Why is the VIX index related to the liquidity premium?

Iman Honarvar*

Abstract

Market makers' compensation for liquidity provision depends on short-term price reversal. Previous empirical studies show that when the VIX is high, the intensity of the short-term price reversal effect is stronger, i.e. market makers charge a higher premium for supplying liquidity to the market. The 3-period theoretical model of this paper explains that this is the case for three reasons; when the VIX is high (1) market makers are more risk averse, (2) asset variances are higher, and thereby, investors have more urgency to trade, and (3) asset correlations are higher, and thus, there is a higher risk of spillover of liquidity shocks amongst assets. Consequently, an escalated level of the VIX index raises market makers' expected return and Sharpe ratio for liquidity provision. Our empirical analyses robustly confirm these theoretical findings.

1 Introduction

The buying and selling orders of a particular asset do not always match. Market makers provide liquidity and immediacy by absorbing this imbalance of orders. At the time of investors' urgency to sell an asset, which usually coincides with a price fall, market makers

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are ready to buy, aiming at selling the asset back to the market in a few hours, when the price recovers. Thus the compensation for market makers' liquidity provision is closely related to short-term price reversal. Nagel (2012) empirically shows that the VIX index positively correlates with the intensity of the short-term reversal effect in stock prices. He argues that when the VIX is high, market makers are financially constrained and therefore they require a higher premium for providing liquidity. Consequently, this higher price of liquidity increase the magnitude of the short-term price reversal effect.

Although the association between the VIX and the short-term reversal effect has been *empirically* highlighted by Nagel (2012), this paper contributes to the literature by providing another *theoretical* explanation for the mechanism that underlies this positive relationship. For this purpose, we extend the theoretical framework of Vayanos and Wang (2012) and show that even in a perfect market with no financial constraints, higher asset covariances and/or more risk-averse market makers contribute to stronger short-term price reversals and a higher price of liquidity. Given that the VIX index is a proxy for stocks' average conditional covariance and to some extent it captures investors' risk aversion (Bollerslev et al. (2011)), we theoretically conclude that larger values of the VIX must coincide with stronger short-term price reversals and a higher liquidity premium in the stock market.

A large trade has a significant price impact. Whether the price reverts or not depends on the information (a)symmetry between the trade parties. Previous theoretical and empirical studies show that a trade with information asymmetry coincides with a permanent price movement that does not revert. For example, the huge buying pressure of an insider trader, who anticipates higher future payoffs, might move the price up. This price increase will not revert, but instead with the gradual release of the good news about the future payoffs, the price continues to rise. On the other hand, a price change in a non-informed trade shortly reverts. For instance, the rush of uninformed investors for selling a particular asset might create a negative jump in the price process, because the capacity of the market for absorbing this liquidity demand is limited. However since the future payoffs are unaffected, over the subsequent periods the price will gradually bounce back.[1] In this study, we investigate

[1] Among many see: Kyle (1985), Glosten and Milgrom (1985), Admati (1991), Campbell et al. (1993), Llorente et al. (2002), Avramov et al. (2006) and Cheng et al. (2014).

the short-term price reversal phenomenon under the assumption of a perfect (frictionless) market, without information asymmetry and funding constraints.

Sometimes due to risk management considerations or a change of perception about the future payoffs, investors infer that they are more- or less-than-optimal exposed to the risk of certain assets, and therefore, they desire to revert back to optimal by re-balancing their portfolio. Following Grossman and Miller (1988), Vayanos (1999), Vayanos (2001) and Vayanos and Wang (2012), our economic model creates this selling or buying motives by giving an extra endowment to one of the trade parties. Before receiving the endowment, this party has been holding an optimal portfolio. Therefore in the absence of any news on the fundamental value of assets, this extra endowment departs her portfolio from the optimal and creates a buying or selling demand. The extra endowment that triggers the trade, the *liquidity shock*, can be asset-specific or systematic. An asset-specific liquidity shock (endowment) resembles the payoff of some futures contracts, written on a particular asset.[2] Similarly, a systematic liquidity shock (endowment) resembles the payoff of a portfolio of futures contracts, written on different risky assets. The weight of the futures contracts of each risky asset in this portfolio depends on the loading of that particular asset on the common systematic liquidity risk.

The model is constituted of equally risk-averse investors, who can trade one riskless bond and N risky assets at three different time points ($t = 0, 1, 2$). The risky assets only yield some random liquidation payoffs at time 2. Investors trade at times 0 and 1 to maximize their expected utility of consumption at time 2. At time 0, investors are identical and therefore they hold the market portfolio. However at time 1 a random fraction of the investors, labeled as *liquidity demanders*, receive the risky endowment. This endowment deviates the liquidity demanders' portfolio from the previous equilibrium that applied to all investors, and thus, it persuades them to trade and share the risk with the rest of the investors, labeled as *liquidity suppliers*.[3] Since the liquidity suppliers' portfolio is already optimal (because they do not receive any endowment), they do not have any incentive to engage in this trade, unless they

[2] For more intuition on our endowment design, see Grossman and Miller (1988).

[3] Instead of labeling these investors as *market makers*, we use the more general term, *liquidity suppliers*. Because nowadays, many other market participants (such as high-frequency traders, hedge-funds, dealers and trading desks) also provide liquidity and immediacy to the market.

receive some price discounts. This deviates the trading prices of the assets at time 1 from their fundamental (risk-adjusted) values. However since the the liquidation payoffs of the assets at time 2 are unaffected, later in the liquidation time, the asset prices revert back to their fundamental values. This phenomenon, in which the price of an asset diverts from its fundamental value and shortly reverts back, is called the short-term price reversal and it yields to a positive return for the liquidity suppliers. In fact, this return is the liquidity suppliers' compensation for providing liquidity. Our theoretical model shows that the price reversals are stronger when the investors are more risk-averse, the liquidity shocks are bigger, or the asset covariances are higher.

Asset covariances increase with the variance of individual assets or the correlations among them. At *individual asset level*, we find that the impact of an identical liquidity shock in creating short-term price reversal is stronger when the asset variance is higher. Because at this time, the future payoff is more risky and the liquidity demanders, whose portfolio has departed from the optimal, feel more urgency to trade. Moreover due to the higher uncertainty about the future payoff, there is a higher chance that after the market makers provide liquidity, the price does not revert. Consequently, the market makers charge a higher liquidity premium and the short-term price reversal effect becomes stronger. This is also the case in assets' cross section; at any point in time there is a higher liquidity premium for more volatile assets. Similarly in an economic model with funding constraints, Brunnermeier and Pedersen (2009) show that market makers charge a higher liquidity premium on volatile assets, as these assets require larger margins. However our theoretical model shows that even in the absence of financial constraints, as long as the market makers are risk averse, the intensity of short-term price reversal increase with asset variance. This can also be inferred from Vayanos and Wang (2012), who develop a single asset model.

More importantly, at *inter-asset level* we show that the correlation among two assets is the channel, through which an asset-specific liquidity shock flows from one asset to the other one. Hence, a higher correlation escalates the risk of liquidity shocks spillover among assets, and consequently, it increases market makers' required return for providing liquidity and intensifies the short-term price reversal effect in the market.

We investigate the validity of these theoretical findings by constructing different portfolios that speculate on short-term reversals in stock prices. These portfolios are re-allocated every day by buying the stocks that had a bad performance and short-selling the stocks that had a good performance, over the last trading day(s). We find that the returns of these portfolios are substantially positively related to the different measures of stocks' average variance and correlation, namely: the VIX index (a proxy for the average covariance under the risk-neutral measure), the daily realized volatility of the S&P500 index (a proxy for the average covariance under the physical measure), the average conditional correlation (Buraschi et al. (2014)) and the average conditional variance (Bakshi et al. (2003)) of the stocks in the S&P100 index.

Our regression analyses, for the time period from 1996:01 to 2014:08, show that one standard deviation increase in the VIX index, stocks' average correlation and stocks' average variance respectively contributes to economically significant higher daily returns of 0.50%, 0.40% and 0.28% on a strategy that exploits daily price reversal in the CRSP stock universe. This higher contribution of stock correlations, compared to stock variances, in creating short-term price reversals underlines the higher risk of liquidity shocks spillover in a market with highly correlated assets. Consistent with our theoretical prediction, this positive relationship also holds for the conditional Sharpe ratio of this strategy.

Nagel (2012) introduces funding constraints (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Acharya et al. (2015)) or market makers' limited risk-appetite (Adrian and Shin (2010)) as the main drivers of the positive relationship between the VIX and the short-term price reversal. However, our robustness tests show that different financial constraint proxies, such as the 1-month USD LIBOR and the Ted-Spread, cannot obsolete the impact of stocks' average covariance in explaining the short-term reversals effect. Hence, the impact of liquidity spillover risk on the short-term price reversals is beyond the funding constraints, proposed by Nagel (2012).

This research is also related to several other studies; the economic model of this paper resembles the theoretical models of Grossman and Miller (1988), Vayanos (1999), Vayanos (2001), Lo et al. (2004), Huang and Wang (2009), Huang and Wang (2010), Cheng et al. (2014), and especially Vayanos and Wang (2012). However in contrast to these single-asset models, our setup includes multiple risky assets and thus it enables us to investigate the connection between asset covariances and liquidity premium. Kodres and Pritsker (2002) and Andrade et al. (2008) develop multi-asset models, however unlike us, they study financial contagion through cross-market re-balancing and return predictability due to cross-stock price pressure.

Our theoretical findings provide an explanation for the empirical results of Bansal et al. (2014) and Chung and Chuwonganant (2014), who find that the VIX index is related to stocks' turnover and illiquidity. Similar to So and Wang (2014) who find that rising uncertainty increases market makers' expected compensation for liquidity provision, we show that higher risk of spillover of liquidity shocks also raises market makers' required return. We provide another reason why investors have aversion to high values of the VIX (Ang et al. (2006)) and correlation (Driessen et al. (2009) and Krishnan et al. (2009)); at this time liquidity becomes expensive. Finally, our model theoretically explains the empirical findings of Pástor and Stambaugh (2003) (the existence of a premium for exposure to systematic liquidity risk), Chordia et al. (2005) (the negative relationship between volatility and liquidity) and Acharya et al. (2015) (escalating asset covariances after a liquidity shock).

2 Model

The economy contains one riskless bond and N risky assets in three different time points ($t = 0, 1, 2$). Investors trade at time 0 and 1, but they liquidate and consume all their wealth at time 2. Moreover, investors have identical exponential utility functions

$$U(C_2) = -exp(-\alpha C_2), \tag{1}$$

where α and C_2 are, respectively, the coefficient of absolute risk-aversion and the final consumption level. For the sake of tractability, we assume the coefficient of absolute risk-aversion is the same for all investors. Exponential utility function eliminates wealth effect, i.e. portfolio reallocation due to a wealth shock, and thus it enables us to focus on liquidity demands caused by risk sharing motives.

There are B units of riskless bond in the market. The risk-free rate is zero and the riskless bond is in perfect elastic supply, i.e. the quantities in which the investors buy or sell the riskless bond do not influence its price. This is the same as assuming that there is no funding constraint in the market. Moreover, the exogenous liquidation payoffs of the risky assets at the final moment ($t = 2$) are jointly normally distributed

$$S_2 \sim N(\bar{S}, \varSigma). \tag{2}$$

Here, S_2 is the $N \times 1$ vector of the risky assets' liquidation payoffs at $t = 2$, and $\varSigma = [\sigma_{ij}]$ is the corresponding $N \times N$ covariance matrix. To rule out information asymmetry, we assume that the liquidation payoffs distribution (equation 2) is public information.

To isolate the short-term reversal effect, we assume that the expected liquidation payoffs do not change over the three time points considered in this model

$$E_0[S_2] = E_1[S_2] = \bar{S}, \tag{3}$$

where $E_t(.)$ is the expectation function conditioned on the information available at time t. This is equivalent to assuming that the economic factors, associated with the fundamental values of the assets, are constant over the horizon of the model, from $t = 0$ to $t = 2$. Since we are studying the short-term reversal effect that materialize within a few hours or days, this is not a strong assumption.

At $t = 0$, investors are identical and indistinguishable from each other. They have the same initial wealth, risk-aversion coefficients and utility functions. Therefore at time 0, all investors hold the market portfolio besides the riskless bond, i.e.

$$\theta_0 = \theta. \tag{4}$$

Here, θ_0 is the $N \times 1$ vector of the investors' portfolio at time 0, and θ is the $N \times 1$ vector of the market portfolio.

At $t = 1$, a fraction $0 < \pi < 1$ of the investors receive some risky endowment of $zM'(S_2 - \bar{S})$. Here z, referred to as the *liquidity shock*, is a normally distributed random variable ($z \sim N(0, \sigma_z^2)$) that is realized at $t = 1$ and it is independent of S_2. Moreover, $M = [m_1, m_2, ..., m_N]'$ is the $N \times 1$ vector of assets' sensitivity to the liquidity shock. This endowment, which has a zero expected value, resembles the payoff of zM' futures contracts written on individual risky assets ($zM'(S_2 - S_1)$), plus $zM'(S_1 - \bar{S})$. The endowment design of our model borrows from Lo et al. (2004), Huang and Wang (2009), Huang and Wang (2010) and especially Vayanos and Wang (2012).

A few points are crucial here; First, the endowment is a private signal that is only observable by the fraction π of investors who receive it. This endowment is the only source of heterogeneity among the investors. Second, at $t = 1$ the liquidity shock (z) is known, however, the liquidation payoffs (S_2) are unknown. Hence at this time, the endowment ($zM'(S_2 - \bar{S})$) is a (normally distributed) random cash flow with a zero expected value. The realization of this endowment will be observed at $t = 2$. Third, this endowment is correlated with the assets' liquidation payoffs (S_2), and thus, the portfolio of the investors who receive this endowment departs from optimal. This is because these investors are already holding the market portfolio (see equation 4), and in addition, they are endowed with some extra cash, which is correlated with the other assets in their portfolio.

To be more specific, let's assume that z is positive and consider an asset-specific liquidity shock that only hits asset i. In other words, all the elements of M are zero except the i^{th} element that is equal to 1. At $t = 1$, a proportion π of the investors receive an endowment equivalent to $zM'(S_2 - \bar{S})$ that will be realized in cash at the liquidation moment ($t = 2$). This endowment is perfectly correlated with the liquidation payoff of asset i in their portfolio. Thus if they do nothing, their portfolio will be more-than-optimal exposed to the risk of this asset. Hence, this risky endowment persuades them to re-balance their portfolio by selling a part of their holdings on asset i or any other asset that is very similar to (correlated with) it.[4] Since the investors, who receive the endowment, initiate the trade they are called the liquidity demanders. The remainder of the investors ($1 - \pi$), who accommodate these demands, are called the liquidity suppliers.

Investors' risk-aversion and preferences endogenously imply the asset prices at time 0 and 1, referred to as S_0 and S_1, respectively. In order to quantify the magnitude of price reversals, first we must find the asset prices at these two time points. The implications of the outlined model are presented in the following four propositions. Appendix A provides the proofs of the propositions.

Proposition 1 - equilibrium portfolios at time 1: By knowing the liquidity shock (z) at time 1, the liquidity demanders re-allocate their portfolios to hold θ_1^d units of the risky

[4] Similarly if the liquidity shock (z) is negative, the liquidity demanders will re-balance their portfolios by buying more shares of asset i.

assets. One can show that the $N \times 1$ vectors of the liquidity demanders' optimal holding (θ_1^d) and the liquidity suppliers' optimal holding (θ_1^s) are respectively

$$\theta_1^d = \frac{1}{\alpha}\Sigma^{-1}(\bar{S} - S_1) - zM, \tag{5}$$

and

$$\theta_1^s = \frac{1}{\alpha}\Sigma^{-1}(\bar{S} - S_1). \tag{6}$$

According to equation 5 and 6, the asset prices (S_1), the riskiness of the liquidation payoffs (Σ) and the investors' risk-aversion (α) negatively affect the amount of the risky assets that both types of investor would hold at $t = 1$.

Proposition 2 - equilibrium prices at time 1: At $t = 1$, both investors post their demand functions (equation 5 and 6) in a Walrasian auction. The equilibrium asset prices in these trades are

$$S_1 = \bar{S} - \alpha\Sigma\theta - \alpha\pi z\Sigma M, \tag{7}$$

where $\bar{S}$ is the vector of the expected payoffs from holding the risky assets (see equation 2), and $\alpha\Sigma\theta$ is the vector of the market risk premia. Therefore, $\bar{S} - \alpha\Sigma\theta$ is the vector of the risk-adjusted asset prices in a market with no liquidity shock (i.e. when $z = 0$). Moreover, $\alpha\pi z\Sigma M$ is the price adjustment vector due to the realized liquidity shock (z). From equation 7, it is clear that the occurrence of a liquidity shock at time 1 ($z \neq 0$) departs the asset prices from their risk-adjusted expected payoffs ($\bar{S} - \alpha\Sigma\theta$).[5]

Corollary 2.1: An asset-specific liquidity shock ($z_i \sim N(0, \sigma_{z_i}^2)$) to asset i diverts the price of this asset from its risk-adjusted expected payoff

$$S_{1i} = \bar{S}_i - \alpha\sum_{k=1}^{N}\theta_k\sigma_{ki} - \alpha\pi z_i\sigma_{ii}, \tag{8}$$

Here, S_{1i} is the prices of asset i at $t = 1$, and σ_{ii} and $\bar{S}_i$ are, respectively, its variance and expected liquidation payoff. Also σ_{ij} is the covariance between assets i and j. Thus $\bar{S}_i - \alpha\sum_{k=1}^{N}\theta_k\sigma_{ki}$ is the risk-adjusted price of asset i in a market with no liquidity shock,

[5] Liquidity risk ($z \sim N(0, \sigma_z^2)$) creates excess covariance in asset prices; $Covar_0(S_2 - S_1) = \Sigma + \alpha^2\pi^2\sigma_z^2\Sigma MM'\Sigma'$. In this equation while Σ is the covariance matrix of the fundamental values of the assets, $\alpha^2\pi^2\sigma_z^2\Sigma MM'\Sigma'$ is the excess covariance induced by the liquidity risk. This confirms the empirical finding of Acharya et al. (2015) that liquidity risk causes excess correlation in asset prices.

and $\alpha\pi z_i\sigma_{ii}$ is the price pressure on this asset due to the asset-specific liquidity shock z_i. Obviously, an identical asset-specific liquidity shock (z_i) affects a volatile asset more vigorously. Because, ceteris paribus, holding more-than-optimal of a volatile asset is much more unfavourable to the liquidity demanders, and thus, when an asset-specific liquidity shock hits a volatile asset they have more urgency to sell it. At the same time, due to the higher uncertainty about the future payoffs, the liquidity suppliers require a higher price discount while providing liquidity on a volatile asset.

Corollary 2.2: An asset-specific liquidity shock ($z_i \sim N(0, \sigma_{z_i}^2)$) to asset i diverts the price of any correlated asset j from its risk-adjusted expected payoff

$$S_{1j} = \bar{S}_j - \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj} - \alpha\pi z_i \sigma_{ij}. \tag{9}$$

Here, $\bar{S}_j - \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj}$ is the risk-adjusted price of asset j in a market with no liquidity shock, and $\alpha\pi z_i\sigma_{ij}$ is the price pressure on this asset due to an asset-specific liquidity shock (z_i) to asset i. Clearly, while asset variances influence the intensity of deviation from the fundamental values (equation 8), the correlation between two assets is the channel, through which a liquidity shock flows from one asset to the other one.

According to equation 9, an asset-specific liquidity shock to the i^{th} asset will be transmitted to the whole market. When z_i is positive, the liquidity demanders are endowed with some risky endowment that is perfectly correlated with the liquidation payoff of asset i. This will depart their portfolio from the optimal. Hence at time 1, they decide to re-optimize their portfolio by selling a portion of their holdings on asset i or any asset which is highly correlated with (similar to) it. However since the liquidity suppliers' portfolio is already optimal, they do not have any incentive to buy, unless these assets are sold cheaper than their risk-adjusted expected payoffs. Consequently, the liquidity suppliers provide liquidity by charging a discount ($\alpha\pi z_i\sigma_{ij}$) on any correlated asset j. These jumps are the compensation that they expect for providing liquidity.

Corollary 2.3: At time 1, after the asset-specific liquidity shock z_i hits asset i, the liquidity suppliers provide liquidity. For example if $z_i > 0$, the liquidity demanders will have excessive exposure to the risk of asset i and they want to sell this asset or any one that is correlated with it. Thus on the other side of the market, the liquidity suppliers will be net buyers. The expected return of holding one more unit of asset j from $t = 1$ to $t = 2$ is

$$E_1[S_{2j} - S_{1j}] = \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj} + \alpha \pi z_i \sigma_{ij}, \tag{10}$$

and the corresponding variance is

$$Var_1[S_{2j} - S_{1j}] = \sigma_{jj}, \tag{11}$$

From 10 and 11, one can show that the Sharpe ratio of a strategy that speculate on the short-term price reversal of asset j is

$$SharpeRatio(j) = \frac{\alpha \sum_{k=1}^{N} \theta_k \sigma_{kj} + \alpha \pi z_i \sigma_{ij}}{\sqrt{\sigma_{jj}}}. \tag{12}$$

From equation 12 it is clear that the Sharpe ratio of the liquidity provision strategy, i.e. speculating on the short-term price reversal, is an increasing function of investors' risk aversion as well as asset variances and correlations.

Proposition 3 - short-term price reversal: According to equation 7, at $t = 1$ the asset prices deviate from their risk-adjusted expected payoffs ($\bar{S} - \alpha \Sigma \theta$). But later at $t = 2$, the liquidation payoffs are realized and the asset prices revert back to their fundamental values (S_2). This phenomenon is called the short-term price reversal and it creates negative auto-covariations in the price processes. One can measure the intensity of this effect with

$$\gamma = -diag\Big(Covar_0[S_2 - S_1, S_1 - S_0]\Big). \tag{13}$$

Here, $Covar(S_2 - S_1, S_1 - S_0)$ is the $N \times N$ auto-covariation matrix of the price processes and $diag(.)$ returns the $N \times 1$ vector of the diagonal elements. According to equation 13, if the price of an asset is serially negatively auto-correlated, then its corresponding elements in γ will be positive. In our setup, one can show that

$$\gamma = \alpha^2 \pi^2 \sigma_z^2 diag(\Sigma M M' \Sigma'). \tag{14}$$

From equation 14, it is clear that the short-term reversals (γ) in the price processes are stronger, when investors are more risk-averse (α), a larger population of the investors are affected by the liquidity shock (π), the liquidity shock is more intensive (σ_z^2), or when the covariance values among asset pairs are higher (Σ). Since the VIX index is a proxy for stocks' average conditional covariance and to some extent it captures investors' risk aversion, we theoretically conclude that the intensity of the short-term reversals in stock prices rises with the level of the VIX index.

Corollary 3.1: If an asset-specific liquidity shock ($z_i \sim N(0, \sigma_{z_i}^2)$) occurs to asset i, then the magnitudes of price reversals in this asset and any asset j are respectively

$$\gamma_i = \alpha^2 \pi^2 \sigma_{z_i}^2 \sigma_{ii}, \tag{15}$$

and

$$\gamma_j = \alpha^2 \pi^2 \sigma_{z_i}^2 \sigma_{ij}, \tag{16}$$

According to equation 15 the intensity of the short-term price reversal in asset i, created with an asset-specific liquidity shock to this asset, increases with the variance of asset i (σ_{ii}) and the size of the liquidity risk ($\sigma_{z_i}^2$); market makers require a higher premium for providing liquidity on an asset with a larger variance or a bigger asset-specific liquidity risk. Moreover based on equation 16, an asset-specific liquidity shock to asset i will be transmitted to any other asset j that has a non-zero correlation ($\sigma_{ij} \neq 0$) with it. When asset correlations are higher, a liquidity shock spread to the rest of the market more efficiently.

Our model provides two reasons of commonality in liquidity, highlighted by Chordia et al. (2000), Huberman and Halka (2001), Chordia et al. (2001), Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008); assets' exposure to common systematic liquidity shock (σ_z in equation 14) or spillover of asset-specific liquidity shocks (σ_{z_i} in equation 16) amongst correlated assets.

Proposition 4 - equilibrium prices at time 0: The asset prices, at time 0, before observing a liquidity shock are

$$S_0 = \bar{S} - \alpha \Sigma \theta - \frac{\kappa \pi}{1 - \pi + \kappa \pi} \Big(\frac{\alpha \Delta_1}{\Delta_0} \Big) \Sigma M, \tag{17}$$

where

$$\Delta_0 = 1 + \alpha^2 \sigma_z^2 (\pi^2 - 2\pi) M' \Sigma M, \tag{18}$$

$$\Delta_1 = \alpha^2 \sigma_z^2 \theta' \Sigma M, \tag{19}$$

and

$$\kappa = \sqrt{\frac{1 + \alpha^2 \pi^2 \sigma_z^2 M' \Sigma M}{1 + \alpha^2 (\pi^2 - 2\pi) \sigma_z^2 M' \Sigma M}} exp\Big(\frac{\alpha^2 \Delta_1 \theta' \Sigma M}{2\Delta_0} \Big). \tag{20}$$

In equation 17, $\bar{S} - \alpha \Sigma \theta$ refers to the $N \times 1$ vector of asset prices adjusted for the market risk, and $\frac{\kappa\pi}{1-\pi+\kappa\pi}\Big(\frac{\alpha\Delta_1}{\Delta_0}\Big)\Sigma M$ is the $N\times 1$ vector of individual assets' liquidity risk premia. In particular, $\frac{\kappa\pi}{1-\pi+\kappa\pi}$ is the risk-neutral probability of being a liquidity demander and $\frac{\alpha\Delta_1}{\Delta_0}\Sigma M$ is the $N \times 1$ vector of liquidity premia that one would expected on the risky assets, conditioned on being a liquidity demander. The size of this liquidity premium depends on investors' level of risk aversion (α), assets' loading on the common liquidity shock (M), the intensity of the liquidity shock (σ_z^2), as well as, asset variances and correlations.

Equation 17 confirms the empirical findings of Pástor and Stambaugh (2003) that firstly, assets with high sensitivity to systematic liquidity risk (i.e. assets with large elements in M) are compensated with higher expected return, and secondly, volatility increase the liquidity premium.[6]

3 Empirical Analysis

The theory predicts that higher asset variances and correlations lead to stronger price reversals (see equation 15 and 16). In this section, we test the validity of this theoretical finding using a portfolio that speculates on stocks short-term price reversals and various measures of average covariance, namely the VIX and the realized volatility of the S&P500 index, as well as, the average conditional correlation and the average conditional variance of the stocks in the S&P100 index. The VIX index and the realized volatility of the S&P500 index are, respectively, proxies for stocks' average covariance under the risk-neutral and the physical measures.

We estimate the daily time series of the realized volatility of the S&P 500 index with the cumulative squared intradaily returns (5-minute) on each day (see e.g. Andersen and

[6] If asset i is prone to an asset-specific liquidity shocks ($z_i \sim N(0, \sigma_{z_i}^2)$), then the ex-ante price of any asset j in this market is $S_{0j} = \bar{S}_j - \alpha \sum_{k=1}^{N} \theta_k \sigma_{kj} - \frac{\kappa_i \pi}{1-\pi+\kappa_i\pi}\Big(\frac{\alpha\Delta_{1,i}}{\Delta_{0,i}}\Big)\sigma_{ij}$, where $\Delta_{0,i} = 1 + \alpha^2\sigma_{z_i}^2(\pi^2 - 2\pi)\sigma_{ii}$, $\Delta_{1,i} = \alpha^2\sigma_{z_i}^2 \sum_{j=1}^{N}\theta_j\sigma_{ij}$, and $\kappa_i = \sqrt{\frac{1+\alpha^2\pi^2\sigma_{z_i}^2\sigma_{ii}}{1+\alpha^2(\pi^2-2\pi)\sigma_{z_i}^2\sigma_{ii}}} exp\Big(\frac{\alpha^2\Delta_{1,i}\sum_{j=1}^{N}\theta_j\sigma_{ij}}{2\Delta_{0,i}}\Big)$.
According to this equation, even though that the liquidity shock only hits asset i, investors expect $\frac{\kappa_i\pi}{1-\pi+\kappa_i\pi}\Big(\frac{\alpha\Delta_{1,i}}{\Delta_{0,i}}\Big)\sigma_{ij}$ as the liquidity risk premium for investing in any asset j in this market. In particular, the size of this liquidity premium depends on the covariance between asset i and j.

Bollerslev (1998)). To make it annualized and thus comparable with the VIX, we multiply the realized volatility of each day by $\sqrt{252}$. We obtain the intradaily return time series of the S&P500 index from Tick Data. Also we use the methodologies of Bakshi et al. (2003) and Buraschi et al. (2014) to compute the average conditional variance and the average conditional correlation of the S&P 100 stocks. For this purpose, we get the daily price of the options traded on this index and its constituents from OptionMetrics database. The horizon for which we calculate stocks' variance expectations is 30 days. Appendix B provides the details of our implementation.

Also, in order to construct a portfolio that exploits the short-term reversals in stock prices we obtain the daily closing prices of the stocks traded at the NYSE, AMEX and NASDAQ from the CRSP database. On each day, this portfolio speculates on price reversion by buying (selling) the stocks that have underperformed (outperformed) the equally-weighted market index over the last trading day. Thus following Lehman (1990), we set the weight of stock i on day t as

$$w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}. \tag{21}$$

Here, $R_{i,t-1}$ and $R_{m,t-1}$ respectively correspond to the returns of stock i and the equally-weighted market portfolio, on day $t-1$.[7] Since this reversal strategy portfolio has both long and short positions on each day, it has less exposure to factors other than the short-term price reversal, such as the market risk.[8]

The weighting strategy of equation 21, by construction, tends to buy (sell) low-beta (high-beta) stocks after a day that the market return is positive and vice versa. To ensure

[7] Hendershott and Menkveld (2014) find that the half-life of the short-term price reversal ranges from 0.54 to 2.11 days for different market capitalization quintiles. Also Hansch et al. (1998) show that especially for illiquid stocks, the price reversion might take more than one day. To capture delayed price reversals, we also create a reversal strategy portfolio, in which the weight of stock i on day t depends on its $\tau = 1, ..., 5$ days lagged returns; $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Appendix C.1 reports the results of this robustness test.

[8] Moreover to check the robustness of our results, we construct alternative reversal strategy portfolios that are proposed by Lo and MacKinlay (1988) and Nagel (2012). Appendix C.2 reports the results of these robustness tests.

that the return of this portfolio is not driven by the market fluctuations, following Nagel (2012), we orthogonalize it with respect to the market using regression equation 22.

$$Reversal_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 \Big(R_{m,t} \times sign(R_{m,t-1}) \Big) + ResReversal_t. \tag{22}$$

Here, $Reversal_t$ is the return of the reversal strategy portfolio constructed by equation 21, and $sign(R_{m,t-1})$ denotes the sign of the market return in the previous trading day. In the next section, we perform the regression analyses based on the intercept plus the residuals of regression equation 22 (i.e. $\beta_0 + ResReversal_t$).

3.1 Summary Statistics

Panel A to C of Table 1 provides summary statistics on the market portfolio, the reversal strategy portfolio, and two proxies for the tightness of the financial constraints. These proxies, which we obtain from the FactSet database, are the 1-month USD LIBOR and the Ted-Spread. The LIBOR is the interest rates that financial institution charge for unsecured loans. Also, the Ted-Spread is the difference between the LIBOR and the T-bill yield, with particular maturities. Since the US government debts are considered risk-free, Ted-Spread is a barometer for the magnitude of credit risk in the market. The frequency of all time series in Table 1 is daily and they range from 1996:01 to 2014:08. Table 2 displays the correlation matrix of these time series.

In contrast to the market portfolio, a reversal strategy requires daily re-allocation and therefore it incurs sizable transaction costs. According to Panel C, our short-term reversal strategy portfolio on average yields to 1.54% return per day, before deducting the transaction costs. Consequently, the annualized Sharpe ratios of this portfolio (13.43) is considerably higher than the same ratio for the market portfolio (0.52). The last column of Panel C reports the corresponding summary statistics for the reversal strategy portfolio, orthogonalized to the market fluctuations using equation 22. As the table shows the effect of the orthogonalization on the distribution of the portfolio return is negligible.

3.2 Regression Analysis

3.2.1 Return

To empirically test the theoretical predictions of the model, we regress the daily return of the constructed reversal strategy (orthogonalized to the market using equation 22) on the VIX, the daily realized volatility of the S&P500 index, the average conditional correlation and the average conditional variance of the stocks in the S&P100 index.[9] We also include a dummy vector that is equal to one before the stock price decimalization (April 9th 2001) and zero after that. The results, reported in Table 3, confirm our theoretical conjecture.

The estimated coefficients for the decimalization dummy are always significantly positive, meaning that before the decimalization the short-term reversal strategies were more profitable. Consistent with Bessembinder (2003), this indicates an improvement in market liquidity after the decimalization. Also Lo and MacKinlay (1988) theoretically show that if stocks react to economic news with different speeds, then a short-term reversal strategy yields to a higher return. Therefore, one reason for the higher profitability of the reversal strategies before the decimalization might be the lower efficiency of the market during this time.

Also Column 1 to 3 show that the higher values of the VIX, the market realized volatility, the average correlation and the average variance are generally associated with a higher return in the short-term reversal strategy. One standard deviation increase in the VIX index (0.084) on average corresponds to ($0.084 \times 5.92 =$) 0.50% higher return, per day. Also one standard deviation increase in stocks' average correlation (0.136) and average variance (0.070) correspond to ($0.136 \times 2.91 =$) 0.40% and ($0.070 \times 4.07 =$) 0.28% higher return in this strategy. This is because when asset variances are higher, liquidity shocks create more

[9] Our model shows that there is no lead-lag effect in the relationship between the intensity of the short-term reversal and the VIX index; these times series correlate contemporaneously. However in contrast to the prediction of our model and to test the predictability of the return on reversal strategies, Nagel (2012) regresses this time series on the 5-days lagged VIX values. Since the VIX index is extremely autocorrelated ($Corr(VIX_t, VIX_{t-5}) = 0.935$) and non-stationary, regressing the return of the reversal strategies on 5-days lagged value of the VIX still gives significant results, as Nagel (2012) finds. For further explanations see Lanne (2002).

urgency to trade. Moreover, rising asset correlations increase the risk of liquidity shock spillover among assets. In both cases, market makers will require a higher premium for providing liquidity, and thus, the intensity of the short-term price reversal increase. Also the inclusion of the other typical control variables, namely the size, value and momentum factors, does not influence the significance of stocks' average correlation and variance in explaining the short-term price reversals in the stock market.

Nagel (2012) introduces market makers' funding constraints (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), captured by the VIX index, as the potential drivers of the positive relationship between the VIX and the short-term price reversal. He argues that when the VIX is high, market makers are probably facing tight financial constraints and thereby they charge a higher premium for liquidity provision. Here, we also investigate whether other proxies of credit-risk and financial constraints can be better explanatory variables than the VIX index, in explaining market makers' expected return and the short-term price reversals effect. For this purpose, we repeat the previous regressions after adding the 1-month USD LIBOR and the Ted-Spread to the independent variables. The results, shown in column 4 to 6, reveal that none of these proxies can obsolete the substantial relationship between stocks' average covariance measures and the short-term price reversals effect.

A positive regression coefficient for the 1-month USD LIBOR and the Ted-Spread means that tighter financial constraints contribute to a stronger short-term price reversal effect. Surprisingly, for the regressions in column 4 to 6, the estimated coefficients of the 1-month USD LIBOR are not always significantly positive and the sign of the estimated coefficients for the Ted-Spread are mostly significantly negative. These findings suggest that financial constraints can not play the role of asset covariances in explaining the short-term price reversals.

3.2.2 Sharpe Ratio

As corollary 2.3 shows the Sharpe ratio of the short-term price reversal strategy is also an increasing function of asset variances and correlations. In this section, we compute the monthly time series of conditional Sharpe ratio for our short-term reversal strategy portfolio and test the reliability of this theoretical finding. We set the Sharpe ratio of each month as the ratio of the average to the standard deviation of the daily return observations in that particular month.[10] We also construct the monthly time series of the asset variance and correlation proxies, by calculating their average value over each month. Table 4 reports the regression results for the conditional Sharpe ratio time series.

As the results in Table 4 displays the Sharpe ration is also an increasing function of stocks' average covariance, but the financial constraint proxies do not show any clear relationship with this ratio.

3.3 Cross Sectional Evidence

Corollary 3.1 also suggests that an asset with a large variance (σ_{ii}) or a large exposure to asset-specific liquidity shocks (σ_{z_i}) experiences stronger short-term price reversals, i.e. it has a higher price of liquidity. In this section, we investigate the validity of this theoretical finding in the cross section of stocks. Thus for each year, we double-sort the cross section of stocks and group them in 3-by-3 categories of variance and exposure to asset-specific liquidity risk. Then we compare the intensity of the short-term price reversals effect for each of these categories over the subsequent year. We calculate individual stocks' variance, in each year, as the sample variance of its daily returns in that particular year.

Exposure to asset-specific liquidity shocks creates abnormally-large trading volumes for a particular stock. We take the residuals of regression equation 23 as the abnormal trading volume of stock i on day t

$$VL_{i,t} = \beta_{0,i} + \beta_{1,i} MrktVL_t + AbnormVL_{i,t}. \tag{23}$$

Here, $VL_{i,t}$ and $MrktVL_t$ represent the trading volumes of stock i and the whole market on day t, in dollar terms (i.e. the number of traded shares, times, the closing prices). We compute the sample skewness of $AbnormVL_{i,t}$ to measure the exposure of stock i to asset-specific liquidity shocks in each year.

[10]Since the average return of the short-term price reversal strategy portfolio is considerably higher that the risk free rate (see Table 1), we do not deducting the risk free rate from the average return. Of course, doing so does not change our results quantitatively and qualitatively.

For every year, we double-sort the stocks universe by splitting their cross section into three different variance terciles, and then within each terciles, forming three different levels of exposure to asset-specific liquidity risk. We perform the short-term reversal strategy of equation 21 for the stocks of each category, over the subsequent year. By repeating this algorithm for the entire sample of stocks in the CRSP database from 1996 to 2014, we obtain the time series of nine reversal strategy portfolios with different levels of exposure to variance and asset-specific liquidity risk.

Table 5 provides summary statistics on these reversal strategy portfolios and reports the estimated coefficients for regressing the corresponding return time series on the VIX index and certain control variables.

According to Table 5 the reversal strategies implemented for the stock categories with higher variance or higher exposure to asset-specific liquidity risk yield better average daily returns. In other words, stocks with higher variance or higher exposure to asset-specific liquidity shocks experience stronger price reversals, as market makers expect a larger compensation for providing liquidity for them. Moreover, the regression results show positive coefficients for the VIX index, meaning that an increase in stocks' average covariance intensifies the short-term price reversals for all of stock categories, as it escalates the risk of liquidity shocks spillover across assets.

4 Concluding Remarks

Market makers provide liquidity to the market, and their compensation depends on short-term price reversal. Nagel (2012) shows that the intensity of the short-term price reversal effect in the stock market increases with the VIX index. He argues that when the VIX is high, the market makers are financially constrained and therefore they charge a higher premium for providing liquidity. This higher price of liquidity intensifies the short-term price reversal.

In this paper, we develop a 3-period economic model and provide another explanation for the strong relationship between the short-term price reversal and the VIX index. Our theoretical model shows that when asset variances increase there is more need for liquidity and when asset correlations increase there is a higher risk of liquidity shocks spillover among assets. Both factors increase market makers' required return. Since the VIX index is a proxy of stocks' average covariance, it must be positively related to the intensity of the short-term price reversal in the stock prices.

Appendix A Proofs

The proofs, provided in this section, are inspired by Vayanos and Wang (2012).

Proposition 1: The liquidity demanders maximize their expected utility of the liquidation time, by choosing the optimal value of θ_1^d at time 1. The liquidity demanders' wealth at $t = 2$ will be constitute of their wealth from time 1 (W_1), their capital gain from investing on the risky assets ($\theta_1^{d\prime}(S_2 - S_1)$), and the endowment that they receive ($zM'(S_2 - \bar{S})$. Thus

$$W_2{}^d = W_1 + \theta_1^{d\prime}(S_2 - S_1) + zM'(S_2 - \bar{S}). \tag{A.1}$$

From equation 1 and A.1, the liquidity demanders' expected utility at time 1 is

$$U_1^d = -E_1\Big[exp\Big(-\alpha W_1 - \alpha\theta_1^{d\prime}(S_2 - S_1) - \alpha zM'(S_2 - \bar{S})\Big)\Big]. \tag{A.2}$$

At time 1, the size of the liquidity shock (z) is known, but the asset liquidation payoffs (S_2) are the only random variables in equation A.2. Thus equation 2 and A.2 yields

$$U_1^d = -exp\Big(-\alpha W_1 + \alpha\theta_1^{d\prime}(S_1 - \bar{S}) + \frac{\alpha^2}{2}(\theta_1^d + zM)'\Sigma(\theta_1^d + zM)\Big). \tag{A.3}$$

To maximize the expected utility in terms of the risky assets weights (θ_1^d), we must set the corresponding derivative to zero, i.e.

$$\frac{\partial U_1^d}{\partial \theta_1^d} = \big(\alpha S_1 - \alpha\bar{S} + \alpha^2\Sigma(\theta_1^d + zM)\big) \times U_1^d = 0. \tag{A.4}$$

Equation A.4 gives the liquidity demanders' optimal holding at time 1 as

$$\theta_1^d = \frac{1}{\alpha}\Sigma^{-1}(\bar{S} - S_1) - zM. \tag{A.5}$$

The liquidity suppliers do not observe any liquidity shock. Thus by setting $z = 0$ in equation A.3, we have the liquidity suppliers' expected utility at time 1 as

$$U_1^s = -exp\Big(-\alpha W_1 + \alpha\theta_1^{s\prime}(S_1 - \bar{S}) + \frac{\alpha^2}{2}\theta_1^{s\prime}\Sigma\theta_1^s\Big). \tag{A.6}$$

From equation A.6, one can show that the liquidity suppliers' optimal holding at time 1 is

$$\theta_1^s = \frac{1}{\alpha}\Sigma^{-1}(\bar{S} - S_1). \tag{A.7}$$

Proposition 2: At time 1, a random population π of the investors (the liquidity demanders) hold θ_1^d and the rest (the liquidity suppliers) hold θ_1^s. The aggregate holdings must be equal to the market portfolio (θ).

$$\pi\theta_1^d + (1-\pi)\theta_1^s = \theta. \tag{A.8}$$

By replacing the values of θ_1^d and θ_1^s from equation A.5 and A.7 into equation A.8, we get the equilibrium asset prices at time 1 as

$$S_1 = \bar{S} - \alpha\Sigma(\theta + \pi z M). \tag{A.9}$$

Proposition 3: One can rewrite equation A.9 as

$$S_2 - S_1 = S_2 - \bar{S} + \alpha\Sigma(\theta + \pi z M), \tag{A.10}$$

$$S_1 - S_0 = \bar{S} - \alpha\Sigma(\theta + \pi z M) - S_0. \tag{A.11}$$

Inserting equation A.10 and A.11 into definition of equation 13 gives

$$\gamma = -diag\Big(Covar_0[S_2 - S_1, S_1 - S_0]\Big) = -diag\Big(Covar_0[S_2 + \alpha\pi z\Sigma M, -\alpha\pi z\Sigma M]\Big). \tag{A.12}$$

Since $E(zS_2) = 0$, we have

$$\gamma = \alpha^2\pi^2\sigma_z^2 diag(\Sigma M M'\Sigma'). \tag{A.13}$$

Proposition 4: We know that investors' wealth at time 1 is equal to their wealth from time 0 (W_0), plus their capital gain from investing in the risky assets ($\theta_0'(S_1 - S_0)$). Thus

$$W_1 = W_0 + \theta_0'(S_1 - S_0). \tag{A.14}$$

By replacing S_1 from equation A.9 into equation A.14, we have

$$W_1 = W_0 + \theta_0'\Big(\bar{S} - S_0 - \Sigma(\alpha\theta + \alpha\pi z M)\Big). \tag{A.15}$$

Moreover from equation A.5 and A.9, we have

$$\theta_1^d = \theta + (\pi - 1)zM. \tag{A.16}$$

If we insert A.15 and A.16 into A.3, we get the liquidity demanders' expected utility at time 1 as

$$U_1^d = -exp\Bigg(\overbrace{-\alpha W_0 - \alpha\theta_0'\Big(\bar{S} - S_0 - \Sigma(\alpha\theta + \alpha\pi zM)\Big)}^{-\alpha W_1} \overbrace{-\alpha^2\Big(\theta + (\pi-1)zM\Big)'\Sigma(\theta + \pi zM)}^{-\alpha\theta_1^{d\prime}(S_1 - \bar{S})} + \overbrace{\frac{\alpha^2}{2}\Big(\theta + (\pi-1)zM + zM\Big)'\Sigma\Big(\theta + (\pi-1)zM + zM\Big)}^{\frac{\alpha^2}{2}(\theta_1^d + zM)'\Sigma(\theta_1^d + zM)}\Bigg) \tag{A.17}$$

At time 0 investors are identical, and thus, they all hold the market portfolio. Therefore, we replace the value of θ_0 from equation 4, and define

$$A^d = W_0 + \theta'\bar{S} - \theta' S_0 - \frac{\alpha}{2}\theta'\Sigma\theta, \tag{A.18}$$

$$B^d = -\alpha\theta'\Sigma M, \tag{A.19}$$

$$C^d = \alpha(\pi^2 - 2\pi)M'\Sigma M. \tag{A.20}$$

Then we can rewrite U_1^d in equation A.17 as

$$U_1^d = -exp\Big(-\alpha(A^d + B^d z + \frac{1}{2}C^d z^2)\Big). \tag{A.21}$$

The expectation of U_1^d at time 0 (i.e. U_0^d) is

$$U_0^d = E[U_1^d] = \frac{-exp\Bigg(-\alpha\overbrace{\Big(A^d - \frac{\alpha {B^d}^2\sigma_z^2}{2\times(1 + \alpha C^d\sigma_z^2)}\Big)}^{F_d}\Bigg)}{\sqrt{1 + \alpha C^d\sigma_z^2}}, \tag{A.22}$$

such that

$$F_d = W_0 + \theta'\bar{S} - \theta' S_0 - \frac{\alpha}{2}\theta'\Sigma\theta - \frac{\alpha^3\sigma_z^2(\theta'\Sigma M)^2}{2\times\Big(1 + \alpha^2\sigma_z^2(\pi^2 - 2\pi)M'\Sigma M\Big)}, \tag{A.23}$$

$$\frac{\partial F_d}{\partial\theta} = \bar{S} - S_0 - \alpha\Sigma\theta - \frac{\alpha^3\sigma_z^2(\theta'\Sigma M)(\Sigma M)}{2\times\Big(1 + \alpha^2\sigma_z^2(\pi^2 - 2\pi)M'\Sigma M\Big)}. \tag{A.24}$$

Moreover from equation A.7 and A.9, we have

$$\theta_1^s = \theta + \pi z M. \tag{A.25}$$

Inserting equation A.15, A.25, into equation A.6 yields

$$U_1^s = -exp\Bigg(\overbrace{-\alpha W_0 - \alpha\theta_0'\Big(\bar{S} - S_0 - \Sigma(\alpha\theta + \alpha\pi z M)\Big)}^{-\alpha W_1} - \overbrace{\alpha^2(\theta + \pi z M)'\Sigma(\theta + \pi z M)}^{-\alpha\theta_1^{s\prime}(S_1 - \bar{S})} + \overbrace{\frac{\alpha^2}{2}(\theta + \pi z M)'\Sigma(\theta + \pi z M)}^{\frac{\alpha^2}{2}\theta_1^{s\prime}\Sigma\theta_1^s}\Bigg) \tag{A.26}$$

At time 0 investors are identical, and thus, they all hold the market portfolio. Therefore, we replace the value of θ_0 from equation 4, and define

$$A^s = W_0 + \theta'\bar{S} - \theta' S_0 - \frac{\alpha}{2}\theta'\Sigma\theta, \tag{A.27}$$

$$B^s = 0, \tag{A.28}$$

$$C^s = \alpha\pi^2 M'\Sigma M, \tag{A.29}$$

to get

$$U_1^s = -exp\Big(-\alpha(A^s + B^s z + \frac{1}{2}C^s z^2)\Big). \tag{A.30}$$

The expectation of U_1^s at time 0 (i.e. U_0^s) is

$$U_0^s = E[U_1^s] = \frac{-exp\Bigg(-\alpha \overbrace{\left(A^s - \frac{\alpha B^{s2}\sigma_z^2}{2 \times (1 + \alpha C^s\sigma_z^2)}\right)}^{F_s}\Bigg)}{\sqrt{1 + \alpha C^s \sigma_z^2}}. \tag{A.31}$$

such that

$$F_s = W_0 + \theta'\bar{S} - \theta' S_0 - \frac{\alpha}{2}\theta'\Sigma\theta, \tag{A.32}$$

$$\frac{\partial F_s}{\partial \theta} = \bar{S} - S_0 - \alpha\Sigma\theta. \tag{A.33}$$

Before a liquidity shock happens, we know that a population π of the investors will be liquidity demanders and the remainder will be liquidity suppliers. Therefore, the expectation of the aggregate utility at time 0 is

$$U_0 = \pi U_0^d + (1 - \pi)U_0^s. \tag{A.34}$$

The expectation of the aggregate utility is maximum when

$$\frac{\partial U_0}{\partial \theta} = \pi \frac{\partial U_0^d}{\partial \theta} + (1-\pi)\frac{\partial U_0^s}{\partial \theta} = 0. \tag{A.35}$$

By inserting the values of $\frac{\partial U_0^d}{\partial \theta}$ and $\frac{\partial U_0^s}{\partial \theta}$ from equation A.22 and A.31, into equation A.35, we get

$$\frac{\alpha\pi}{\sqrt{1+\alpha C^d \sigma_z^2}} exp(-\alpha F_d)\frac{\partial F_d}{\partial \theta} + \frac{\alpha(1-\pi)}{\sqrt{1+\alpha C^s \sigma_z^2}} exp(-\alpha F_s)\frac{\partial F_s}{\partial \theta} = 0. \tag{A.36}$$

We define $\Delta_0 = 1 + \alpha^2\sigma_z^2(\pi^2 - 2\pi)M'\Sigma M$ and $\Delta_1 = \alpha^2\sigma_z^2\theta'\Sigma M$. Thus from equation A.23 and A.32, one can show that

$$F_d - F_s = \frac{-\alpha\Delta_1\theta'\Sigma M}{2\Delta_0}, \tag{A.37}$$

which transforms equation A.36 into

$$\frac{\pi}{1-\pi}\sqrt{\frac{1+\alpha C^s \sigma_z^2}{1+\alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2\Delta_1\theta'\Sigma M}{2\Delta_0}\Big)(\frac{\partial F_d}{\partial \theta}) + (\frac{\partial F_s}{\partial \theta}) = 0. \tag{A.38}$$

By inserting the values of $\frac{\partial F_d}{\partial \theta}$ and $\frac{\partial F_s}{\partial \theta}$ from equation A.24 and A.33, we get

$$\frac{\pi}{1-\pi}\sqrt{\frac{1+\alpha C^s \sigma_z^2}{1+\alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2\Delta_1\theta'\Sigma M}{2\Delta_0}\Big)\Big(\bar{S} - S_0 - \alpha\Sigma\theta - \frac{\alpha\Delta_1\Sigma M}{\Delta_0}\Big) + (\bar{S} - S_0 - \alpha\Sigma\theta) = 0. \tag{A.39}$$

We define $\kappa = \sqrt{\frac{1+\alpha C^s \sigma_z^2}{1+\alpha C^d \sigma_z^2}} exp\Big(\frac{\alpha^2\Delta_1\theta'\Sigma M}{2\Delta_0}\Big)$. In this case, $\kappa > 0$ and A.39 gives the equilibrium price of the risky assets at time 0 as

$$S_0 = \bar{S} - \alpha\mathit{\Sigma}\theta - \frac{\kappa\pi}{1-\pi+\kappa\pi}\Big(\frac{\alpha\Delta_1}{\Delta_0}\Big)\mathit{\Sigma} M, \tag{A.40}$$

Appendix B Option-Implied Correlation and Variance

For each stock (or index), the Bakshi et al. (2003) methodology exploits the variance expectation in each day from the out-of-the-money [OTM] European options traded on that specific day. The computed variance is under the risk-neutral measure. According to this model, the annualized expected variance of a stock between time t and $t+\tau$ is computed as

$$Var^Q(S(t)) = \frac{exp(r\tau)V(t, t+\tau) - \mu(t, t+\tau)^2}{\tau}, \tag{B.1}$$

where

$$\mu(t,t+\tau) = exp(r\tau)-1-\frac{exp(r\tau)}{2}V(t,t+\tau)-\frac{exp(r\tau)}{6}W(t,t+\tau)-\frac{exp(r\tau)}{24}X(t,t+\tau), \quad \text{(B.2)}$$

$$V(t,t+\tau) = \int_{S(t)}^{\infty} \frac{2\Big(1-ln\Big(\frac{K}{S(t)}\Big)\Big)}{K^2}C(t,t+\tau;K)dK+ \int_{0}^{S(t)} \frac{2\Big(1+ln\Big(\frac{S(t)}{K}\Big)\Big)}{K^2}P(t,t+\tau;K)dK, \quad \text{(B.3)}$$

$$W(t,t+\tau) = \int_{S(t)}^{\infty} \frac{6ln\Big(\frac{K}{S(t)}\Big)-3\Big(ln\Big(\frac{K}{S(t)}\Big)\Big)^2}{K^2}C(t,t+\tau;K)dK- \int_{0}^{S(t)} \frac{6ln\Big(\frac{S(t)}{K}\Big)+3\Big(ln\Big(\frac{S(t)}{K}\Big)\Big)^2}{K^2}P(t,t+\tau;K)dK, \quad \text{(B.4)}$$

and,

$$X(t,t+\tau) = \int_{S(t)}^{\infty} \frac{12\Big(ln\Big(\frac{K}{S(t)}\Big)\Big)^2-4\Big(ln\Big(\frac{K}{S(t)}\Big)\Big)^3}{K^2}C(t,t+\tau;K)dK+ \int_{0}^{S(t)} \frac{12\Big(ln\Big(\frac{S(t)}{K}\Big)\Big)^2+4\Big(ln\Big(\frac{S(t)}{K}\Big)\Big)^3}{K^2}P(t,t+\tau;K)dK. \quad \text{(B.5)}$$

Here $S(t)$ is the stock price (or the index value) at time t, τ represents the horizon for which we calculate the variance expectation and r is the risk-free rate. Moreover, $P(t,t+\tau;K)$ and $C(t,t+\tau;K)$ respectively denote the price of the European put and call options at time t, with the strike price of K and τ years to maturity.

According to equation B.1 to B.5, to calculate the expected variance of each day, we need a continuum of OTM options with different strike prices. Thus for each day from 1996:01 to 2014:08, we obtain the volatility smile of the S&P 100 index and its constituents from the Standardized Options file of the OptionMetrics database. This database provides us with the implied volatility and the strike price of synthetic OTM European put and call options, with delta values ranging from -0.80 to 0.80, in 0.05 intervals.

For the S&P 100 index and its constituents, on each day, we fit a cubic spline to the volatility smile of the synthetic options with 30 days to maturity. Hence, we estimated the implied volatility of 100 uniformly-spaced options on this spline that have moneyness values ($S(t)/K$) between 0.01 and 2.01. If a moneyness value exceeds the domain of the cubic spline, we set its implied volatility equal to the implied volatility of the closest point on the spline. The prices of the OTM options with moneyness values beyond [0.01, 2.01] are negligible.

Using the Black and Scholes formula, we convert the estimated implied volatilities to option prices, and we estimate the expected variances of the S&P 100 index and its constituents, from equation B.1 to B.5.

Having estimated the daily time series of expected variance for the S&P 100 index and its constituents, we use the methodology of Buraschi et al. (2014) to calculate the average option-implied correlation of the S&P 100 stocks. In this method the average correlation on day t is computed as

$$\overline{Corr_t^Q} = \frac{Var^Q\Big(S\&P100(t)\Big) - \sum_{i=1}^{100} w_{i,t}^2 Var^Q\Big(S(i,t)\Big)}{\sum_{i=1}^{100}\sum_{j=1,i\neq j}^{100}\sqrt{Var^Q\Big(S(i,t)\Big) \times Var^Q\Big(S(j,t)\Big)}}. \tag{B.6}$$

In equation B.6, $Var^Q(S\&P100(t))$ and $Var^Q(S(i,t))$, respectively, represent the variance of the S&P 100 index and stock i, computed from equation B.1 to B.5. Moreover, $w_{i,t}$ is the relative weight of stock i in the S&P 100 index on day t.

In order to calculate $w_{i,t}$ accurately, we get the dates of stocks inclusion to and exclusion from the S&P 100 index, from the Compustat database. We also obtain stocks' daily market capitalization from the CRSP database. For each trading day over our sample, on average, we can compute $w_{i,t}$ and $Var^Q(S(i,t))$ for 97 of the S&P 100 stocks. More details about the implementation are available upon request.

Appendix C Robustness Tests

C.1 Robustness Tests with More Lagged Returns

Here, we test the robustness of our results in table 3 to 5 with the reversal strategy $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$, which captures delayed reversal in less liquid stocks. Table 6 to 8 report the results of our regression analysis for this weighting strategy.

C.2 Robustness Tests with Other Weighting Strategies

This section provides robustness tests, based on some alternative short-term reversal strategies. Table 9 and 10 correspond to the weighting strategy proposed by Lo and MacKinlay (1988) and table 11 and 12 show the results for a reversal strategy introduced by Nagel (2012).

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Table 1: Summary Statistic

	Panel A: Control Variables								Panel B: Financial Constraint Proxies		Panel C: Reversal Strategy Portfolio	
Statistic	VIX Index	S&P500 Realized Volatility	S&P100 Average Correlation	S&P100 Average Variance	Market Portfolio	SMB	HML	Momentum	1M-LIBOR	Ted-Spread	Simple	Ortho.
5th Percentile	0.118	0.064	0.237	0.034	-1.92%	-0.99%	-0.95%	-1.39%	0.18%	0.16%	-0.64%	-0.56%
25th Percentile	0.155	0.090	0.360	0.046	-0.52%	-0.35%	-0.29%	-0.35%	0.28%	0.22%	0.39%	0.39%
Median	0.198	0.125	0.438	0.071	0.09%	0.03%	0.01%	0.07%	2.48%	0.38%	1.16%	1.16%
75th Percentile	0.247	0.171	0.532	0.119	0.65%	0.37%	0.29%	0.44%	5.33%	0.64%	2.55%	2.51%
95th Percentile	0.366	0.287	0.697	0.233	1.83%	0.97%	0.99%	1.34%	6.00%	1.27%	4.64%	4.55%
Market Beta					1.00	0.03	-0.07	-0.20	-0.01	-0.01	0.19	0.00
Average	0.21	0.15	0.45	0.094	0.04%	0.01%	0.01%	0.02%	2.92%	0.50%	1.54%	1.53%
St. Dev.	0.084	0.087	0.136	0.070	1.25%	0.63%	0.66%	0.97%	2.32%	0.43%	1.82%	1.77%
Ann. Sharpe Ratio					0.52	0.22	0.33	0.38	19.99	18.64	13.43	13.77
Skewness	1.96	3.22	0.43	2.47	-0.11	-0.28	0.08	-0.88	0.10	3.21	0.73	0.63
Kurtosis	9.66	22.25	3.18	13.20	10.03	7.18	9.14	12.84	1.35	20.19	11.30	11.54

Note: We proxy the daily time series of the realized volatility of the S&P 500 index with the cumulative squared intradaily returns on each day, and scale it by $\sqrt{252}$ to make it annualized. We follow Buraschi et al. (2014) to calculate the option-implied correlation time series. Moreover we use the model-free methodology of Bakshi et al. (2003) to compute the average option-implied volatility of the stocks in the S&P 100 index. For the portfolio in Panel C, the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The time series frequency is daily and they range from 1996:01 to 2014:08. There are 4696 observations per each time series. The annualized Sharpe ratio is calculated as the ratio of the average daily return to the daily standard deviation, multiplied by $\sqrt{252}$.

Table 2: Correlation Matrix

	Panel A: Control Variables								Panel B: Financial Constraint Proxies		Panel C: Reversal Strategy Portfolio	
Correlations	VIX Index (1)	S&P500 Realized Volatility (2)	S&P100 Average Correlation (3)	S&P100 Average Variance (4)	Market Portfolio (5)	SMB (6)	HML (7)	Momentum (8)	1M-LIBOR (9)	Ted-Spread (10)	Simple (11)	Ortho. (12)
(1)	1.00											
(2)	0.79	1.00										
(3)	0.61	0.40	1.00									
(4)	0.86	0.76	0.18	1.00								
(5)	-0.13	-0.13	-0.11	-0.10	1.00							
(6)	-0.04	-0.06	-0.04	-0.02	0.07	1.00						
(7)	-0.04	-0.02	-0.01	-0.03	-0.13	-0.15	1.00					
(8)	0.00	-0.05	-0.02	0.01	-0.26	0.08	-0.28	1.00				
(9)	-0.03	0.02	-0.42	0.21	-0.01	-0.02	0.01	0.04	1.00			
(10)	0.51	0.48	0.08	0.57	-0.03	-0.02	-0.03	0.01	0.40	1.00		
(11)	0.31	0.26	0.14	0.30	0.13	-0.04	-0.02	0.02	0.28	0.20	1.00	
(12)	0.32	0.28	0.15	0.31	0.00	-0.04	0.00	0.04	0.30	0.20	0.97	1.00

Note: We proxy the daily time series of the realized volatility of the S&P 500 index with the cumulative squared intradaily returns on each day, and scale it by $\sqrt{252}$ to make it annualized. We follow Buraschi et al. (2014) to calculate the option-implied correlation time series. Moreover we use the model-free methodology of Bakshi et al. (2003) to compute the average option-implied volatility of the stocks in the S&P 100 index. For the portfolio in Panel C, the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The time series frequency is daily and they range from 1996:01 to 2014:08. There are 4696 observations per each time series.

Table 3: Regression Analysis for Return

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.20	0.34	-0.66	-0.30	0.43	-0.88
	(-1.62)	(4.48)	(-3.85)	(-1.96)	(4.62)	(-3.70)
Decimalization Dummy	1.65	1.68	1.78	1.63	1.85	1.60
	(10.93)	(11.39)	(13.33)	(9.19)	(11.37)	(9.29)
VIX Index	5.91			7.00		
	(8.96)			(7.98)		
S&P500 Realized Volatility		4.95			5.16	
		(8.49)			(6.37)	
S&P100 Average Correlation			2.91			3.25
			(6.72)			(6.39)
S&P100 Average Variance			4.08			4.85
			(4.26)			(3.97)
SMB	-6.54	-5.90	-6.36	-6.27	-5.99	-5.98
	(-1.00)	(-0.87)	(-1.02)	(-0.96)	(-0.88)	(-0.95)
HML	4.71	4.08	3.80	4.31	4.06	3.31
	(0.86)	(0.73)	(0.71)	(0.77)	(0.72)	(0.61)
Momentum	6.59	8.53	6.54	6.51	8.81	6.26
	(1.79)	(2.25)	(1.84)	(1.78)	(2.33)	(1.76)
1M-LIBOR				2.74	-3.90	6.58
				(0.98)	(-1.40)	(2.05)
Ted-Spread				-40.57	-11.18	-29.97
				(-2.03)	(-0.66)	(-1.53)
R-Squared	0.28	0.26	0.29	0.29	0.26	0.30

Note: We regress the return of our reversal strategy portfolio on certain proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock i on day t is calculated as $w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The time series frequency is daily and they range from 1996:01 to 2014:08. There are 4696 observations per each time series. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 4: Regression Analysis for Sharpe Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.57	0.69	0.40	0.51	0.68	0.27
	(9.60)	(14.40)	(5.22)	(6.99)	(11.04)	(2.37)
Decimalization Dummy	0.28	0.29	0.33	0.25	0.30	0.24
	(5.64)	(5.83)	(8.24)	(3.59)	(4.42)	(3.35)
VIX Index	1.07			1.51		
	(4.22)			(4.90)		
S&P500 Realized Volatility		0.77			0.98	
		(2.74)			(2.20)	
S&P100 Average Correlation			0.76			0.96
			(4.56)			(4.54)
S&P100 Average Variance			0.48			0.77
			(1.50)			(1.78)
SMB	-0.47	-0.52	-0.30	-0.49	-0.52	-0.23
	(-0.69)	(-0.73)	(-0.48)	(-0.70)	(-0.71)	(-0.38)
HML	1.05	0.78	1.23	0.92	0.71	1.13
	(1.95)	(1.45)	(2.45)	(1.82)	(1.39)	(2.42)
Momentum	0.52	0.44	0.51	0.57	0.48	0.49
	(1.92)	(1.53)	(2.02)	(2.24)	(1.66)	(1.95)
1M-LIBOR				1.65	0.07	3.35
				(1.08)	(0.05)	(1.92)
Ted-Spread				-15.01	-6.64	-11.86
				(-2.34)	(-0.83)	(-1.76)
R-Squared	0.33	0.28	0.36	0.35	0.28	0.39

Note: We regress the monthly (conditional) Sharpe Ratio of our reversal strategy portfolio on the proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock i on day t is calculated as $w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. We set the Sharpe ratio of each month as the ratio of the average to the standard deviation of the daily return observations in that particular month. The time series frequency is monthly and they range from 1996:01 to 2014:08. There are 224 observations per each time series. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 2 lags.

Table 5: Short-Term Price Reversal in the Cross Section

Asset-specific Liquidity	Lowest			Middle			Highest		
Variance	Lowest	Middle	Highest	Lowest	Middle	Highest	Lowest	Middle	Highest
Summary Statistics									
5th Percentile	-0.76%	-1.40%	-2.46%	-0.65%	-0.79%	-1.29%	-0.60%	-0.68%	-1.26%
25th Percentile	-0.14%	-0.27%	-0.22%	-0.03%	0.04%	0.46%	0.06%	0.18%	0.85%
Median	0.14%	0.27%	1.10%	0.28%	0.58%	1.77%	0.41%	0.79%	2.39%
75th Percentile	0.43%	0.90%	3.26%	0.64%	1.32%	4.11%	0.84%	1.63%	4.86%
95th Percentile	1.09%	2.49%	7.12%	1.46%	2.83%	7.63%	2.02%	3.28%	9.29%
Average	0.16%	0.37%	1.61%	0.34%	0.77%	2.39%	0.64%	1.02%	3.10%
St. Dev.	0.77%	1.44%	3.70%	0.89%	1.58%	3.32%	2.69%	1.50%	4.03%
Ann. Sharpe Ratio	3.20	4.05	6.91	6.12	7.79	11.42	3.81	10.81	12.23
Regression Analysis									
Intercept	-0.09	-0.16	-0.39	-0.16	-0.17	-0.46	0.30	-0.29	-0.68
	(-2.03)	(-1.75)	(-1.88)	(-2.46)	(-1.57)	(-2.49)	(1.20)	(-3.21)	(-2.55)
Decimalization Dummy	0.12	0.47	3.02	0.18	0.80	2.87	-0.02	0.79	2.77
	(4.08)	(6.13)	(12.57)	(5.02)	(11.70)	(11.13)	(-0.24)	(9.87)	(9.01)
VIX Index	1.01	1.83	5.37	2.12	3.36	9.55	1.64	5.11	14.08
	(4.01)	(3.71)	(4.68)	(5.98)	(5.78)	(8.90)	(1.89)	(10.17)	(9.39)
SMB	-5.18	-1.30	-17.63	-2.43	-7.49	-14.83	6.23	-0.68	-5.83
	(-1.35)	(-0.24)	(-1.30)	(-0.86)	(-1.42)	(-1.35)	(0.64)	(-0.14)	(-0.45)
HML	8.52	18.38	-14.47	2.73	16.38	-2.81	10.65	9.78	7.83
	(2.39)	(3.77)	(-1.24)	(0.88)	(4.06)	(-0.25)	(2.36)	(2.70)	(0.59)
Momentum	-0.27	4.81	17.63	-1.32	-0.71	13.18	3.39	0.61	5.76
	(-0.12)	(1.42)	(2.45)	(-0.69)	(-0.24)	(1.69)	(0.82)	(0.21)	(0.68)
R-Squared	0.03	0.04	0.16	0.05	0.10	0.23	0.00	0.15	0.20

Note: This table reports the summary statistics and the regression results of the reversal strategy portfolios, constructed for 3-by-3 different categories of stocks. In each year stocks are categorized into terciles, based on their variance and their exposure to asset-specific liquidity shock. Then we perform the reversal strategy of equation 21 on the next-year returns of the nine stock categories, created from intersection of these terciles. By rolling the window one year ahead and repeating the same procedure, we obtain nine reversal strategy portfolios. We proxy stocks' exposure to asset-specific liquidity risk with the sample skewness of their daily abnormal trading volume. The weight of stock i on day t is calculated as $w_{i,t} = \dfrac{R_{m,t-1} - R_{i,t-1}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-1} - R_{i,t-1}|}$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 6: (C.1) Regression Analysis for Return with 5 Days Lags

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.04	0.07	-0.14	-0.07	0.08	-0.19
	(-1.84)	(4.38)	(-4.03)	(-2.26)	(4.44)	(-3.93)
Decimalization Dummy	0.33	0.34	0.36	0.32	0.37	0.32
	(11.03)	(11.49)	(13.43)	(9.18)	(11.38)	(9.29)
VIX Index	1.20			1.43		
	(9.03)			(8.21)		
S&P500 Realized Volatility		0.99			1.03	
		(8.45)			(6.36)	
S&P100 Average Correlation			0.59			0.66
			(6.80)			(6.52)
S&P100 Average Variance			0.83			1.00
			(4.33)			(4.09)
SMB	-1.35	-1.23	-1.31	-1.28	-1.24	-1.23
	(-1.03)	(-0.90)	(-1.05)	(-0.98)	(-0.92)	(-0.98)
HML	0.90	0.76	0.72	0.81	0.76	0.61
	(0.82)	(0.68)	(0.67)	(0.72)	(0.67)	(0.56)
Momentum	1.28	1.66	1.27	1.26	1.72	1.20
	(1.72)	(2.18)	(1.78)	(1.71)	(2.27)	(1.69)
1M-LIBOR				0.68	-0.71	1.46
				(1.21)	(-1.27)	(2.27)
Ted-Spread				-8.66	-2.37	-6.50
				(-2.17)	(-0.69)	(-1.66)
R-Squared	0.29	0.27	0.30	0.30	0.27	0.30

Note: We regress the return of our reversal strategy portfolio on certain proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock i on day t is calculated as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The time series frequency is daily and they range from 1996:01 to 2014:08. There are 4696 observations per each time series. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 7: (C.1) Regression Analysis for Sharpe Ratio with 5 Days Lags

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.57	0.69	0.39	0.51	0.69	0.25
	(9.11)	(14.50)	(4.89)	(6.49)	(11.01)	(2.10)
Decimalization Dummy	0.28	0.29	0.34	0.25	0.30	0.23
	(5.64)	(5.83)	(8.19)	(3.53)	(4.40)	(3.30)
VIX Index	1.09			1.52		
	(4.16)			(4.80)		
S&P500 Realized Volatility		0.75			0.93	
		(2.69)			(2.07)	
S&P100 Average Correlation			0.78			0.98
			(4.61)			(4.51)
S&P100 Average Variance			0.49			0.77
			(1.52)			(1.80)
SMB	-0.45	-0.51	-0.26	-0.46	-0.51	-0.18
	(-0.65)	(-0.72)	(-0.43)	(-0.66)	(-0.70)	(-0.31)
HML	1.06	0.78	1.25	0.94	0.72	1.17
	(1.96)	(1.45)	(2.48)	(1.83)	(1.40)	(2.47)
Momentum	0.53	0.45	0.52	0.58	0.48	0.50
	(1.99)	(1.57)	(2.10)	(2.29)	(1.68)	(2.00)
1M-LIBOR				1.71	0.04	3.49
				(1.08)	(0.03)	(1.93)
Ted-Spread				-14.80	-5.65	-11.65
				(-2.31)	(-0.70)	(-1.75)
R-Squared	0.32	0.27	0.36	0.34	0.27	0.38

Note: We regress the monthly (conditional) Sharpe Ratio of our reversal strategy portfolio on the proxies of stocks' average covariance and the market financial constraints. In this reversal strategy the weight of stock i on day t is calculated as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the equally-weighted market portfolio and stock i on day t. The return of this portfolio is then orthogonalized with respect to the market fluctuations. We set the Sharpe ratio of each month as the ratio of the average to the standard deviation of the daily return observations in that particular month. The time series frequency is monthly and they range from 1996:01 to 2014:08. There are 224 observations per each time series. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 2 lags.

Table 8: (C.1) Short-Term Price Reversal in the Cross section and 5 Days Lags

Asset-specific Liquidity	Lowest			Middle			Highest		
Variance	Lowest	Middle	Highest	Lowest	Middle	Highest	Lowest	Middle	Highest
Summary Statistics									
5th Percentile	-0.40%	-0.64%	-1.19%	-0.34%	-0.43%	-0.69%	-0.33%	-0.37%	-0.61%
25th Percentile	-0.07%	-0.14%	-0.18%	-0.05%	-0.05%	0.05%	-0.04%	-0.01%	0.16%
Median	0.05%	0.10%	0.35%	0.08%	0.16%	0.52%	0.10%	0.21%	0.69%
75th Percentile	0.18%	0.37%	1.03%	0.22%	0.42%	1.14%	0.26%	0.48%	1.33%
95th Percentile	0.54%	1.05%	2.38%	0.60%	1.05%	2.27%	0.70%	1.06%	2.51%
Average	0.06%	0.14%	0.45%	0.10%	0.22%	0.63%	0.16%	0.27%	0.79%
St. Dev.	0.39%	0.62%	1.31%	0.35%	0.56%	1.06%	1.20%	0.51%	1.25%
Ann. Sharpe Ratio	2.55	3.56	5.46	4.54	6.25	9.47	2.09	8.20	10.09
Regression Analysis									
Intercept	-0.09	-0.08	-0.17	-0.08	-0.13	-0.15	0.03	-0.12	-0.21
	(-2.42)	(-2.25)	(-3.10)	(-2.85)	(-3.94)	(-3.69)	(0.44)	(-4.52)	(-3.84)
Decimalization Dummy	0.02	0.19	0.70	0.02	0.21	0.61	-0.01	0.19	0.60
	(1.37)	(7.44)	(12.31)	(1.78)	(9.81)	(11.82)	(-0.60)	(9.21)	(9.93)
VIX Index	0.68	0.77	1.99	0.82	1.35	2.86	0.60	1.54	3.92
	(3.32)	(4.16)	(6.67)	(5.19)	(7.98)	(13.04)	(2.18)	(11.10)	(12.92)
SMB	-4.80	1.62	5.58	-2.66	0.78	1.31	2.18	0.78	5.21
	(-2.01)	(0.62)	(0.89)	(-1.76)	(0.36)	(0.24)	(0.69)	(0.35)	(0.81)
HML	4.09	1.83	-8.24	1.98	3.99	-3.35	4.39	1.40	-0.37
	(1.93)	(0.67)	(-1.22)	(1.25)	(1.81)	(-0.68)	(2.51)	(0.76)	(-0.08)
Momentum	-2.50	-0.73	6.22	-2.94	-1.56	5.14	-2.61	-0.33	4.29
	(-1.95)	(-0.33)	(1.17)	(-2.96)	(-0.90)	(1.40)	(-2.05)	(-0.24)	(1.14)
R-Squared	0.04	0.03	0.09	0.05	0.08	0.13	0.00	0.10	0.13

Note: This table reports the summary statistics and the regression results of the reversal strategy portfolios, constructed for 3-by-3 different categories of stocks. In each year stocks are categorized into terciles, based on their variance and their exposure to asset-specific liquidity shock. Then we perform the reversal strategy of equation 21 on the next-year returns of the nine stock categories, created from intersection of these terciles. By rolling the window one year ahead and repeating the same procedure, we obtain nine reversal strategy portfolios. We proxy stocks' exposure to asset-specific liquidity risk with the sample skewness of their daily abnormal trading volume. The weight of stock i on day t is calculated as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\frac{1}{2}\sum_{i=0}^{N} |R_{m,t-\tau} - R_{i,t-\tau}|}$. The return of this portfolio is then orthogonalized with respect to the market fluctuations. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 9: (C.2) Robustness Test of the Regression Analysis for Return with Alternative Portfolio Weighting (1)

	Panel A: Reversal Strategy with 1-day Lagged Returns						Panel B: Reversal Strategy with 5-days Lagged Returns					
Intercept	-0.02	-0.01	-0.02	-0.02	-0.00	-0.02	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-8.64)	(-4.22)	(-5.71)	(-8.44)	(-3.51)	(-5.54)	(-8.79)	(-4.27)	(-5.83)	(-8.64)	(-3.58)	(-5.69)
Decimalization Dummy	0.03	0.03	0.02	0.02	0.03	0.02	0.01	0.01	0.00	0.00	0.01	0.00
	(11.74)	(12.30)	(11.83)	(8.23)	(10.70)	(8.07)	(11.84)	(12.37)	(11.91)	(8.25)	(10.72)	(8.09)
VIX Index	0.14			0.15			0.03			0.03		
	(12.70)			(10.40)			(12.79)			(10.55)		
S&P500 Realized Volatility		0.13			0.12			0.03			0.02	
		(11.70)			(8.63)			(11.66)			(8.63)	
S&P100 Average Correlation			0.04			0.04			0.01			0.01
			(4.91)			(5.04)			(4.96)			(5.12)
S&P100 Average Variance			0.14			0.15			0.03			0.03
			(8.43)			(7.28)			(8.49)			(7.36)
SMB	-0.21	-0.19	-0.23	-0.20	-0.19	-0.22	-0.04	-0.04	-0.05	-0.04	-0.04	-0.04
	(-1.81)	(-1.46)	(-1.85)	(-1.74)	(-1.49)	(-1.79)	(-1.84)	(-1.49)	(-1.88)	(-1.77)	(-1.53)	(-1.82)
HML	0.05	0.04	0.03	0.04	0.04	0.03	0.01	0.01	0.01	0.01	0.01	0.00
	(0.46)	(0.36)	(0.30)	(0.41)	(0.38)	(0.25)	(0.44)	(0.32)	(0.27)	(0.38)	(0.35)	(0.21)
Momentum	0.05	0.10	0.05	0.05	0.10	0.04	0.01	0.02	0.01	0.01	0.02	0.01
	(0.75)	(1.43)	(0.66)	(0.68)	(1.40)	(0.60)	(0.73)	(1.41)	(0.64)	(0.66)	(1.38)	(0.58)
1M-LIBOR				0.11	-0.02	0.11				0.02	-0.00	0.02
				(2.54)	(-0.35)	(2.40)				(2.66)	(-0.30)	(2.53)
Ted-Spread				-0.31	0.21	-0.23				-0.07	0.04	-0.05
				(-0.77)	(0.65)	(-0.64)				(-0.83)	(0.62)	(-0.71)
R-Squared	0.35	0.33	0.35	0.35	0.33	0.35	0.35	0.33	0.35	0.35	0.33	0.36

Note: To test the robustness of our results, in this table, we repeat the regression analysis of Table 3 with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{N}$. Panel B corresponds to a portfolio, in which the weight of stock i on day t is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{N}$. Here, N is the number of stocks in the market on day t. Also, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock i on day t. Both of these portfolios are orthogonalized to the market return, using equation 22. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 10: (C.2) Robustness Test of the Regression Analysis for Sharpe Ratio with Alternative Portfolio Weighting (1)

	Panel A: Reversal Strategy with 1-day Lagged Returns						Panel B: Reversal Strategy with 5-days Lagged Returns					
Intercept	0.49	0.61	0.29	0.44	0.63	0.19	0.48	0.61	0.28	0.43	0.63	0.17
	(7.55)	(11.45)	(3.91)	(5.74)	(9.50)	(1.60)	(7.15)	(11.51)	(3.57)	(5.29)	(9.45)	(1.33)
Decimalization Dummy	0.33	0.33	0.38	0.32	0.38	0.31	0.33	0.34	0.39	0.32	0.38	0.30
	(6.10)	(6.30)	(8.64)	(4.17)	(5.03)	(3.85)	(6.12)	(6.33)	(8.61)	(4.12)	(5.02)	(3.79)
VIX Index	1.18			1.67			1.21			1.71		
	(4.17)			(5.13)			(4.15)			(5.13)		
S&P500 Realized Volatility		0.86			1.13			0.84			1.10	
		(2.66)			(2.33)			(2.64)			(2.25)	
S&P100 Average Correlation			0.85			1.02			0.88			1.06
			(5.38)			(4.69)			(5.44)			(4.70)
S&P100 Average Variance			0.51			0.90			0.52			0.91
			(1.47)			(1.94)			(1.51)			(1.99)
SMB	-0.33	-0.38	-0.12	-0.38	-0.40	-0.11	-0.30	-0.36	-0.08	-0.34	-0.38	-0.06
	(-0.46)	(-0.51)	(-0.19)	(-0.53)	(-0.52)	(-0.18)	(-0.42)	(-0.49)	(-0.13)	(-0.48)	(-0.50)	(-0.10)
HML	1.20	0.91	1.41	1.06	0.83	1.26	1.23	0.92	1.45	1.08	0.84	1.30
	(2.08)	(1.56)	(2.66)	(1.96)	(1.53)	(2.60)	(2.11)	(1.58)	(2.71)	(1.99)	(1.55)	(2.66)
Momentum	0.53	0.45	0.53	0.62	0.53	0.54	0.54	0.45	0.53	0.63	0.52	0.54
	(1.80)	(1.42)	(1.90)	(2.29)	(1.70)	(2.01)	(1.83)	(1.43)	(1.94)	(2.32)	(1.69)	(2.02)
1M-LIBOR				1.01	-0.67	2.76				1.16	-0.63	3.00
				(0.62)	(-0.40)	(1.40)				(0.69)	(-0.37)	(1.48)
Ted-Spread				-17.77	-9.03	-14.37				-17.98	-8.39	-14.53
				(-2.43)	(-1.00)	(-1.89)				(-2.48)	(-0.93)	(-1.94)
R-Squared	0.34	0.29	0.39	0.37	0.31	0.41	0.34	0.29	0.38	0.37	0.30	0.40

Note: To test the robustness of our results, in this table, we repeat the regression analysis of Table 4 with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{N}$. Panel B corresponds to a portfolio, in which the weight of stock i on day t is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{N}$. Here, N is the number of stocks in the market on day t. Also, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock i on day t. Both of these portfolios are orthogonalized to the market return, using equation 22. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 2 lags.

Table 11: (C.2) Robustness Test of the Regression Analysis for Return with Alternative Portfolio Weighting (2)

	Panel A: Reversal Strategy with 1-day Lagged Returns						Panel B: Reversal Strategy with 5-days Lagged Returns					
Intercept	2.65	4.49	-1.50	2.37	5.02	-2.93	0.51	0.90	-0.33	0.44	1.00	-0.63
	(4.12)	(10.74)	(-1.85)	(3.05)	(9.74)	(-2.58)	(3.94)	(10.77)	(-2.01)	(2.84)	(9.71)	(-2.80)
Decimalization Dummy	7.99	8.09	9.35	8.30	9.11	8.14	1.60	1.62	1.88	1.65	1.82	1.62
	(9.34)	(9.68)	(12.85)	(8.56)	(10.13)	(8.91)	(9.40)	(9.75)	(12.93)	(8.54)	(10.14)	(8.91)
VIX Index	20.19			25.69			4.12			5.28		
	(6.13)			(6.38)			(6.19)			(6.56)		
S&P500 Realized Volatility		16.76			19.01			3.33			3.79	
		(5.85)			(5.01)			(5.81)			(4.97)	
S&P100 Average Correlation			17.23			19.39			3.48			3.94
			(8.64)			(8.18)			(8.73)			(8.32)
S&P100 Average Variance			3.52			7.08			0.77			1.52
			(0.79)			(1.26)			(0.86)			(1.36)
SMB	1.08	3.16	6.39	1.93	3.02	9.00	0.09	0.45	1.15	0.29	0.43	1.71
	(0.03)	(0.09)	(0.22)	(0.06)	(0.09)	(0.31)	(0.01)	(0.07)	(0.20)	(0.04)	(0.06)	(0.29)
HML	50.76	48.53	46.41	48.77	47.87	43.78	9.96	9.46	9.08	9.54	9.32	8.52
	(1.90)	(1.80)	(1.89)	(1.79)	(1.76)	(1.75)	(1.86)	(1.75)	(1.84)	(1.74)	(1.71)	(1.70)
Momentum	69.37	75.92	69.93	69.42	77.87	68.16	13.88	15.17	13.99	13.87	15.56	13.62
	(3.89)	(4.17)	(4.29)	(3.87)	(4.26)	(4.15)	(3.86)	(4.15)	(4.26)	(3.84)	(4.23)	(4.12)
1M-LIBOR				3.74	-20.50	41.60				1.24	-3.90	8.89
				(0.27)	(-1.52)	(2.56)				(0.44)	(-1.43)	(2.75)
Ted-Spread				-216.37	-109.40	-147.21				-45.37	-22.04	-31.41
				(-2.32)	(-1.39)	(-1.54)				(-2.43)	(-1.40)	(-1.64)
R-Squared	0.21	0.20	0.24	0.22	0.20	0.24	0.21	0.20	0.25	0.22	0.21	0.25

Note: To test the robustness of our results, in this table, we repeat the regression analysis of Table 3 with the short-term reversal strategy portfolios, proposed by Nagel (2012). Panel A shows the results for a portfolio, in which the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N}(R_{m,t-1} - R_{i,t-1})^2}$. Panel B corresponds to a portfolio, in which the weight of stock i on day t is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\sum_{i=0}^{N}(R_{m,t-\tau} - R_{i,t-\tau})^2}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock i on day t. Both of these portfolios are orthogonalized to the market return, using equation 22. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 22 lags.

Table 12: (C.2) Robustness Test of the Regression Analysis for Sharpe Ratio with Alternative Portfolio Weighting (2)

	Panel A: Reversal Strategy with 1-day Lagged Returns						Panel B: Reversal Strategy with 5-days Lagged Returns					
Intercept	0.61	0.73	0.46	0.56	0.73	0.34	0.61	0.72	0.45	0.56	0.73	0.34
	(10.06)	(15.47)	(5.52)	(7.24)	(11.65)	(2.89)	(9.90)	(15.40)	(5.42)	(7.13)	(11.63)	(2.81)
Decimalization Dummy	0.27	0.28	0.32	0.24	0.29	0.23	0.27	0.28	0.32	0.24	0.29	0.23
	(5.56)	(5.77)	(8.10)	(3.53)	(4.33)	(3.36)	(5.58)	(5.79)	(8.11)	(3.53)	(4.34)	(3.38)
VIX Index	0.99			1.34			1.00			1.35		
	(3.87)			(4.11)			(3.87)			(4.15)		
S&P500 Realized Volatility		0.66			0.76			0.66			0.76	
		(2.43)			(1.72)			(2.43)			(1.73)	
S&P100 Average Correlation			0.69			0.87			0.70			0.88
			(3.79)			(3.95)			(3.85)			(3.99)
S&P100 Average Variance			0.46			0.67			0.46			0.68
			(1.40)			(1.55)			(1.43)			(1.59)
SMB	-0.26	-0.32	-0.10	-0.27	-0.33	-0.02	-0.25	-0.32	-0.09	-0.27	-0.33	-0.02
	(-0.36)	(-0.44)	(-0.15)	(-0.37)	(-0.44)	(-0.04)	(-0.36)	(-0.45)	(-0.14)	(-0.37)	(-0.45)	(-0.03)
HML	1.02	0.76	1.18	0.92	0.73	1.12	1.02	0.75	1.19	0.92	0.72	1.13
	(2.03)	(1.50)	(2.48)	(1.90)	(1.47)	(2.44)	(2.03)	(1.50)	(2.50)	(1.90)	(1.47)	(2.46)
Momentum	0.45	0.38	0.45	0.50	0.40	0.43	0.46	0.38	0.45	0.50	0.40	0.43
	(1.67)	(1.28)	(1.73)	(1.87)	(1.36)	(1.61)	(1.69)	(1.30)	(1.76)	(1.90)	(1.37)	(1.63)
1M-LIBOR				1.38	-0.15	2.96				1.38	-0.18	2.98
				(0.85)	(-0.09)	(1.66)				(0.84)	(-0.11)	(1.67)
Ted-Spread				-11.98	-3.27	-9.19				-12.09	-3.22	-9.29
				(-1.92)	(-0.43)	(-1.43)				(-1.95)	(-0.42)	(-1.47)
R-Squared	0.30	0.25	0.33	0.32	0.26	0.35	0.30	0.25	0.34	0.32	0.25	0.35

Note: To test the robustness of our results, in this table, we repeat the regression analysis of Table 4 with the short-term reversal strategy portfolios, proposed by Lo and MacKinlay (1988). Panel A shows the results for a portfolio, in which the weight of stock i on day t is calculated as $w_{i,t} = \frac{R_{m,t-1} - R_{i,t-1}}{\sum_{i=0}^{N}(R_{m,t-1} - R_{i,t-1})^2}$. Panel B corresponds to a portfolio, in which the weight of stock i on day t is computed as $w_{i,t} = \frac{1}{5}\sum_{\tau=1}^{5} \frac{R_{m,t-\tau} - R_{i,t-\tau}}{\sum_{i=0}^{N}(R_{m,t-\tau} - R_{i,t-\tau})^2}$. Here, $R_{m,t}$ and $R_{i,t}$ denotes the returns of the market portfolio and stock i on day t. Both of these portfolios are orthogonalized to the market return, using equation 22. The t-statistics, reported in parenthesis, are adjusted with the Newey-West technique with 2 lags.