume turns negative when calculated only across low-liquidity months. Also, Longstaff's (2009) calibrated model suggests that the presence of illiquid assets in the market, associated with higher liquidity risk, actually leads to higher aggregate trading volume. Consistent with Pastor and Stambaugh (2003) and Longstaff (2009), our evidence suggests that the ability of trading volume concentration in capturing market-wide liquidity risk is not driven by aggregate trading volume per se.

The overall results in Table III suggest that our TC-based liquidity factor (ΔTC) is the most sensitive to funding liquidity compared to other liquidity factors. This provides the first supportive evidence that TC plays a more important role in capturing the flight to liquidity/quality aspect of market liquidity risk.

B. Cross-sectional Effect of TC on Volatility Portfolios

Brunnermeier and Pedersen (2009) suggest that, due to funding constraint of market makers, market liquidity is subject to flight to liquidity. Since liquid and low risk assets require fewer margins, market makers optimally choose to provide more liquidity for these assets compared to illiquid and high risk assets when their funding is tight. Vayanos (2004) presents an asset pricing model where investors need to liquidate when asset prices fall below a lower bound. Vayanos (2004) further links the risk of needing to liquidate to volatility. These models predict a liquidity shock increases the differential liquidity and thus price impact between high and low quality stocks.

If TC contains more information about the tendency of flight to liquidity, the TC-based liquidity factor would explain the return spreads of portfolios sorted by individual stocks' quality (risk) more significantly than other liquidity factors. Following Novy-Marx (2014) and others, we employ an intuitive measure, idiosyncratic volatility, as a proxy for the quality (or risk) of individual stocks. For each month *t*, NYSE/AMEX stocks (with CRSP share code 10 or 11) are sorted into quintiles based on their NYSE breakpoints of idiosyncratic volatility on month *t*-2.[13] The equally-weighted monthly returns for each quintile on month *t* are then calculated. We then test our hypotheses by regressing the monthly excess returns of the idiosyncratic volatility quintiles ($RIV_{p,t}$) on various liquidity factors. Specifically, we run the following time-series regressions on a sample period from January 1986 to December 2012:

$$RIV_{p,t} = \gamma_{p,0} + \gamma_{p,1}\Delta TC_t + \gamma_{p,2}\Delta ADVOL_t + \gamma_{p,3}\Delta Amihud_t + \gamma_{p,4}\Delta Amihud_t^-$$

[13] Individual stock's idiosyncratic volatility is defined as the standard deviation of residuals estimated by regressing individual stocks' daily excess returns on the Fama-French three factors in a given month.

$$+\gamma_{p,5}\Delta Liu_t + \gamma_{p,6}\Delta PS_t + \gamma_{p,7}\Delta Sadka_t + \gamma_{p,8}\mathbf{X}_t + \epsilon_{p,t} \quad (7)$$

where $RIV_{p,t}$, *p*=High, Q4, Q3, Q2, and Low, are the excess returns on idiosyncratic volatility portfolios in month *t*. For comparison, we standardize each liquidity factor (i.e., ΔTC, $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS and $\Delta Sadka$) and thus allow it to have an equal mean of zero and an equal standard deviation of one. $\mathbf{X}_t$ is a set of control variables that include ΔTED_t, $R_{m,t}$, VIX_t, $\Delta Up/Down_t$, ΔDEF_t, $\Delta TERM_t$, and JAN_t, which are defined in Table III. Table IV presents the result.

【Table IV Insert Here】

The second row shows the return impact of our TC-based liquidity factor on the idiosyncratic volatility sorted portfolios from high (High *IV*) to low (Low *IV*). As expected, we find that the coefficients on ΔTC decrease monotonically from High *IV* to Low *IV*, suggesting that the return impact from TC-based liquidity risk is larger for high risk (low quality) stocks than for low risk (high quality) stocks. The last column shows the result of testing whether the coefficients on ΔTC for the High *IV* and Low *IV* portfolios are equal. We find that a *t*-statistic for the test is 3.37, indicating that the return impact for the High *IV* and Low *IV* portfolios is significantly different. From the third to eighth rows, we find instead that the differences in coefficients on other liquidity factors are insignificant in most cases. This result thus provides second evidence to support the argument that our TC-based liquidity factor is better than others in capturing the flight to liquidity risk.

IV. Pricing TC-based Liquidity Risk in the Cross-Section

It has been broadly accepted that the market-wide liquidity risk is an important risk factor in determining the cross-section of asset returns since Pastor and Stambaugh (2003) first propose and show that it can be a priced state variable, (see, e.g., Pastor and Stambaugh (2003), Acharya and Pederson (2005), Liu (2006), and Sadka (2006)). As ΔTC, designed to capture flight to liquidity, is distinct from other measures of market-wide liquidity risk, showing ΔTC a priced factor would provide strong support for flight to liquidity to be an important liquidity risk not captured by existing liquidity risk measures. We start by testing if ΔTC is a priced liquidity factor based on a portfolio test that is similar to Pastor and Stambaugh (2003). Then, similar to Core, Guay and Verdi (2008) and Hirshleifer and Jiang (2010), we run a Two Stage Cross-Sectional Regression (2SCSR) of individual stock returns. This regression allows us to control simultaneously for existing liquidity risk measures as well as for other firm characteristics and thus can provide direct evidence to support that TC's pricing impact goes beyond those of existing liquidity risk measures. Finally, to verify that *TC* captures the ex-ante flight to liquidity risk, we examine weather stocks with higher ex-ante liquidity risk associated *TC* suffer greater price impact during the periods of extremely negative liquidity shocks (i.e., months of flight).

A. Portfolio Tests

Following Pastor and Stambaugh (2003), we measure TC-based liquidity risk as the loading on ΔTC based on a liquidity-augmented Fama−French three-factor model, using prior 60-month data:

$$R_{i,t} = \beta_0 + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,\Delta TC} \Delta TC_t + \varepsilon_{i,t} \tag{8}$$

where $R_{i,t}$ is stock *i*'s excess return relative to the 30-day T-bill rate in month *t*. As discussed in Section II, we define ΔTC as the negative sign of TC innovations estimated from a first-order VAR model. Since a higher innovation in TC corresponds to market illiquidity, the negative sign makes ΔTC positively correlated with market liquidity. Based on this convention, stocks with higher TC-beta ($\beta_{\Delta TC}$) are those stocks earning lower returns and not a good hedge when market is illiquid. Thus, stocks with higher $\beta_{\Delta TC}$ are considered more risky and should earn higher liquidity risk premium.

We test the hypothesis by investigating the expected returns of portfolios sorted by $\beta_{\Delta TC}$. Our test sample contains NYSE/AMEX stocks with share codes of 10 or 11 and with year-end prices less than \$5. Since the first observation for ΔTC is for January 1972 and we require data on five years of monthly returns continuing through the current year-end to estimate $\beta_{\Delta TC}$, the first observation on $\beta_{\Delta TC}$ is for December 1976. At the end of each year during 1976−2012, we sort sample stocks into $\beta_{\Delta TC}$ quintiles using their NYSE breakpoints and trace subsequent equally-weighted and value-weighted monthly returns over a 12-month holding period for each quintile. The portfolio returns for the 12 post-ranking months are linked across years (1977−2013) to construct one series of post-ranking returns for each portfolio.

【Table V Insert Here】

Panel A of Table V reports the average equally-weighted excess monthly returns (*EXRET*) and risk-adjusted returns (alphas) estimated from the regressions of excess portfolio post-ranking returns by the CAPM (*CAPM* α), the three-factor model (*FF-3* α), and the four-factor model (*FF-4* α). Consistent with Pastor and Stambaugh (2003), among others, we find a significant liquidity risk premium: stocks with higher (lower) liquidity risk have higher (lower) expected returns. The first row in Panel A shows that the expected returns monotonically decrease from the quintile with the highest TC-based liquidity risk (High) to the quintile with the lowest TC-based liquidity risk (Low). The average equally-weighted excess monthly return for quintile High is 1.006% per month while that for quintile Low is lower at 0.764% per month. The return spread between the High and Low quintiles (H−L) is 0.241% per month, statistically significant with a *t*-statistic of 2.89.[14] The annualized return spread is about 3%. The high-minus-low $\beta_{\Delta TC}$ (H−L) return spreads after risk-adjusting by the CAPM, the Fama−French three-factor model, and the four-factor model are 0.285%, 0.284%, and 0.222% per month, respectively, and they are all statistically significant.

The last row in Panel A of Table V shows the post-ranking TC-betas (Ex post $\beta_{\Delta TC}$), which are estimated by regressing the equally-weighted excess monthly returns on the Fama−French three factors and ΔTC. We observe that ex-post $\beta_{\Delta TC}$ generally decreases from 1.339 for the high

[14] To control for the potential January/turn of the year effect, we also calculate the return spreads without Januarys. The results are qualitatively similar.

pre-ranking $\beta_{\Delta TC}$ quintile (High) to −0.787 for the low pre-ranking $\beta_{\Delta TC}$ quintile (Low). The H−L portfolio has a significant ex-post $\beta_{\Delta TC}$ of 2.126 (with a t-statistic = 3.88). This pattern of post-ranking $\beta_{\Delta TC}$ across pre-ranking quintiles suggests that the pre-ranking estimated beta is persistent at least for a one-year holding horizon and provides a good estimation for the liquidity risk of stocks.

To make sure our results are not driven by the fact that high beta stocks tend to be smaller and high returns, we also present value-weighted results in Panel B of Table V. The average value-weighted monthly return still decreases monotonically from the High to Low $\beta_{\Delta TC}$ quintiles. Compared to the equally-weighted results in Panel A, the average value-weighted return spread between High to Low $\beta_{\Delta TC}$ quintiles is higher and retains significantly positive. The average spread in value-weighted excess monthly returns is 0.384% per month, or 4.6% annually (with a t-statistic = 2.72) and the risk-adjusted alphas by the CAPM and the Fama−French three- and four-factor models are 0.476%, 0.475%, and 0.366% per month, respectively (all statistically significant). These return premiums from TC-based liquidity risk are comparable to Pastor and Stambaugh (2003) and Sadka (2006) in economic magnitude. For example, the CAPM-adjusted alpha to high-minus-low $\beta_{\Delta TC}$ quintile is 0.476% per month (or 5.71% annually). Pastor and Stambaugh (2003) show that the value-weighted liquidity risk premium (the CAPM-adjusted alpha) sorted on their historical liquidity beta is about 4.66% annually during January 1968 to December 1999. Sadka (2006) also concludes that the variable component of liquidity risk is priced with a premium of about 5–6% annually. In sum, both results from equally- and value-weighted portfolios consistently support that our TC-based liquidity risk is priced in the cross-section of stock returns.

In Panel C of Table V, we shows the characteristics of the portfolios sorted by $\beta_{\Delta TC}$. Generally speaking, we observe that our TC-based liquidity risks capture somewhat different liquidity characteristics from liquidity levels of individual stocks. For example, Amihud's (2002) illiquidity measure (RV) is U-shaped across the $\beta_{\Delta TC}$ quintiles. Not surprisingly, the highest liquidity risk quintile (High) generally comprises more of illiquidity stocks (average RV of 0.259). But we also observe that the lowest liquidity risk quintile (Low) also comprises more of illiquidity stocks (average RV of 0.408). Instead, we observe that the average RVs are lower among the middle liquidity-risk quintiles (Q3 and Q4). This is consistent with Lou and Sadka (2011) that liquidity level and liquidity risk (liquidity betas) capture different dimensions of liquidity characteristics in the cross-section of stocks. Similarly, characteristics that are associated with liquidity levels (e.g., market capitalization (ME), share turnover ($TURN$) and idiosyncratic risk (IV)) are also U-shaped or reverse U-shaped across the $\beta_{\Delta TC}$ quintiles. In sharp contrast with Liu (2006), who shows that the book-to-market ratio (BM) increases monotonically from the low liquidity risk portfolio to the high liquidity risk portfolio, the liquidity risk estimated by our liquidity factor ΔTC exhibits no obvious association with the book-to-market ratio (BM). In Panel D of Table V, we further investigate the correlations between $\beta_{\Delta TC}$ and liquidity betas estimated by other liquidity factors. In general, stocks with high liquidity risk exposure to ΔTC also have higher liquidity risk exposure to other liquidity factors.[15] To examine if the pricing power of ΔTC goes beyond those of existing liquidity risk measures and other firm characteristics, we conduct a regression-based test to control for these variables in the next subsection.

B. Two Stage Cross-Sectional Regression Test for Individual Stocks

So far, we have shown that stocks with higher $\beta_{\Delta TC}$ (i.e., higher TC-based liquidity risk) on average earn higher subsequent returns. This subsection further tests whether $\beta_{\Delta TC}$ predicts the cross-sectional returns of individual stocks based on Fama and MacBeth (1973) style cross-sectional regressions, which control for various firm characteristics and enable us to compare the return predicting power of all liquidity betas simultaneously. Ang, Liu, and Schwarz (2010) suggest that using individual stocks increases the cross-sectional dispersion in factor loadings and the precision for the estimation of the risk premium. We hence utilize individual stock returns to generate stock-level TC-*betas* when conducting a two-step Fama and MacBeth (1973) procedure.

[15] In Panel D of Table V, the negative correlations between $\beta_{\Delta TC}$ and $\beta_{\Delta Amihud}$, $\beta_{\Delta Amihud^-}$, or $\beta_{\Delta Liu}$ is because ΔTC measures market liquidity while $\Delta Amihud$, $\Delta Amihud^-$, and ΔLiu measure market illiquidity.

In particular, we run a stock-level Fama−MacBeth (1973) regression with excess monthly returns of individual stocks as the dependent variable and $\beta_{\Delta TC}$ as the key independent variable. At the end of each year, $\beta_{\Delta TC}$ is estimated based on a time-series rolling regression (annually rebalanced) that includes the Fama−French three factors and ΔTC, using prior 60-month data (five years of monthly returns continuing through the current year-end). We then keep the values of $\beta_{\Delta TC}$ constant for the following 12 months to forecast stock returns in the regressions.

$\beta_{\Delta ADVOL}$, $\beta_{\Delta Amihud}$, $\beta_{\Delta Amihud^-}$, $\beta_{\Delta Liu}$, $\beta_{\Delta PS}$, and $\beta_{\Delta Sadka}$ are those liquidity betas used to compare with $\beta_{\Delta TC}$.[16] When making the pairwise comparison of $\beta_{\Delta TC}$ and $\beta_{\Delta PS}$ in a model, for instance, we estimate them simultaneously based on a time-series rolling regression (annually rebalanced) that includes the Fama−French three factors augmented with ΔTC and ΔPS. Other liquidity betas are estimated using the similar procedure in various model specifications. For comparison, we standardize each liquidity beta at monthly frequency and thus allow it to have an equal mean of zero and an equal standard deviation of one.

We also incorporate a set of control variables in the regression. β_{MKT}, β_{SMB}, and β_{HML} are individual stock *i*'s Fama−French three-factor loadings, estimated from a time-series model with the liquidity-augmented Fama-French three-factor models using prior 60-month data (annually rebalanced) at the end of prior year. We keep the values of β_{MKT}, β_{SMB}, and β_{HML} constant for the following 12 months to be control variables in the regressions. $RET_{(-12,-7)}$ is the cumulative return from *t*−7 to *t*−12 month. RET_{t-1} is the stock return on month *t*−1. $RET_{(-36,-13)}$ is the cumulative return from *t*−13 to *t*−36 month. Following Brennan et al. (2012), we lag other control variables of firm characteristics by two months to avoid the bid-ask bounce effect (Jegadeesh (1990); and Brennan et al. (1998)). $\ln ME_{t-2}$ is natural log of market capitalization on month *t*−2. BM_{t-2} is the book-to-market ratio on month *t*−2. $\ln TURN_{t-2}$ is natural log of share turnover on month *t*−2. IV_{t-2} is the idiosyncratic volatility on month *t*−2. $\ln RV^-_{t-2}$ is natural log of RV^- on month *t*−2. $\ln RV_{t-2}$ is natural log of RV on month *t*−2. $\ln LM12_{t-2}$ is natural log of $LM12$ on

[16] As the sample period of $\Delta Sadka$ runs from April 1983 to December 2012, $\beta_{\Delta Sadka}$ is estimated beginning on December 1988.

month t−2. To address the error in variable problem, we report the associated t-statistics based on standard errors that are Shanken (1992) corrected. Table VI reports the regression results.

【Table VI Insert Here】

The overall results of Table VI show that the coefficients on $\beta_{\Delta TC}$ are positive and significant for all model specifications with and without comparing other liquidity betas. At first, Models I and II focus on the explanatory power of $\beta_{\Delta TC}$ for expected returns without considering other liquidity betas. Model I includes β_{MKT}, β_{SMB}, and β_{HML} as controls for other factor risks and shows that the coefficient on $\beta_{\Delta TC}$ is 0.107 (with a t-statistic = 2.74), which represents a price of risk for TC-based liquidity risk. For individual stocks, the 1st-percentile standardized $\beta_{\Delta TC}$ is −2.85, while the 99th-percentile standardized $\beta_{\Delta TC}$ is 2.37. This suggests that as $\beta_{\Delta TC}$ moves from the 1st to the 99th percentile, the expected return will increase by about 0.56% per month (= (2.37−(−2.85))×0.107%). After controlling for a set of standard predictors of returns, Model II shows that the coefficient on $\beta_{\Delta TC}$ is 0.103, which remains statistically significant (t-statistic = 2.83).

Further, we conduct a set of horse race between $\beta_{\Delta TC}$ and other liquidity betas and show that $\beta_{\Delta TC}$ have an ability to predict the cross-section of returns incremental to well-known liquidity risk betas. In all the pairwise comparisons from Models III to VIII, $\beta_{\Delta TC}$ consistently dominates other liquidity betas in determining expected returns in magnitude and in statistical significance. From these models, we find that coefficients on $\beta_{\Delta TC}$ remain statistically significant while others are insignificant or weakly significant. For example, Model V shows that the coefficient on $\beta_{\Delta TC}$ is 0.108 with a t-statistic of 2.68, after controlling for $\beta_{\Delta Amihud^-}$ and other firm characteristics. In addition, based on a full specification including all other liquidity betas and other control variables in Model XI that covers the period from January 1989 to December 2012, we observe that $\beta_{\Delta TC}$ is still significantly priced at 0.109 with a t-statistic of 2.00 while others remain insignificant. Finally, as shown in Model XII, we exclude Januarys from our sample periods and find that the ability of

$\beta_{\Delta TC}$ in predicting future returns is still significant (0.119 with a *t*-statistic of 2.14) and slightly higher than that in Model XI with Januarys included.

Overall, the evidence in Table VI confirms that stocks with higher TC*-betas* on average earn higher subsequent return over a 12-month holding period, even after controlling for well-known return predictors and other existing liquidity betas. Compared to existing liquidity risk factors, TC*-beta* is the superior one in terms of economic significance and statistical significance in predicting the cross-section of stock returns. This result empirically supports the notion that TC is a priced state variable whose pricing impact goes beyond those of existing liquidity risk measures. It also implies that the flight to liquidity risk, fear of becoming extremely illiquid when a large shock to market liquidity occurs, is an important aspect of liquidity risk that compensates liquidity risk premium beyond those that is captured by existing liquidity risk measures.

***C. Do Stocks with High TC-beta Stock Ex-ante Suffer More in the Months of Flight to Liquidity*?**

If the higher expected return earned by *TC-beta* stocks, as shown in the section above, indeed reflects the risk premium of flight to liquidity, high TC*-beta* stocks, as compared to low TC*-beta* stocks, should experience more negative price impact during the months in which flight to liquidity presumes to have occurred according to our TC measure (see Figure 1).

Lou and Sadka (2011), who use Pastor and Stambaugh's (2003) factor and Sadka's (2006) factor, find that the return spread between stocks with high and low liquidity risk reversed during the 2008–2009 financial crisis. That is, high-liquidity-risk stocks declined more than low-liquidity-risk stocks during the crisis period. We extend Lou and Sadka (2011) by investigating the average stock returns during the months when flight to liquidity occurred (abbreviate as flight months, identified as the bottom 5% of ΔTC in our sample period) as explained by various liquidity betas (i.e., $\beta_{\Delta TC}$, $\beta_{\Delta ADVOL}$, $\beta_{\Delta Amihud}$, $\beta_{\Delta Amihud^{-}}$, $\beta_{\Delta Liu}$, $\beta_{\Delta PS}$, or $\beta_{\Delta Sadka}$) and control variables. Particularly, we run the following Fama-Macbeth (1973) regression during flight months:

$$R_{i,t} = a_0 + a_1\beta^{H}_{\Delta TC,i,t-1} + a_2\beta^{L}_{\Delta TC,i,t-1} + a_3\beta^{H}_{\Delta ADVOL,i,t-1} + a_4\beta^{L}_{\Delta ADVOL,i,t-1}$$
$$+a_5\beta^{H}_{\Delta Amihud,i,t-1} + a_6\beta^{L}_{\Delta Amihud,i,t-1} + a_7\beta^{H}_{\Delta Amihud^{-},i,t-1} + a_8\beta^{L}_{\Delta Amihud^{-},i,t-1}$$

$$+a_9\beta^H_{\Delta Liu,i,t-1} + a_{10}\beta^L_{\Delta Liu,i,t-1} + a_{11}\beta^H_{\Delta PS,i,t-1} + a_{12}\beta^L_{\Delta PS,i,t-1} + a_{13}\beta^H_{\Delta Sadka,i,t-1}$$

$$+a_{14}\beta^L_{\Delta Sadka,i,t-1} + a_{15}\mathbf{X}_i + \varepsilon_{i,t} \quad (9)$$

where $R_{i,t}$ is stock *i*'s excess return relative to the 30-day T-bill rate in flight month *t*. $\beta^H_{\Delta TC,i,t-1}$ ($\beta^L_{\Delta TC,i,t-1}$) is high (low) *TC*-beta dummy variable that equals one if stock *i*'s *TC*-beta in the month prior to flight month is in the top (bottom) quintile based on their NYSE breakpoints, and zero otherwise. The dummy variables $\beta^H_{\Delta ADVOL,i,t-1}$, $\beta^L_{\Delta ADVOL,i,t-1}$, $\beta^H_{\Delta Amihud,i,t-1}$, $\beta^L_{\Delta Amihud,i,t-1}$, $\beta^H_{\Delta Amihud^-,i,t-1}$, $\beta^L_{\Delta Amihud^-,i,t-1}$, $\beta^H_{\Delta Liu,i,t-1}$, $\beta^L_{\Delta Liu,i,t-1}$, $\beta^H_{\Delta PS,i,t-1}$, $\beta^L_{\Delta PS,i,t-1}$, $\beta^H_{\Delta Sadka,i,t-1}$, $\beta^L_{\Delta Sadka,i,t-1}$ are defined similarly. To be comparable, various liquidity betas for stock *i* in month *t*-1 are estimated simultaneously using a model that includes the Fama−French three factors augmented with all liquidity factors using prior 60-month data (five years of monthly returns continuing through month *t*-1). $\mathbf{X}_i$ is a set of control variables that contains high and low Fama−French three-factor loadings dummy variables for $\beta_{MKT,i,t-1}$, $\beta_{SMB,i,t-1}$, $\beta_{HML,i,t-1}$ and those described in Table VI. For comparison, all independent variables are demeaned. For brevity, we present only the intercepts and coefficients on dummy variables of various liquidity betas.

【Table VII Insert Here】

Table VII reports the results. Our baseline result (Model I) covers the period from January 1977 to December 2013 and excludes $\beta_{\Delta Sadka,i,t-1}$ as explanatory variable (due to data availability). It shows that controlling other liquidity betas and control variables to be zero (as their mean values), the average return during the flight month for stocks in the top *TC*-beta quintile is -4.29% (the sum of intercept and coefficient on $\beta^H_{\Delta TC,i,t-1}$) and that for stocks in the bottom *TC*-beta quintile is -3.53% (the sum of intercept and coefficient on $\beta^L_{\Delta TC,i,t-1}$). This result confirms Lou and Sadka's (2011) finding that, during the recent financial crisis period, high-liquidity-risk stocks declined significantly more than low-liquidity-risk stocks. More importantly, when comparing the return spread explained by other liquidity betas, we find that the explanatory power of $\beta_{\Delta TC}$ dominates the others in magnitude and statistical significance. In the second half of the table, we find that the return spread between top and bottom TC-beta quintile (i.e., coefficient difference for $\beta^{H}_{\Delta TC} - \beta^{L}_{\Delta TC}$) is −0.76 (with a *t*-statistic = −2.28), which is larger in magnitude and more significant than the others. In most cases, the coefficient differences for other liquidity betas are statistically insignificant. Finally, when including also the dummy variables on Sadka's liquidity beta ($\beta^{H}_{\Delta Sadka,i,t-1}$ and $\beta^{L}_{\Delta Sadka,i,t-1}$) as explanatory variables and covering the shorter period from January 1989 to December 2012, as shown in Model II, we still find that the explanatory power of $\beta_{\Delta TC}$ for the return spread during periods of flight to liquidity dominates the other liquidity betas. The overall result indicates that liquidity risk with respect to TC factor is the most effective in capturing the cross-sectional return impact of liquidity risk when flight to liquidity occurs.

D. Robustness Checks

In this subsection, we provide further evidence to confirm thatTC's pricing effect is robust to two sub-periods and to various estimations of TC-based liquidity factor. Table VIII reports the robustness tests that repeat 2SCSR of Models X and Model XII in Table VI. To save space, we report only the regression coefficients on $\beta_{\Delta TC}$ and other liquidity betas for comparison.

【Table VIII Insert Here】

D.1 Sub-periods

French (2008) documents that the aggregate trading volume (measured by market turnover) of U.S. stock market has increased dramatically since 1990s. The pricing effect of our TC-based liquidity risk may also experience structural change after 1990 because the measure uses information that is related to market trading volume. To test the robustness of the pricing effect of ΔTC to various periods, we run the Model X of Table VI for two sub-periods: January 1977 to December 1995 and January 1996 to December 2013. Models I and II in Table VIII report the regression results for the two sub-periods. We find that the coefficients on $\beta_{\Delta TC}$ are roughly equal and both are significant, indicating that the pricing power of $\beta_{\Delta TC}$ is robust across the two sub-periods. For comparison, we find that among other liquidity betas, only the coefficient on $\beta_{\Delta Liu}$ for the first sub-period (Model I) is marginally significant but it becomes insignificant for the second sub-period (Model II). The results confirm the predictability of TC-*beta* is not due to a specific sub-period.

D.2 Alternative measures of innovations in TC

One advantage of using information from trading volume concentration to capture the flight to liquidity risk is that it is easy to calculate and model free. Our TC-based liquidity risk factor in the previous pricing tests use innovations constructed from the first-order VAR model that also controls for the Fama−French three factors. One may be curious if using a simple way to extract innovations from TC time series is also robust to pricing the cross section of stock returns. From Models III to VI of Table VIII, we use two alternative and easier ways to construct ΔTC and replicate the 2SCSR tests in Table VI. In models III and IV, we generate simply the reverse residuals from estimating the AR (2) model with a time-trend indicator using data available up to month *t* to construct the liquidity factor, ΔTC_t^{AR2}, and estimate its loadings, $\beta_{\Delta TC^{AR2}}$. As shown in Model III (not covering the beta on Sadka's (2006) factor), liquidity beta estimated based on ΔTC^{AR2} ($\beta_{\Delta TC^{AR2}}$) remains a significant predictor for future returns of individual stocks. Also, for a test period from January 1989 to December 2012, Model IV (covering the beta on Sadka's (2006) factor) shows that the significance of the coefficient on $\beta_{\Delta TC^{AR2}}$ becomes weaker while its *t*-statistic of 1.81 remains the largest in magnitude when comparing with other liquidity betas.

Liquidity factor constructed as simple as the first-order difference also delivers the similar and robust results. In Models V and VI, we use ΔTC_t^{FD}, defined as reverse monthly first differences in TC, to run the regressions and find that $\beta_{\Delta TC^{FD}}$ remains a significant and positive explanatory variable for future returns of individual stocks.

In sum, the robustness tests in Table VIII show that the pricing power of liquidity risk as an exposure to our TC-based liquidity factor is close to those in Table VI. The overall result thus supports that the pricing power of TC-based liquidity factor is not subject to specific periods or to methods in constructing factors.

V. Conclusion

This paper develops a new market-wide liquidity risk factor from the time variation of trading volume concentration (*TC*) in the cross-section of stock market. In contrast to existing liquidity risk measures that capture the risk of aggregate liquidity, TC-based liquidity factor captures the market-wide liquidity risk generated from the liquidity shift manifested in the flight to liquidity.

As predicted by Brunnermeier and Pedersen (2009) that market is subject to "flight to liquidity" when the funding liquidity is tight, we find that TC-based liquidity factor is better than other liquidity factors in capturing the link between market liquidity and funding liquidity. We also show that TC-based liquidity factor is better than other liquidity factors in detecting the effect of liquidity shocks on the cross-sectional returns across idiosyncratic volatility portfolios, a commonly-used proxy for quality of stocks. The overall results suggest that TC-based liquidity factor captures flight to liquidity risk in the market and enables us to test if it is priced.

We find that TC-based liquidity risk is priced in the cross-section of stock returns. In portfolio tests, the average value-weighted stock return in the highest *TC-beta* quintile significantly outperforms that in the lowest *TC-beta* quintile by about 5% annually. The return premium remains significantly positive after risk-adjusting by the CAPM and the Fama−French (1993) three- and four-factor models.

We also perform 2SCSR on individual stocks and run horse-race tests comparing the return predictive powers of the beta of different liquidity risk factors. We find the coefficients on *TC*-beta are positive and significant for all model specifications with and without comparing other liquidity betas. Moreover, *TC*-beta consistently dominates other liquidity betas in predicting returns both in magnitude and in statistical significance. Our results are robust to controlling for firm characteristics, to risk-adjusting by traditional factor loadings, to controlling for the pricing effects from existing liquidity measures, to various sub-periods, and to different method to generate innovations in TC. Furthermore, we show that stocks with highest TC-beta prior to the flight months exhibits the largest price decline during the flight period, but earn higher return in normal time, indicating that TC is good at capturing the flight to liquidity risk and its pricing impact goes beyond those captured by existing liquidity risk measures.

One important implication of our empirical results is that distribution rather than level of aggregate trading volume may reveal more information about market dynamics. Pastor and Stambaugh (2003) suggest that measures of trading activity such as volume and turnover do not appear to capture time variation in market liquidity though it is useful in explaining cross-sectional differences in liquidity. While aggregate trading volume level does not appear to capture time variation in market liquidity, our evidence shows that trading volume distribution does.

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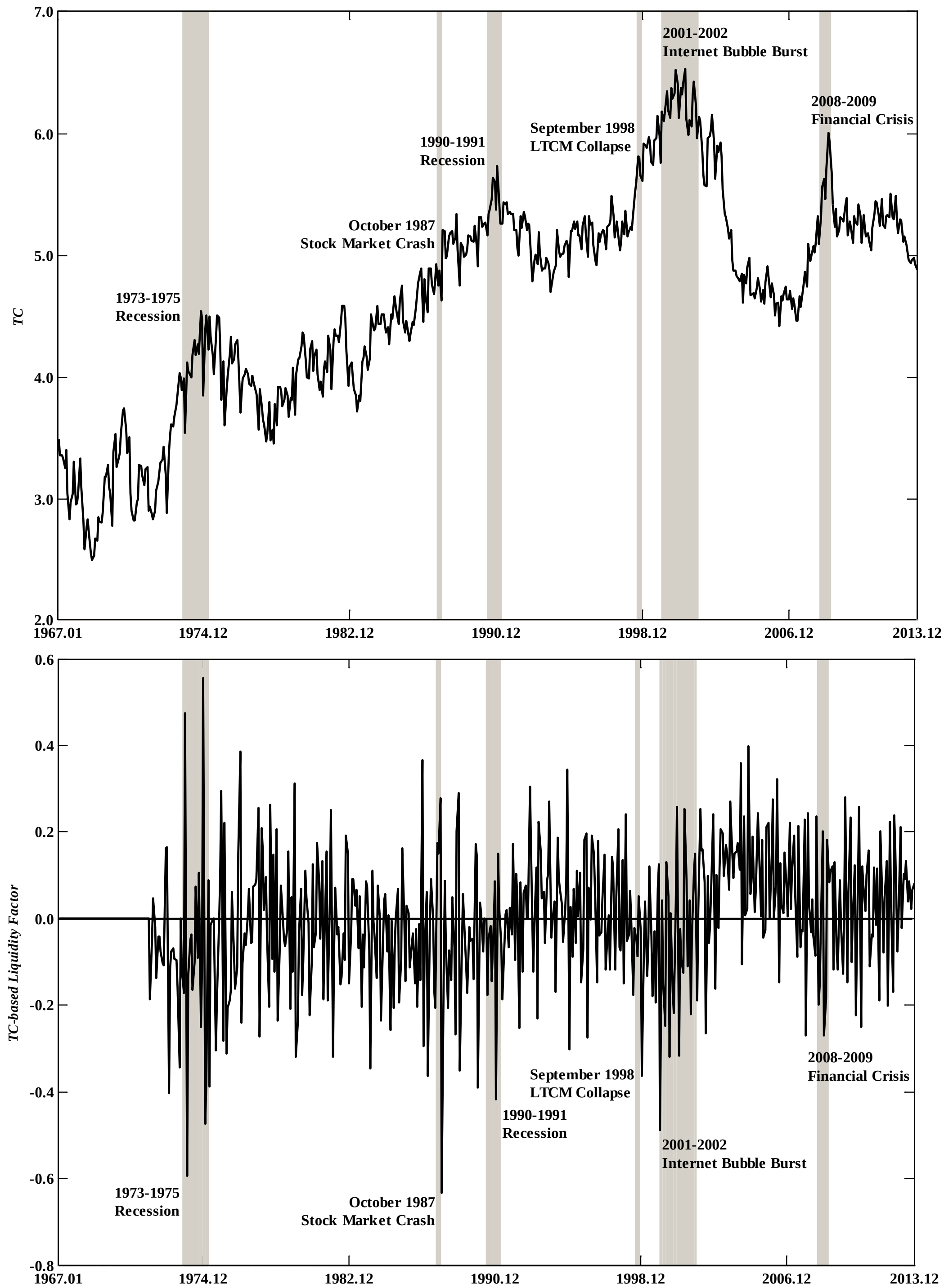

Figure 1. Time Series of Trading Volume Concentration (*TC*) and *TC*-based Liquidity Factor

This figure displays the time series of trading volume concentration (TC) and TC-based liquidity factor (ΔTC). $TC_t = \ln\left(\frac{TDH_t}{TDL_t}\right)$, where TDH_t (TDL_t) is the dollar volume density of quintile High (Low) in month *t*. To create TC, we require the sample to contain NYSE/AMEX stocks with CRSP share codes of 10 or 11 over the period January 1967 to December 2013. ΔTC at each month *t* is generated by estimating the first-order VAR model using data available up to month *t*:

$$\begin{bmatrix} MKT_t \\ SMB_t \\ HML_t \\ TC_t \end{bmatrix} = A \begin{bmatrix} MKT_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \\ TC_{t-1} \end{bmatrix} + B[t] + e_t$$

where MKT, SMB, and HML are the Fama−French three factors and *t* is the time trend indicator. e_t represents a vector of innovations for each variable in the state vector. From $\hat{e}_t$, we extract our TC-based liquidity factor (ΔTC) as the *negative* sign of innovations in TC. The first observation for ΔTC is January 1972 since we require the estimation of the VAR model to contain at least 60 months.

Table I
Characteristics of Quintiles by Dollar Trading Volume

This table summarizes descriptive statistics for dollar volume ($DVOL$) quintiles. The sample contains NYSE/AMEX stocks with share codes of 10 or 11 over the period from January 1967 to December 2013. Stocks are sorted into quintiles (denoted as High, Q4, Q3, Q2, and Low) based on the NYSE breakpoints of dollar volume at the end of each month. TD is the trading-volume density, measured as the total dollar volume in each dollar-volume quintile divided by aggregate dollar volume of all sample stocks for each month. $SVOL$ is the monthly share volume. $TURN$ is the monthly share turnover. Monthly data on $DVOL$, $SVOL$, and $TURN$ are computed using the daily trading volume first and then are aggregated over a month. ME is the market capitalization at the end of each month. RV is the average of Amihud's (2002) daily return-to-volume illiquidity measures within a month. IV is the standard deviation of residuals estimated by regressing individual stocks' daily excess returns on the Fama−French three factors over a month. The values in each quintile are cross-sectionally equally-weighted month by month (except TD) and then the time-series averages of those values are presented. Number of stocks for each month ranges from 1,511 to 2,598, with a time-series average of 2,109.

	High	Q4	Q3	Q2	Low
DVOL ($m)	1498.19	274.05	97.68	33.96	3.98
TD (%)	75.85	14.88	5.82	2.44	1.01
SVOL (m)	43.01	10.92	4.89	2.46	0.68
TURN (%)	12.91	11.83	9.79	7.42	3.51
ME ($b)	12.76	2.15	0.87	0.41	0.09
RV	0.01	0.03	0.10	0.29	12.91
IV (%)	1.75	1.90	2.07	2.31	3.26

Table II

Descriptive Statistics and Correlation Matrix

This table reports descriptive statistics on ΔTC and other risk factors and liquidity factors in Panel A, their Pearson correlations among each other in Panel B, and the time-series regression results of ΔTC on other liquidity factors in Panel C. ΔTC is our TC-based liquidity factor, defined as the *negative* sign of innovations in TC, estimated from a first-order VAR model. The first observation for ΔTC is January 1972 and thus the sample period in this table runs from January 1972 to December 2013 (504 months). MKT, SMB, HML, and MOM are the Fama–French four factors obtained from French's website. $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^{-}$, ΔLiu, ΔPS, and $\Delta Sadka$ are those commonly used liquidity factors, defined in Section II. Data on $\Delta Sadka$ runs from April 1983 to December 2012, which is obtained from Sadka's website. Numbers in square brackets in Panel B (C) are *p*-values (Newy-West (1987) *t*-statistics with four lags).

Panel A: Descriptive Statistics

	Mean	STD	Median	Min	Max
ΔTC	0.00	0.16	0.00	-0.63	0.55
MKT (%)	0.53	4.61	0.90	-23.24	16.10
SMB (%)	0.20	3.13	0.07	-16.40	22.02
HML (%)	0.40	3.00	0.39	-12.61	13.88
MOM (%)	0.71	4.47	0.78	-34.72	18.39
$\Delta ADVOL$	0.02	0.16	0.01	-0.43	0.67
$\Delta Amihud$	0.02	0.29	0.00	-0.81	0.95
$\Delta Amihud^{-}$	-0.01	0.16	0.00	-0.83	0.62
ΔLiu	0.00	0.01	0.00	-0.04	0.04
ΔPS	0.00	0.06	0.01	-0.38	0.29
$\Delta Sadka$	0.00	0.01	0.00	-0.04	0.02

Panel B: Correlations Matrix

	MKT	SMB	HML	MOM	$\Delta ADVOL$	$\Delta Amihud$	$\Delta Amihud^{-}$	ΔLiu	ΔPS	$\Delta Sadka$
ΔTC	0.099	0.161	-0.047	0.053	-0.170	-0.156	-0.133	-0.541	0.146	0.196
	[0.03]	[0.00]	[0.29]	[0.24]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$\Delta ADVOL$						0.230	-0.171	-0.192	-0.071	-0.245
						[0.00]	[0.00]	[0.00]	[0.11]	[0.00]
$\Delta Amihud$							0.224	0.103	-0.090	-0.061
							[0.00]	[0.03]	[0.04]	[0.25]
$\Delta Amihud^{-}$								0.189	-0.272	-0.185
								[0.00]	[0.00]	[0.00]
ΔLiu									-0.067	0.005
									[0.14]	[0.93]
ΔPS										0.224
										[0.00]

Panel C: ΔTC Regressed on Other Liquidity Factors

Intercept	$\Delta ADVOL$	$\Delta Amihud$	$\Delta Amihud^{-}$	ΔLiu	ΔPS	$\Delta Sadka$	N	Adj. R^2
0.003	-0.284	-0.008	-0.050	-12.417	0.202		504	0.375
[0.52]	[-7.30]	[-0.35]	[-1.20]	[-15.85]	[1.62]			
0.014	-0.271	-0.006	-0.069	-14.683	0.135	2.660	357	0.298
[1.91]	[-5.26]	[-0.24]	[-1.37]	[-8.32]	[0.92]	[2.41]		

Table III
Market Liquidity and Funding Liquidity

This table reports the results by running a time-series regression of various liquidity factors on funding liquidity and other controls during January 1986 to December 2012:

$$\Delta Liq_t = \gamma_0 + \gamma_1 \Delta TED_t + \gamma_2 R_{m,t} + \gamma_3 VIX_t + \gamma_4 \Delta Up/Down_t + \gamma_5 \Delta DEF_t + \gamma_6 \Delta TERM_t + \gamma_7 JAN_t + \epsilon_t$$

where ΔLiq_t are various liquidity factors (i.e., ΔTC, $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^-$, ΔLiu, ΔPS and $\Delta Sadka$). ΔTED_t is used to proxy for funding liquidity, defined the change in the TED spread (the difference between the 3 months LIBOR Eurodollar rate and the 3 months T-bill rate). $R_{m,t}$is monthly return on the value-weighted CRSP NYSE/AMEX/NASDAQ index in month *t*. VIX_t is the CBOE VIX option implied volatility index. $\Delta Up/Down_t$ is change in the ratio of the number of stocks with a positive return to that with a negative return in month *t*. ΔDEF_t is change in default yield premium in month *t*, where DEF_t is defined as BAA-rated minus AAA-rated bond yield in month *t*. $\Delta TERM_t$ is change in term yield premium in month *t*, where $TERM_t$ is defined as 10-year minus 3-momth bond yield in month *t*. JAN_t is a dummy variable that equals one in the month of January and zero otherwise. For comparison, we standardize each dependent variable and thus allow it to have an equal mean of zero and an equal standard deviation of one. Numbers in square brackets are Newey-West (1987) *t*-statistics with four lags for each of regression coefficients.

	ΔTC	$\Delta ADVOL$	$\Delta Amihud$	$\Delta Amihud^-$	ΔLiu	ΔPS	$\Delta Sadka$
Intercept	0.578	-0.937	-0.438	-0.188	-0.138	0.674	0.338
	[3.69]	[-7.71]	[-3.59]	[-1.37]	[-0.96]	[4.37]	[2.16]
$\boldsymbol{\Delta TED_t}$	**-0.331**	**0.310**	**0.093**	**0.083**	**0.058**	**-0.240**	**-0.285**
	[-2.09]	**[2.01]**	**[0.65]**	**[0.71]**	**[0.26]**	**[-1.35]**	**[-1.65]**
$R_{m,t}$	0.006	0.023	-0.016	-0.087	-0.034	0.046	0.031
	[0.41]	[1.82]	[-1.28]	[-6.12]	[-2.07]	[2.25]	[1.73]
VIX_t	-0.021	0.039	0.021	0.014	0.004	-0.033	-0.015
	[-3.04]	[7.70]	[3.86]	[2.19]	[0.68]	[-4.12]	[-1.85]
$\Delta Up/Down_t$	0.114	0.005	-0.062	-0.206	0.047	0.032	-0.086
	[3.29]	[0.14]	[-1.65]	[-4.80]	[1.55]	[0.89]	[-2.27]
ΔDEF_t	0.461	0.260	0.365	0.675	-0.689	0.941	-1.154
	[0.90]	[0.67]	[0.95]	[1.27]	[-1.27]	[1.30]	[-1.08]
$\Delta TERM_t$	-0.036	-0.277	-0.126	0.109	0.115	0.403	-0.255
	[-0.15]	[-1.61]	[-0.72]	[0.67]	[0.44]	[1.61]	[-1.04]
JAN_t	-1.600	1.064	0.157	-0.395	1.030	-0.093	-0.590
	[-8.01]	[7.05]	[0.88]	[-2.54]	[3.34]	[-0.56]	[-2.35]
Adj. R^2	0.259	0.178	0.046	0.455	0.087	0.146	0.111

Table IV
The Effect of Liquidity Factors on Returns across Idiosyncratic Volatility Portfolios

This table reports the results by regressing the excess returns across idiosyncratic volatility portfolios on various liquidity factors and other controls during January 1986 to December 2012:

$$RIV_{p,t} = \gamma_{p,0} + \gamma_{p,1}\Delta TC_t + \gamma_{p,2}\Delta ADVOL_t + \gamma_{p,3}\Delta Amihud_t + \gamma_{p,4}\Delta Amihud_t^- + \gamma_{p,5}\Delta Liu_t + \gamma_{p,6}\Delta PS_t + \gamma_{p,7}\Delta Sadka_t + \gamma_{p,8}\mathbf{X}_t + \epsilon_{p,t}$$

where $RIV_{p,t}$, p=High, Q4, Q3, Q2, and Low, are the excess returns on idiosyncratic volatility portfolios in month t. NYSE/AMEX stocks (with CRSP share code 10 or 11) are sorted into quintiles based on their NYSE breakpoints of idiosyncratic volatility on month t-2. The equally-weighted monthly returns for each quintile on month t are calculated. Individual stock's idiosyncratic volatility is measured as the standard deviation of residuals estimated by regressing individual stocks' daily excess returns on the Fama−French three factors in a given month. For comparison, we standardize each liquidity factor (i.e., ΔTC, $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^-$, ΔLiu, ΔPS and $\Delta Sadka$) and thus allow it to have an equal mean of zero and an equal standard deviation of one. $\mathbf{X}_t$ is a set of control variables that include ΔTED_t, $R_{m,t}$, VIX_t, $\Delta Up/Down_t$, ΔDEF_t, $\Delta TERM_t$, and JAN_t, which are defined in Table III. Numbers in square brackets are Newey-West (1987) *t*-statistics with four lags for each of regression coefficients.

	High *IV*	Q4	Q3	Q2	Low *IV*	H-L
Intercept	-2.109	-0.621	0.236	0.134	0.383	-2.493
	[-2.25]	[-1.06]	[0.52]	[0.46]	[1.51]	[-2.55]
$\boldsymbol{\Delta TC_t}$	**1.171**	**0.757**	**0.522**	**0.360**	**0.116**	**1.055**
	[3.30]	**[3.32]**	**[2.76]**	**[2.16]**	**[0.82]**	**[3.37]**
$\Delta ADVOL_t$	0.231	-0.036	-0.058	-0.121	-0.117	0.349
	[1.03]	[-0.26]	[-0.48]	[-1.13]	[-1.20]	[1.66]
$\Delta Amihud_t$	-0.455	-0.046	-0.004	0.024	0.062	-0.517
	[-1.93]	[-0.30]	[-0.03]	[0.19]	[0.59]	[-2.32]
$\Delta Amihud_t^-$	0.299	-0.073	-0.155	-0.273	-0.306	0.605
	[0.77]	[-0.33]	[-0.81]	[-1.77]	[-2.21]	[1.66]
ΔLiu_t	0.079	0.048	0.086	0.082	0.055	0.024
	[0.23]	[0.24]	[0.51]	[0.62]	[0.50]	[0.08]
ΔPS_t	-0.067	0.093	0.038	0.094	0.089	-0.156
	[-0.24]	[0.43]	[0.20]	[0.62]	[0.81]	[-0.66]
$\Delta Sadka_t$	0.397	0.337	0.296	0.200	0.192	0.206
	[1.53]	[2.01]	[2.02]	[1.58]	[1.95]	[0.82]
ΔTED_t	-0.867	-0.387	-0.130	-0.023	0.359	-1.226
	[-1.13]	[-0.82]	[-0.35]	[-0.09]	[1.75]	[-1.73]
$R_{m,t}$	1.319	1.080	0.931	0.810	0.589	0.730
	[9.96]	[11.91]	[11.91]	[12.44]	[11.22]	[5.62]
VIX_t	0.046	0.013	-0.015	-0.003	-0.006	0.053
	[1.04]	[0.48]	[-0.72]	[-0.21]	[-0.54]	[1.13]
$\Delta Up/Down_t$	-0.222	0.033	0.151	0.103	0.066	-0.288
	[-0.96]	[0.23]	[1.38]	[1.18]	[0.84]	[-1.26]
ΔDEF_t	-8.026	-2.950	-2.299	-0.566	-0.527	-7.499
	[-3.14]	[-1.68]	[-1.19]	[-0.41]	[-0.56]	[-3.41]
$\Delta TERM_t$	3.374	1.260	0.555	-0.308	-0.765	4.139
	[3.30]	[2.11]	[1.09]	[-0.71]	[-2.31]	[4.12]
JAN_t	8.319	2.424	1.177	0.295	-0.390	8.709
	[4.54]	[3.52]	[2.21]	[0.67]	[-1.04]	[4.90]
Adj. R^2	0.670	0.789	0.812	0.813	0.773	0.442

Table V
Post-Ranking Returns and Characteristics of $\beta_{\Delta TC}$ Portfolios

This table reports post-ranking returns and characteristics of quintiles sorted by $\beta_{\Delta TC}$, which is estimated using prior 60-month data (five years of monthly returns continuing through the current year-end) based on the following model:

$$R_{i,t} = \beta_0 + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,\Delta TC}\Delta TC_t + \varepsilon_{i,t}$$

where $R_{i,t}$ is stock *i*'s excess return relative to the 30-day T-bill rate in month *t*. MKT, SMB, and HML are the Fama−French three factors. ΔTC_t is TC-based liquidity factor. The first observation for ΔTC is for January 1972. At the end of each year during 1976−2012, we sort sample stocks into $\beta_{\Delta TC}$ quintiles using their NYSE breakpoints and trace subsequent monthly returns for a 12-month holding period for each quintile. High (Low) denotes the quintile with high (low) pre-ranking $\beta_{\Delta TC}$. The portfolio returns for the 12 post-ranking months are linked across years (1977−2013) to construct one series of post-ranking returns for each quintile. Panel A (B) reports average equally-weighted (value-weighted) post-ranking returns. Portfolio H−L is a zero-cost hedge portfolio that longs on the high pre-ranking $\beta_{\Delta TC}$ quintile and shorts on the low pre-ranking $\beta_{\Delta TC}$ quintile. *EXRET* is the average excess monthly returns (excess of the 30-day T-bill rate). *CAPM* α, *FF-3* α, and *FF-4* α are the alphas estimated from the regression of the full sample monthly portfolio returns on MKT, on the Fama−French three factors, and on the Fama−French four factors, respectively. Ex post $\beta_{\Delta TC}$ is estimated by regressing quintiles' post-ranking excess returns on the Fama−French three factors and ΔTC. Panel C reports portfolio characteristics in the portfolio formation month at each year end between 1976 and 2012. ME is market capitalization on formation month. RV is Amihud (2002) return-to-volume illiquidity measure on formation month. BM is the book-to-market ratio, which is measured using only sample of non-negative BM. $RET_{(-12,-7)}$ is cumulative return from *t*−7 to *t*−12 month prior to formation month. $TURN$ is monthly share turnover on formation month. IV is the standard deviation of return residuals estimated by regressing individual stocks' daily excess returns on the Fama−French three factors over the formation month. Panel D reports the correlations between $\beta_{\Delta TC}$ and other liquidity betas, $\beta_{\Delta ADVOL}$, $\beta_{\Delta Amihud}$, $\beta_{\Delta Amihud^-}$, $\beta_{\Delta Liu}$, $\beta_{\Delta PS}$, or $\beta_{\Delta Sadka}$, estimated using prior 60-month data based on the model that includes the Fama−French three factors augmented either with $\Delta ADVOL$, $\Delta Amihud$, $\Delta Amihud^-$, ΔLiu, ΔPS, or $\Delta Sadka$. Data on $\beta_{\Delta Sadka}$ covering the period at the end of each year during 1988−2011. The sample contains NYSE/AMEX stocks with CRSP share codes of 10 or 11 and with the year-end prices less than \$5. Numbers in square brackets are *t*-statistics.

Panel A: Equally-Weighted Portfolios

	High	Q4	Q3	Q2	Low	H-L
EXRET (%)	1.006	0.941	0.870	0.798	0.764	0.241
	[3.98]	[4.17]	[4.01]	[3.58]	[2.87]	[2.89]
CAPM α (%)	0.372	0.368	0.319	0.232	0.087	0.285
	[3.19]	[3.72]	[3.36]	[2.38]	[0.75]	[3.43]
FF-3 α (%)	0.081	0.118	0.063	-0.043	-0.204	0.284
	[0.95]	[1.57]	[0.93]	[-0.64]	[-2.63]	[3.42]
FF-4α (%)	0.129	0.173	0.101	0.047	-0.093	0.222
	[1.50]	[2.29]	[1.47]	[0.73]	[-1.25]	[2.66]
Ex post $\beta_{\Delta TC}$	1.339	1.123	1.330	0.721	-0.787	2.126
	[2.37]	[2.24]	[2.95]	[1.62]	[-1.52]	[3.88]

Panel B: Value-Weighted Portfolios

	High	Q4	Q3	Q2	Low	H-L
EXRET (%)	0.868	0.758	0.687	0.612	0.484	0.384
	[3.79]	[3.57]	[3.46]	[2.97]	[1.83]	[2.72]
CAPM α (%)	0.275	0.208	0.176	0.082	-0.201	0.476
	[3.04]	[2.48]	[2.15]	[0.95]	[-1.94]	[3.43]
FF-3 α (%)	0.164	0.126	0.087	-0.007	-0.311	0.475
	[1.93]	[1.72]	[1.29]	[-0.10]	[-3.09]	[3.36]
FF-4α (%)	0.150	0.156	0.097	0.050	-0.216	0.366
	[1.73]	[2.09]	[1.42]	[0.74]	[-2.16]	[2.58]
Ex post $\beta_{\Delta TC}$	1.553	0.886	0.992	0.798	-0.777	2.330
	[2.74]	[1.81]	[2.21]	[1.75]	[-1.16]	[2.48]

Panel C: Portfolio Characteristics

	High	Q4	Q3	Q2	Low	H-L
ME (\$b)	3.007	5.278	6.151	5.424	3.825	-0.818
RV	0.259	0.207	0.219	0.272	0.408	-0.149
BM	0.729	0.686	0.708	0.725	0.779	-0.050
$RET_{(-12,-7)}$ (%)	15.828	12.691	12.058	12.768	17.217	-1.390
TURN (%)	9.701	8.035	8.039	8.575	10.719	-1.018
IV (%)	1.985	1.653	1.611	1.704	2.069	-0.085

Panel D: Correlations with Other Liquidity Betas

	$\beta_{\Delta TC}$	$\beta_{\Delta ADVOL}$	$\beta_{\Delta Amihud}$	$\beta_{\Delta Amihud^-}$	$\beta_{\Delta Liu}$	$\beta_{\Delta PS}$
$\beta_{\Delta ADVOL}$	-0.170					
$\beta_{\Delta Amihud}$	-0.102	0.302				
$\beta_{\Delta Amihud^-}$	-0.171	0.098	0.185			
$\beta_{\Delta Liu}$	-0.347	-0.087	-0.014	0.035		
$\beta_{\Delta PS}$	0.100	-0.175	-0.054	-0.158	0.030	
$\beta_{\Delta Sadka}$	0.215	-0.287	-0.071	-0.283	-0.093	0.187

Table VI
Two Stage Cross-Sectional Regression of Individual Stock Returns

This table reports the firm-level Fama−MacBeth (1973) regression results with excess monthly returns of individual stocks as a dependent variable and $\beta_{\Delta TC}$ as the key independent variable. At the end of each year during 1976−2012, $\beta_{\Delta TC}$ is estimated based on a time-series rolling regression (annually rebalanced) that includes the Fama-French three factors and ΔTC, using prior 60-month data (five years of monthly returns continuing through the current year-end). We then keep those values of $\beta_{\Delta TC}$ constant for the following 12 months in the regressions. $\beta_{\Delta ADVOL}$, $\beta_{\Delta Amihud}$, $\beta_{\Delta Amihud^-}$, $\beta_{\Delta Liu}$, $\beta_{\Delta PS}$, and $\beta_{\Delta Sadka}$ are those liquidity betas used to compare with $\beta_{\Delta TC}$ (As the sample period of $\Delta Sadka$ runs from April 1983 to December 2012 and $\beta_{\Delta Sadka}$ is estimated beginning on December 1988, the analyses in model VIII, XI, and XII cover the period from January 1989 to December 2012). When we make a pairwise comparison of $\beta_{\Delta TC}$ and $\beta_{\Delta ADVOL}$ in model III, for example, we estimate them simultaneously based on a model that includes the Fama−French three factors plus ΔTC and $\Delta ADVOL$. Other liquidity betas are estimated using the similar procedure in various model specifications. For comparison, we standardize each liquidity beta at monthly frequency and thus allow it to have an equal mean of zero and an equal standard deviation of one. We also incorporate a set of control variables in the regression. β_{MKT}, β_{SMB}, and β_{HML} are individual stock *i*'s Fama−French three-factor loadings, estimated from a time-series model with the liquidity-augmented Fama−French three-factor models using prior 60-month data (annually rebalanced) at the end of the year. We keep the values of β_{MKT}, β_{SMB}, and β_{HML} constant for the following 12 months to be control variables in the regressions. $\ln ME_{t-2}$ is natural log of market capitalization on month *t*−2. BM_{t-2} is the book-to-market ratio on month *t*−2. $RET_{(-12,-7)}$ is the cumulative return from *t*−7 to *t*−12 month. RET_{t-1} is stock return on month *t*−1. $RET_{(-36,-13)}$ is cumulative return from *t*−13 to *t*−36 month. $\ln TURN_{t-2}$ is natural log of share turnover on month *t*−2. IV_{t-2} is the standard deviation of return residuals estimated by regressing individual stocks' daily excess returns on the Fama−French three factors over the month *t*−2. $\ln RV^-_{t-2}$ is natural log of RV^- on month *t*−2. $\ln RV_{t-2}$ is natural log of RV on month *t*−2. $\ln LM12_{t-2}$ is natural log of $LM12$ on month *t*−2. Ex. January is the sample period excluding January. The sample contains NYSE/AMEX stocks with CRSP share codes of 10 or 11 and with the year-end prices less than $5. The *t*-statistics adjusted for errors-in-variables by following Shanken (1992) are reported in square brackets.

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Intercept	0.632	4.592	4.525	4.563	4.513	4.580	4.592	5.110	4.463	3.813	5.080	4.979
	[3.82]	[4.16]	[3.91]	[4.14]	[3.74]	[4.03]	[4.25]	[3.56]	[3.69]	[3.09]	[3.55]	[3.35]
$\boldsymbol{\beta_{\Delta TC}}$	**0.107**	**0.103**	**0.102**	**0.103**	**0.108**	**0.115**	**0.098**	**0.096**	**0.124**	**0.154**	**0.109**	**0.119**
	[2.74]	**[2.83]**	**[2.66]**	**[2.90]**	**[2.68]**	**[2.65]**	**[2.77]**	**[2.07]**	**[2.53]**	**[3.08]**	**[2.00]**	**[2.14]**
$\beta_{\Delta ADVOL}$			0.043						0.064	0.054	0.031	0.025
			[0.94]						[1.24]	[1.01]	[0.53]	[0.41]
$\beta_{\Delta Amihud}$				-0.021					-0.022	-0.023	-0.034	-0.019
				[-0.65]					[-0.58]	[-0.57]	[-0.76]	[-0.41]
$\beta_{\Delta Amihud^-}$					-0.096				-0.098	-0.094	-0.106	-0.073
					[-1.74]				[-1.71]	[-1.55]	[-1.61]	[-1.08]
$\beta_{\Delta Liu}$						-0.064			-0.069	-0.093	-0.041	-0.048
						[-1.48]			[-1.45]	[-1.89]	[-0.87]	[-1.01]
$\beta_{\Delta PS}$							0.059		0.054	0.037	0.064	0.033
							[1.35]		[1.10]	[0.75]	[1.11]	[0.59]
$\beta_{\Delta Sadka}$								-0.042			-0.052	-0.056
								[-0.86]			[-1.06]	[-1.10]
$\beta_{\Delta MKT}$	0.125	0.245	0.238	0.244	0.243	0.250	0.235	0.346	0.231	0.143	0.321	0.194
	[0.71]	[1.75]	[1.61]	[1.76]	[1.59]	[1.74]	[1.72]	[1.94]	[1.49]	[0.92]	[1.80]	[1.11]
$\beta_{\Delta SMB}$	0.087	0.049	0.049	0.047	0.051	0.054	0.052	-0.009	0.053	0.018	-0.002	-0.055
	[0.86]	[0.64]	[0.61]	[0.62]	[0.62]	[0.70]	[0.70]	[-0.09]	[0.63]	[0.20]	[-0.03]	[-0.54]
$\beta_{\Delta HML}$	0.157	0.068	0.067	0.068	0.065	0.076	0.075	0.021	0.070	0.126	0.034	0.114
	[1.48]	[0.71]	[0.66]	[0.71]	[0.63]	[0.77]	[0.80]	[0.16]	[0.67]	[1.21]	[0.26]	[0.90]
$\ln ME_{t-2}$		-0.393	-0.380	-0.386	-0.383	-0.395	-0.393	-0.524	-0.372	-0.308	-0.504	-0.503
		[-2.75]	[-2.54]	[-2.70]	[-2.46]	[-2.68]	[-2.80]	[-2.75]	[-2.37]	[-1.92]	[-2.64]	[-2.56]
BM_{t-2}		0.203	0.189	0.200	0.210	0.201	0.196	0.137	0.183	0.119	0.097	0.057
		[2.16]	[1.92]	[2.13]	[2.04]	[2.08]	[2.10]	[1.07]	[1.76]	[1.13]	[0.76]	[0.44]
$RET_{(-12,-7)}$		0.670	0.662	0.667	0.651	0.653	0.666	0.482	0.621	0.763	0.402	0.528
		[3.25]	[3.07]	[3.25]	[2.89]	[3.06]	[3.30]	[1.83]	[2.70]	[3.18]	[1.52]	[1.90]
RET_{t-1}		-0.026	-0.026	-0.026	-0.026	-0.026	-0.026	-0.023	-0.026	-0.021	-0.023	-0.016
		[-5.54]	[-5.30]	[-5.58]	[-5.12]	[-5.40]	[-5.69]	[-3.65]	[-5.11]	[-4.11]	[-3.74]	[-2.70]
$RET_{(-36,-13)}$		-0.013	-0.019	-0.018	-0.010	-0.014	-0.017	-0.039	-0.036	0.014	-0.054	-0.009
		[-0.21]	[-0.29]	[-0.29]	[-0.14]	[-0.22]	[-0.29]	[-0.47]	[-0.51]	[0.19]	[-0.64]	[-0.10]
$\ln TURN_{t-2}$		0.160	0.161	0.166	0.164	0.151	0.160	0.091	0.158	0.136	0.099	0.054
		[1.42]	[1.37]	[1.48]	[1.34]	[1.32]	[1.45]	[0.58]	[1.28]	[1.08]	[0.65]	[0.35]
IV_{t-2}		-0.142	-0.140	-0.144	-0.143	-0.143	-0.142	-0.027	-0.140	-0.144	-0.032	-0.031
		[-3.13]	[-2.93]	[-3.18]	[-2.88]	[-3.05]	[-3.18]	[-0.47]	[-2.77]	[-2.73]	[-0.57]	[-0.53]
$\ln RV^-_{t-2}$		0.347	0.330	0.344	0.339	0.342	0.347	0.408	0.323	0.280	0.387	0.371
		[3.11]	[2.88]	[3.10]	[2.80]	[3.00]	[3.22]	[2.67]	[2.70]	[2.18]	[2.58]	[2.29]
$\ln RV_{t-2}$		-0.270	-0.255	-0.261	-0.259	-0.272	-0.271	-0.426	-0.248	-0.202	-0.402	-0.402
		[-1.55]	[-1.35]	[-1.47]	[-1.30]	[-1.50]	[-1.59]	[-1.60]	[-1.21]	[-1.06]	[-1.62]	[-1.59]
$\ln LM12_{t-2}$		0.001	0.001	0.001	-0.002	0.001	0.001	-0.002	0.001	-0.005	0.001	-0.008
		[0.01]	[0.04]	[0.03]	[-0.07]	[0.01]	[0.03]	[-0.07]	[0.01]	[-0.42]	[0.03]	[-0.53]
Ex. January	N	N	N	N	N	N	N	N	N	Y	N	Y
Sample Period	1977.01-2013.12	1977.01-2013.12	1977.01-2013.12	1977.01-2013.12	1977.01-2013.12	1977.01-2013.12	1977.01-2013.12	1989.01-2012.12	1977.01-2013.12	1977.01-2013.12	1989.01-2012.12	1989.01-2012.12
Avg. N per month	1,283	967	967	967	967	967	967	938	967	969	938	943
Avg. R^2	0.042	0.094	0.097	0.096	0.096	0.096	0.097	0.102	0.106	0.104	0.115	0.112

Table VII
Price Impact of Liquidity Betas in the Flight Months

This table reports the impact of various liquidity betas on stock returns in the months of flights by estimating the Fama−MacBeth (1973) regression model:

$$R_{i,t} = a_0 + a_1\beta^{H}_{\Delta TC,i,t-1} + a_2\beta^{L}_{\Delta TC,i,t-1} + a_3\beta^{H}_{\Delta ADVOL,i,t-1} + a_4\beta^{L}_{\Delta ADVOL,i,t-1} + a_5\beta^{H}_{\Delta Amihud,i,t-1} + a_6\beta^{L}_{\Delta Amihud,i,t-1}$$
$$+a_7\beta^{H}_{\Delta Amihud^-,i,t-1} + a_8\beta^{L}_{\Delta Amihud^-,i,t-1} + a_9\beta^{H}_{\Delta Liu,i,t-1} + a_{10}\beta^{L}_{\Delta Liu,i,t-1} + a_{11}\beta^{H}_{\Delta PS,i,t-1} + a_{12}\beta^{L}_{\Delta PS,i,t-1}$$
$$+a_{13}\beta^{H}_{\Delta Sadka,i,t-1} + a_{14}\beta^{L}_{\Delta Sadka,i,t-1} + a_{15}\mathbf{X}_i + \varepsilon_{i,t}$$

where $R_{i,t}$ is stock *i*'s excess return relative to the 30-day T-bill rate in flight month *t*. Flight month is identified by the bottom 5% of ΔTC. $\beta^{H}_{\Delta TC,i,t-1}$ ($\beta^{L}_{\Delta TC,i,t-1}$) is high (low) *TC*-beta dummy variable that equals one if stock *i*'s *TC*-beta in the month prior to flight month is in the top (bottom) quintile sorted based on their NYSE breakpoints, and zero otherwise. The dummy variables $\beta^{H}_{\Delta ADVOL,i,t-1}$, $\beta^{L}_{\Delta ADVOL,i,t-1}$, $\beta^{H}_{\Delta Amihud,i,t-1}$, $\beta^{L}_{\Delta Amihud,i,t-1}$, $\beta^{H}_{\Delta Amihud^-,i,t-1}$, $\beta^{L}_{\Delta Amihud^-,i,t-1}$, $\beta^{H}_{\Delta Liu,i,t-1}$, $\beta^{L}_{\Delta Liu,i,t-1}$, $\beta^{H}_{\Delta PS,i,t-1}$, $\beta^{L}_{\Delta PS,i,t-1}$, $\beta^{H}_{\Delta Sadka,i,t-1}$, and $\beta^{L}_{\Delta Sadka,i,t-1}$ are defined similarly. Various liquidity betas for stock *i* in month *t*-1 are estimated simultaneously using a model that includes the Fama−French three factors augmented with all liquidity factors using prior 60-month data (five years of monthly returns continuing through month *t*-1). $\mathbf{X}_i$ is a set of control variables that contains high and low Fama−French three-factor loadings dummy variables for $\beta_{MKT,i,t-1}$, $\beta_{SMB,i,t-1}$, $\beta_{HML,i,t-1}$ and those described in Table V. All independent variables are demeaned. The sample contains NYSE/AMEX stocks with CRSP share codes of 10 or 11 during a period from January 1977 to December 2013 (Analyses regarding $\beta_{\Delta Sadka,i,t-1}$ cover a period from January 1989 to December 2012 due to data available). For brevity, we present only the intercepts and coefficients on dummy variables of various liquidity betas. The *t*-statistic to test whether the average of coefficient is different from zero is reported in square brackets.

	I	II
Intercept	-4.215	-0.706
	[-0.91]	[-0.47]
$\boldsymbol{\beta^{H}_{\Delta TC}}$	**-0.076**	**0.099**
	[-0.33]	**[0.30]**
$\boldsymbol{\beta^{L}_{\Delta TC}}$	**0.683**	**0.802**
	[2.84]	**[3.02]**
$\beta^{H}_{\Delta ADVOL}$	-0.234	-0.535
	[-1.02]	[-1.94]
$\beta^{L}_{\Delta ADVOL}$	-0.058	-0.006
	[-0.19]	[-0.01]
$\beta^{H}_{\Delta Amihud}$	0.125	0.353
	[0.65]	[1.45]
$\beta^{L}_{\Delta Amihud}$	-0.042	0.147
	[-0.18]	[0.49]
$\beta^{H}_{\Delta Amihud^-}$	0.316	0.170
	[1.49]	[0.54]
$\beta^{L}_{\Delta Amihud^-}$	-0.232	-0.496
	[-0.90]	[-1.36]
$\beta^{H}_{\Delta Liu}$	-0.037	-0.516
	[-0.13]	[-1.30]
$\beta^{L}_{\Delta Liu}$	-0.695	-0.518
	[-4.13]	[-1.80]
$\beta^{H}_{\Delta PS}$	-0.059	0.349
	[-0.19]	[0.74]
$\beta^{L}_{\Delta PS}$	-0.176	-0.286
	[-0.66]	[-0.87]
$\beta^{H}_{\Delta Sadka}$		-0.541
		[-1.67]
$\beta^{L}_{\Delta Sadka}$		-0.288
		[-1.02]
$\boldsymbol{\beta^{H}_{\Delta TC} - \beta^{L}_{\Delta TC}}$	**-0.760**	**-0.703**
	[-2.28]	**[-2.24]**
$\beta^{H}_{\Delta ADVOL} - \beta^{L}_{\Delta ADVOL}$	-0.176	-0.529
	[-0.43]	[-0.90]
$\beta^{H}_{\Delta Amihud} - \beta^{L}_{\Delta Amihud}$	0.167	0.205
	[0.57]	[0.58]
$\beta^{H}_{\Delta Amihud^-} - \beta^{L}_{\Delta Amihud^-}$	0.548	0.666
	[1.48]	[1.48]
$\beta^{H}_{\Delta Liu} - \beta^{L}_{\Delta Liu}$	0.658	0.002
	[1.98]	[0.01]
$\beta^{H}_{\Delta PS} - \beta^{L}_{\Delta PS}$	0.117	0.635
	[0.24]	[0.91]
$\beta^{H}_{\Delta Sadka} - \beta^{L}_{\Delta Sadka}$		-0.253
		[-0.48]
Sample Period	1977.01-2013.12	1989.01-2012.12
Avg. N per month	1,051	1,014
Avg. R^2	0.168	0.171

Table VIII
Two Stage Cross-Sectional Regression of Individual Stock Returns: Robustness

This table presents a set of robust results by replicating Models X and XII of Table V. Models I and II replicate Model X of Table V for two sub-periods: January 1977 to December 1995 and January 1996 to December 2013. Models III−VI replicate Models X and XII of Table V by using alternative measures of TC innovations. In Models III and IV, we use ΔTC_t^{AR2}, defined as the reverse residuals from estimating the AR (2) model with a time-trend indictor ($TC_t = a_0 + a_1 TC_{t-1} + a_2 TC_{t-2} + a_3 t + u_t$) using data available up to month *t*; and in Models V and VI, we use ΔTC^{FD}, defined as reverse monthly first differences in TC. For comparison, we standardize each liquidity beta at monthly frequency and thus allow it to have an equal mean of zero and an equal standard deviation of one. For brevity, we present only the regression coefficients on $\beta_{\Delta TC}$ and other liquidity betas for comparison. Ex. January is the sample period excluding January. The sample contains NYSE/AMEX stocks with CRSP share codes of 10 or 11 and with the year-end prices less than $5. The *t*-statistics adjusted for errors-in-variables by following Shanken (1992) are reported in square brackets.

	Sub-periods		Alternative Measures of TC Innovations			
	I	II	III	IV	V	VI
$\boldsymbol{\beta_{\Delta TC}}$	**0.151**	**0.157**				
	[2.49]	**[2.41]**				
$\boldsymbol{\beta_{\Delta TC^{AR2}}}$			**0.149**	**0.113**		
			[2.77]	**[1.81]**		
$\boldsymbol{\beta_{\Delta TC^{FD}}}$					**0.151**	**0.108**
					[2.95]	**[1.90]**
$\beta_{\Delta ADVOL}$	0.072	0.034	0.056	0.027	0.058	0.031
	[1.26]	[0.45]	[1.15]	[0.45]	[1.19]	[0.52]
$\beta_{\Delta Amihud}$	0.004	-0.051	-0.025	-0.022	-0.022	-0.019
	[0.08]	[-0.90]	[-0.70]	[-0.48]	[-0.63]	[-0.42]
$\beta_{\Delta Amihud^-}$	-0.115	-0.071	-0.092	-0.074	-0.088	-0.068
	[-1.51]	[-0.95]	[-1.69]	[-1.10]	[-1.66]	[-1.06]
$\beta_{\Delta Liu}$	-0.118	-0.067	-0.100	-0.053	-0.096	-0.051
	[-1.79]	[-1.17]	[-2.03]	[-1.00]	[-1.99]	[-1.00]
$\beta_{\Delta PS}$	0.014	0.062	0.036	0.031	0.034	0.027
	[0.24]	[0.94]	[0.81]	[0.57]	[0.77]	[0.50]
$\beta_{\Delta Sadka}$				-0.060		-0.058
				[-1.16]		[-1.19]
Control Variables	Y	Y	Y	Y	Y	Y
Ex. January	Y	Y	Y	Y	Y	Y
Sample Period	1977.01-1995.12	1996.01-2013.12	1977.01-2013.12	1989.01-2012.12	1977.01-2013.12	1989.01-2012.12
Avg. N per month	965	974	969	943	969	943
Avg. R^2	0.093	0.116	0.104	0.111	0.104	0.111