Evaporating Liquidity

Stefan Nagel
Stanford University, NBER, and CEPR

The returns of short-term reversal strategies in equity markets can be interpreted as a proxy for the returns from liquidity provision. Using this approach, this article shows that the return from liquidity provision is highly predictable with the VIX index. Expected returns and conditional Sharpe ratios from liquidity provision spike during periods of financial market turmoil. The results point to withdrawal of liquidity supply and an associated increase in the expected returns from liquidity provision, as a main driver behind the evaporation of liquidity during times of financial market turmoil, consistent with theories of liquidity provision by financially constrained intermediaries. (*JEL* G12, G01)

Liquidity evaporated in many sectors of financial markets during the financial crisis of 2007–09. In some markets, such as those for "toxic" asset-backed securities, trading activity reportedly came to a complete halt.[1] There are at least two possible explanations for this disappearance of market liquidity. One is that the crisis amplified asymmetric information problems. For example, Gorton and Metrick (2010) argue that large adverse shocks strongly increased the information sensitivity of securitized debt. According to this view, the reduction in liquidity is a symptom for aggravated adverse selection problems. An alternative and complementary theory is that the market turmoil strained the inventory-absorption capacity of the market-making sector, either because of a surge in liquidity demand from the public or because market makers reduced liquidity supply in response to elevated levels of risk, tighter funding constraints, and reduced competition. According to this second view, the conditions during the crisis raised the expected return from liquidity provision.

This article studies this second channel using data from equity markets. The main objective is to estimate the extent to which the expected return from liquidity provision rises in times of financial market turmoil. The notion

I thank Miguel Ferreira, Terrence Hendershott, David Hirshleifer, Charles Jones, Ron Kaniel, Ian Martin, Konstantin Milbradt, Laura Starks, Dimitry Vayanos, an anonymous referee, and seminar participants at the University of Amsterdam, University of Arizona, University of British Columbia, Columbia University, Federal Reserve Bank of New York, University of Maastricht, Princeton, Rice, Stanford, the American Finance Association Meetings, the NBER Summer Institute, and the Gutmann Center Symposium at WU Vienna for useful comments. Send correspondence to Stefan Nagel, Stanford University, Graduate School of Business, 655 Knight Way, Stanford, CA 94305. E-mail: Nagel_Stefan@gsb.stanford.edu.

[1] See Brunnermeier (2009) for a review.

doi:10.1093/rfs/hhs066

of "liquidity providers" adopted in this article is broad and not restricted to designated market makers. Liquidity provision in equity markets is increasingly performed by algorithmic traders and other quantitative investors that perform, effectively, a market-making role, but without being officially designated as market makers (Hendershott, Jones, and Menkveld 2011). Even individual investors could perform a liquidity provision role to some extent (Kaniel, Saar, and Titman 2008).

To construct a proxy for the returns from liquidity provision, I examine reversal strategies that buy stocks that went down over the prior days and sell stocks that went up during the prior days, as in Lehman (1990) and Lo and MacKinlay (1990). This pattern of buying and selling in reversal strategies resembles the trading of a market maker who sells when the public buys (which tends to coincide with rising prices) and who buys when the public sells (which tends to coincide with falling prices). Setting up a model in which the public trades for liquidity and informational reasons, and in which market makers have limited risk-bearing capacity, I show that reversal strategy returns closely track the returns earned by liquidity providers. Reversal strategies effectively use lagged returns as a noisy proxy for unobserved market-maker inventory imbalances. They profit from the transitory price impact of order flow and the negative serial correlation in price changes that arises from market makers' aversion to absorbing inventory. Price impact due to private information, in contrast, is permanent and does not induce negative serial correlation (Glosten and Milgrom 1985), which allows me to isolate the variation in the expected returns from liquidity provision from adverse selection effects.[2]

The focus of this article is to examine whether there is predictable time variation in the returns from liquidity provision. Recent work on risk taking of financial intermediaries suggests that the VIX index of implied volatilities of S&P 500 index options is a natural candidate predictor. The theories in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predict that higher volatility tightens funding constraints of market makers and thereby reduces their liquidity-provision capacity. Adrian and Shin (2010) argue that risk-management constraints reduce the risk appetite of financial intermediaries in times of high VIX. Ang, Gorovyy, and van Inwegen (2011) and Ben-David, Franzoni, and Moussawi (2012) find that hedge funds lose assets under management and reduce leverage in times of market turmoil and high VIX. Motivating evidence also comes from a recent body of literature that finds the VIX to be related to various asset-pricing phenomena in which risk taking of financial intermediaries may play a role, such as corporate bond liquidity (Bao, Pan, and Wang 2011), foreign exchange carry trades (Brunnermeier, Nagel, and Pedersen 2008) or sovereign credit-default swaps (Longstaff et al. 2010).

[2] In Glosten and Milgrom's model, greater adverse selection leads to a wider bid-ask spread, but transaction prices always follow a martingale (i.e., there is no bid-ask bounce), and market makers, as well as reversal strategies, earn zero expected return.

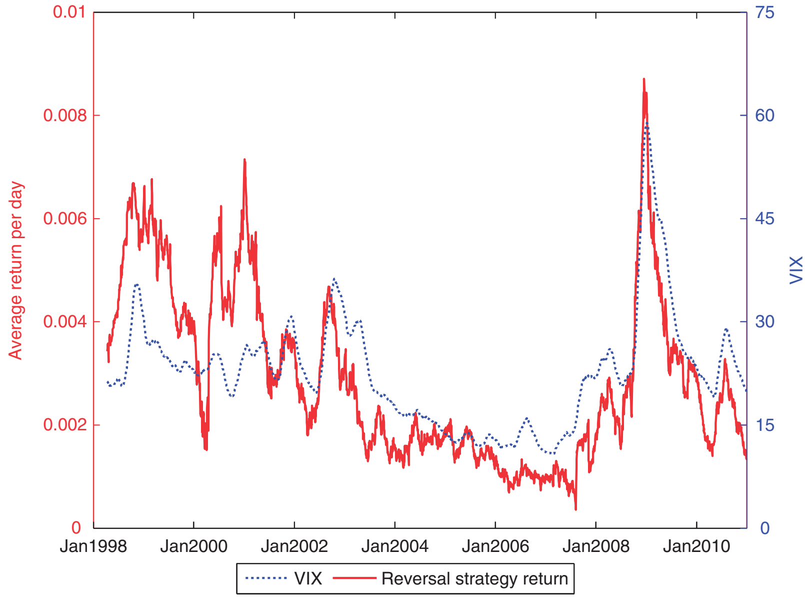

Figure 1
Three-month moving averages of daily return-reversal strategy returns and the CBOE S&P 500 implied volatility index (VIX)
Each day t, the reversal strategy returns are calculated as the average of returns from five reversal strategies that weight stocks proportional to the negative of market-adjusted returns on days $t-1$, $t-2$, ..., $t-5$, with weights scaled to add up to \$1 short and \$1 long. Returns are calculated from daily CRSP closing transaction prices, and returns are hedged against conditional market factor exposure.

Figure 1 illustrates some of the key findings of the article. The solid line plots a three-month moving average of daily returns from a reversal strategy that invests \$1 of capital each day (with 50% margin for long and short positions) and weights stocks based on their prior five days' returns. Returns from the reversal strategy are close to 1% per day during the Long-Term Capital Management (LTCM) crisis in 1998 and the Nasdaq decline in 2000–01. Subsequently, until 2007, reversal strategy returns declined steadily to less than 0.2% per day, but then they virtually exploded during the financial crisis, reaching levels that exceeded those seen during the LTCM crisis. As the figure shows, this time variation in the reversal strategy return is remarkably highly correlated with the VIX index shown as the dotted line in terms of a three-month moving average. Since the start of the financial crisis in 2007, reversal strategy returns and the VIX track each other extremely closely.

Predictive regressions confirm that the correlation between VIX and reversal strategy returns is predictive—that is, VIX forecasts reversal strategy returns. Both transaction-price and quote-midpoint returns of reversal strategies are highly predictable with the VIX, but the association is particularly strong with transaction-price returns. The strong relationship between reversal strategy returns and VIX also persists when reversal strategy returns are standardized by their conditional volatility, which effectively shows that the conditional Sharpe ratio of reversal strategies is positively related to the VIX. Thus, not only does the level of expected return from liquidity provision rise with the VIX, but the risk premium earned by liquidity providers increases as well.

Khandani and Lo (2007) examine returns of a similar reversal strategy during the "quant crisis" in August 2007 and find that it produced substantial but largely transitory losses over a period of a few days. The results in this article show that reversal strategies were, in contrast, highly profitable during the subsequent financial crisis period. Moreover, the downside risk of these strategies is generally low. Returns are positively skewed, and as Figure 1 shows, there was not a single three-month period from 1998 to 2010 in which this strategy lost money (before costs of carrying out the trades). Thus, the experience during the "quant crisis" was exceptional. Downside risk is unlikely to be the explanation for the high Sharpe ratios of liquidity provision strategies during times of high VIX.

While reversal strategies at the individual stock level are known to be profitable (and this article adds the evidence that profits are time varying and highly predictable), I am not aware of prior evidence in the literature that reversal strategies constructed from more aggregated portfolios earn positive returns. Yet, common factors in order imbalances might be particularly volatile during times of market turmoil, and market makers particularly averse to absorbing them. To investigate this possibility, I also examine a reversal strategy constructed from long-short positions in value-weighted industry portfolios. The evidence shows that this inter-industry reversal strategy, too, earns high returns and high Sharpe ratios when VIX is high, which indicates that liquidity providers earn compensation for absorbing industry-level order imbalances in times of market turmoil.

The fact that expected returns from liquidity provision are strongly related to the VIX index does not necessarily imply that the VIX index itself is the state variable driving expected returns from liquidity provision. More likely, the VIX proxies for the underlying state variables that drive the willingness of market makers to provide liquidity and the public's demand for liquidity. Uncovering these underlying state variables is difficult, as they are likely to be highly correlated with VIX and among one another, but I present some tentative evidence using alternative predictor variables. Decomposing the VIX into conditional volatility and a volatility risk premium shows that both components predict reversal strategy returns, although the conditional volatility part seems to be a somewhat stronger predictor. Several proxies for liquidity supply factors predict reversal strategy returns. Idiosyncratic volatility, which might be a concern for imperfectly diversified market makers, and the Treasury-Eurodollar (TED) spread, a popular proxy for funding costs of financial intermediaries, are positively related to future returns from liquidity provision. Growth in primary dealer repo financing, shown by Adrian and Shin (2010) to be positively related to balance sheet size and risk appetite of financial intermediaries, is negatively related to the expected return from liquidity provision. However, these variables do not fully subsume the explanatory power of VIX in the forecasting regression.

The findings in this article relate to earlier work showing that market makers extract price concessions for absorbing order imbalances over and above compensation for adverse selection. As a result, inventory positions affect prices and liquidity (Hansch, Naik, and Viswanathan 1998; Comerton-Forde et al. 2010), and the level of inventory positions predicts returns over a horizon of several days (Hendershott and Seasholes 2007). The inventory data used in these studies are private information, while the reversal strategies that I examine in this article utilize only publicly available information, but over a longer time period, which allows me to study time variation in the expected return from liquidity provision, particularly during the financial crisis of 2007–09.

Existing work shows that volatility is negatively related to liquidity. Chordia, Sarkar, and Subrahmanyam (2005) find that positive volatility innovations in stock and bond markets predict an increase in quoted spreads and a reduction of depth in those markets. Deuskar (2008) finds that price impact of trades is higher when the volatility risk premium component in VIX is high. The liquidity measures used in these articles capture adverse selection as well as inventory imperfections. When these measures indicate illiquidity, this does not necessarily imply high expected returns from liquidity provision. The reversal strategies examined in this article isolate the inventory-related component that drives the return from liquidity provision.

Pástor and Stambaugh (2003) develop a liquidity measure related to short-term reversals, but, unlike the reversal strategies in this article, their liquidity measure is not interpretable as a return (per dollar of capital) on a trading strategy, which makes it unsuitable for a study of time variation in the returns from liquidity provision. Hameed, Kang, and Viswanathan (2010) find that bid-ask spreads and reversal strategy returns increase in the weeks following large stock market declines. I show that the VIX is a much more powerful predictor of reversal strategy returns than lagged market returns, that Sharpe ratios of reversal strategies increase during times of high VIX, and that reversal strategy returns formed from industry portfolios also have high expected returns when VIX is high.

1. Measuring Returns from Liquidity Provision

While it is intuitively clear that short-term reversal strategies approximate the trading patterns of liquidity providers, and that they benefit from the negative serial correlation in price changes induced by imperfect liquidity provision, it is less clear precisely which specification of reversal strategies provides the best approximation of the returns from liquidity provision. The returns of different versions of reversal strategies can all be represented as scaled autocovariances of market-adjusted returns. But it is not clear which scaling of autocovariances is most suitable for an assessment of the returns from liquidity provision. To clarify these issues, this section presents a model that contains the key features of market microstructure models: The public trades for both informational and liquidity reasons (as in Kyle 1985), and market makers in this model are averse to taking on inventory (as in Grossman and Miller 1988). Within this model, one can compute the return from liquidity provision and compare it to reversal strategy returns. This helps us understand which reversal strategy specification best approximates the returns from liquidity provision and which factors could interfere with this proxy relationship. The model should be thought of as applying to a relatively short time period in which the parameters determining the expected return from liquidity provision are roughly constant, while the subsequent empirical analysis will look at time variation in the expected return from liquidity provision at lower frequencies.

1.1 Model

Consider an asset market with a single risky asset in zero net supply, a riskless asset in perfectly elastic supply at interest rate of zero, and discrete time, $t = 0, 1, 2, ..., T$. There are three groups of market participants: informed traders, market makers, and liquidity traders. The latter group trades an exogeneous amount z_t each period.

The value of the risky asset in the final period T is

$$v_T = v_0 + \sum_{\tau=1}^{T} \delta_t + \sum_{\tau=1}^{T} \xi_t, \tag{1}$$

which is paid as a terminal dividend. The innovations δ_t, ξ_t, and z_t are jointly normal, IID over time, and mutually uncorrelated, and have variances σ_δ^2, σ_ξ^2, and σ_z^2, respectively.

The signal ξ_t is public and observed at time t by all market participants. In contrast, δ_t becomes public information at t, but informed traders observe a signal $s_{t-1} = \delta_t$ one period earlier, which means they have a short-lived informational advantage, as in Admati and Pfleiderer (1988). Informed traders are competitive and myopic with CARA utility.[3] Informed traders submit market orders—that is, they cannot condition their demand on the price in the current trading round, similar to Kyle (1985). As a result, the demand function of the representative informed trader is

$$y_t = \beta s_t, \tag{2}$$

where β is increasing in the aggregate risk-bearing capacity of informed traders and decreasing in the level of risk they perceive and the price impact that they expect to have in aggregate (see Appendix A).

[3] Assuming the variance of ξ_t to increase at an appropriate rate as $t \to T$ to compensate for the reduced variance stemming from a lower number of remaining δ_t shocks, one could make the setting IID in which non-myopic demand functions would be equivalent to the myopic ones. For simplicity of exposition, I assume myopia.

The representative competitive market maker has CARA utility with (myopic) asset demand

$$m_t = \gamma \left(E[\delta_{t+1} | \mathcal{M}_t] + v_t - P_t \right), \tag{3}$$

where $\mathcal{M}_t$ denotes market makers' information set at time t, which includes prices and order imbalances up to time t. The slope of demand, γ, captures the aggressiveness with which market makers supply liquidity, which is increasing in the risk-bearing capacity of the market-making sector, and decreasing in the level of risk. More generally, margin constraints, as in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009), or risk management constraints, as in Adrian and Shin (2010), effectively induce risk-averse behavior, and a finite γ can be thought of as a reduced-form representation of these frictions. As shown in Appendix A, $E[\delta_{t+1} | \mathcal{M}_t] = \phi x_t$, where $x_t \equiv y_t + z_t$ is the total asset demand imbalance from informed and liquidity traders absorbed by the market maker (which equals the negative of the inventory position of the market maker in period t), and

$$\phi = \frac{\beta \sigma_\delta^2}{\beta^2 \sigma_\delta^2 + \sigma_z^2} \tag{4}$$

captures the informativeness of x_t about δ_{t+1}. Thus, $E[\delta_{t+1} | \mathcal{M}_t] = \phi x_t$ represents the market maker's best estimate of the information about $s_t = \delta_{t+1}$ contained in x_t.

In equilibrium, dollar returns $R_{t+1} \equiv P_{t+1} - P_t$ follow

$$R_{t+1} = \xi_{t+1} + \eta_{t+1} + \left(\frac{1}{\gamma} + \phi \right) x_{t+1} - \left(\frac{1}{\gamma} \right) x_t. \tag{5}$$

In this model, order flow $\Delta x_{t+1} = x_{t+1} - x_t$ follows an MA(1) process with an MA-coefficient of -1. The market maker provides immediacy and absorbs intertemporal imbalances in order flow, but over time these imbalances tend to cancel out, as in Grossman and Miller (1988), and the market maker's inventory is stationary.[4]

Equation (5) shows that returns have a predictable and an unpredictable component. Since s_{t+1} and z_{t+1} are IID over time, x_{t+1} is not predictable based on information at time t (neither the market makers' nor the informed traders') and hence x_{t+1} represents unexpected period $t+1$ order flow, which has price impact both for informational reasons (captured by ϕ) and because of imperfect supply of liquidity (captured by $1/\gamma$). In contrast, $-x_t$ represents the expected component of period $t+1$ order flow, and it is associated with a predictable return $-(1/\gamma)x_t$ that compensates market makers for bearing inventory risk. For example, if market makers are long inventory in period t ($x_t < 0$), then

[4] In Grossman and Miller (1988), order-flow imbalances have perfect negative serial correlation, while in this model the correlation is not perfect because of the presence of the innovation of the MA(1) process.

the return expected in period $t+1$ is positive. Market makers' limited risk-bearing capacity implies an imperfect supply of immediacy, which in turn induces predictability and negative serial correlation into the return process. By providing liquidity (in the form of immediacy), market makers earn positive expected profits.

1.2 Returns from liquidity provision

To calculate these returns from supplying liquidity, I now extend the model in a simple way to a cross-section of $i=1,2,...,N$ securities. Let all variables in the model now carry i-subscripts, and let δ_{it} and z_{it} be jointly normal IID in the cross-section. I allow the public information component of returns to be correlated across stocks by specifying a simple factor structure $\xi_{it}=f_t+e_{it}$, where f is a serially uncorrelated common factor (for simplicity, all stocks are assumed to have identical factor loadings, hence f is also the market factor) and e_{it} are cross-sectionally normal IID factor-model residuals.

The market-making sector's dollar gain in period t, aggregated across all N securities, is $-\sum_{i=1}^{N} x_{it-1}R_{it}$. A calculation of market-maker returns requires calculation of the capital needed for carrying these inventory positions. One complication that arises in a CARA-normal model is that prices can be negative, which is not realistic for stocks. To abstract from such complications arising from the cross-sectional distribution of prices, and from scale differences between stocks, I assume that prices of all securities at $t-1$ are equal and normalized to $P_{it-1}=1$.[5] Assuming a 50% margin for both long and short positions,[6] the required capital is $(1/2)\sum_{i=1}^{N}|x_{it-1}|$, and hence market makers' return per dollar of capital is

$$L_t^{MM}=-\left(\frac{1}{2}\sum_{i=1}^{N}|x_{it-1}|\right)^{-1}\sum_{i=1}^{N}x_{it-1}R_{it}. \tag{6}$$

Appendix A shows that as $N\to\infty$, market makers' return converges to

$$\lim_{N\to\infty} L_t^{MM}=\sqrt{2\pi}\left(\frac{1}{\gamma}\right)\sigma_x. \tag{7}$$

The returns from supplying liquidity earned by market makers are decreasing in market makers' aggressiveness γ and increasing in the volatility of unexpected

[5] Approximately, this could hold, for example, if $v_{0i}=1$, and the price impacts of inventory imbalances since $t=0$ are small relative to the initial values v_{0i}.

[6] This choice of margin is motivated by Regulation T, which is not necessarily the appropriate constraint for hedge funds or market makers that may be able to use cross-margining or benefit from exceptions (see, e.g., the appendix in Brunnermeier and Pedersen 2009). However, the empirical evidence on leverage of equity hedge funds in Ang, Gorovyy, and van Inwegen (2011) is at least roughly consistent with 50% margins. In any case, any other margin requirements can easily be accomodated here by scaling reversal strategy returns up or down accordingly.

order flow

$$\sigma_x = \sqrt{\beta^2 \sigma_\delta^2 + \sigma_z^2}. \tag{8}$$

Changing γ can be thought of as changing the supply of liquidity, while changing σ_x can be thought of as changing the demand for liquidity. Within the model, γ and σ_x are assumed to be constant, while the focus of the empirical analysis below is on the effects of time variation in γ and σ_x. To connect the model with the empirical analysis, it is useful to think of repetitions of this finite-horizon model, where γ and σ_x are constant over the modeling horizon T but vary across repetitions.

In this setting, with cross-sectionally uncorrelated order flow, and with securities that have identical loadings on the common factor in the public information component of returns, market-maker returns converge to a constant as the number of securities goes to infinity. In reality, a market maker's risk is unlikely to be fully diversifiable. First, market makers specialize their market-making activities on a finite subset of securities, limiting their ability to diversify. For example, Naik and Yadav (2003) find that the liquidity provision of individual dealers on the London Stock Exchange is affected by dealer-specific inventory risks that are diversifiable within the firm employing the dealers. Second, stocks have dispersed loadings on common factors in order flow and public information. Generalizing the model to allow for dispersed factor loadings would yield the result that the reversal strategy loads on common factors and therefore, as $N \to \infty$, market-maker returns converge to a nondegenerate random variable.

Extending the model to capture limited diversifiability of risk exposures would not change the basic message of the model that a finite γ induces negative serial correlation, which results in profitable reversal strategies. The benefit of such an extension would be that one could endogenize γ. The model above is silent about the reasons why γ is finite. Limited diversifiability, possibly combined with margin or risk-management constraints, would allow for endogenizing the limited risk-bearing capacity of market makers implied by the assumption of a finite γ.

1.3 Empirical proxies for returns from liquidity provision

Empirically, the inventory positions of the entire market-making sector are not observable, which renders infeasible a direct calculation of aggregate returns from market-making activities according to Equation (7). Some researchers have obtained proprietary data sets on designated market-maker inventory positions (e.g., Comerton-Forde et al. 2010 for the NYSE). A limitation of these data is that they do not capture the increasingly important activities of hedge funds and other market participants that do not have an official market-making role, but effectively compete with official market makers in providing liquidity. The data of Comerton-Forde et al. also do not include the financial crisis of 2007–09. This section shows that trading strategies that condition on past returns can be used to approximate the return from liquidity provision earned by the market-making sector. Moreover, some of the liquidity providers outside the set of official market makers might actually employ precisely these kinds of trading strategies that condition on past returns in their efforts to capture some of the returns from liquidity provision that are available in the marketplace.

Consider a trading strategy with portfolio weight for stock i at the beginning of period t:

$$w_{it}^{R} = -\left(\frac{1}{2}\sum_{i=1}^{N}|R_{it-1} - R_{mt-1}|\right)^{-1}(R_{it-1} - R_{mt-1}), \tag{9}$$

where $R_{mt-1} \equiv \frac{1}{N}\sum_{i=1}^{N} R_{it-1}$ is the equal-weighted market index return. This is the reversal strategy examined by Lehman (1990). The strategy earns positive returns if $t-1$ returns partly reverse in period t. The scaling by the first term in parentheses in (9) ensures that the strategy is always \$1 short and \$1 long. With 50% margin on long and short positions, this requires \$1 of capital, and hence the payoffs of this strategy,

$$L_{t}^{R} = -\left(\frac{1}{2}\sum_{i=1}^{N}|R_{it-1} - R_{mt-1}|\right)^{-1}\sum_{i=1}^{N}(R_{it-1} - R_{mt-1})R_{it}, \tag{10}$$

can be interpreted as a return per dollar of capital invested. Appendix A shows that with a large cross-section of securities, the realized time-t return from this strategy is

$$\lim_{N\to\infty} L_{t}^{R} = \rho\sqrt{2\pi}\left(\frac{1}{\gamma}\right)\sigma_{x}, \tag{11}$$

where

$$\rho \equiv \frac{\left(\frac{1}{\gamma}+\phi\right)\sigma_{x}}{\sigma_{R}} \tag{12}$$

is the volatility of the unexpected return driven by order flow divided by the total cross-sectional standard deviation of returns σ_R. If ρ does not change over time, then time variation in reversal strategy profits tracks time variation in the market-maker profits in (7) (scaled by ρ). The presence of ρ in (11) arises from the fact that past returns are a noisy proxy for market makers' inventory positions $-x_{it-1}$ because the public information component in returns adds noise unrelated to inventory imbalances. As a consequence, the reversal strategy effectively uses up more capital than the market makers' strategy, because it takes positions proportional to $-(R_{it-1} - R_{mt-1})$ rather than proportional to only the component of $-(R_{it-1} - R_{mt-1})$ driven by x_{it-1}.

The model helps us understand how the specification of the reversal strategy influences the degree to which it approximates market makers' returns from liquidity provision. In the empirical analysis, two concerns might arise: (i) High values of L_t^R might be the result of a low variance of public information shocks (which lowers the denominator ρ but does not affect the numerator) rather than high L_t^{MM}; (ii) high values of L_t^R might reflect high ϕ (which raises ρ toward one) rather than high L_t^{MM}.

With regard to (i), it seems plausible that the variance share of the public information component increases rather than decreases in times of market turmoil. If so, L_t^R would actually understate the extent to which market-maker profits increase during these times. In any case, one can eliminate the dependence on the variance share of public information shocks by considering an alternative reversal strategy with weights

$$w_{it} = -(1/N)(R_{it-1} - R_{mt-1}), \tag{13}$$

as in Lo and MacKinlay (1990). The returns of this strategy converge to the negative of the market-adjusted return autocovariance, which equals

$$\left(\frac{1}{\gamma}+\phi\right)\left(\frac{1}{\gamma}\right)\sigma_x^2, \tag{14}$$

and which is insensitive to changes in the volatility of the public information component.

With regard to (ii), the elasticity of L_t^R with respect to changes in ϕ is

$$\frac{\phi}{\frac{1}{\gamma}+\phi}(1-\rho^2). \tag{15}$$

Thus, since $0 \le \rho \le 1$, L_t^R will typically increase when ϕ rises. However, one can construct an alternative reversal strategy that is less sensitive to variation in ϕ. Consider portfolio weights

$$w_{it} = -\left(\sum_{i=1}^{N}(R_{it-1} - R_{mt-1})^2\right)^{-1}(R_{it-1} - R_{mt-1}). \tag{16}$$

With these weights, the reversal strategy profit is, effectively, a cross-sectional estimate of the negative of the autocorrelation of market-adjusted returns. In this case, the elasticity of the reversal strategy profit with respect to changes in ϕ is

$$\frac{\phi}{\frac{1}{\gamma}+\phi}(1-2\rho^2). \tag{17}$$

For $\rho^2 > 0.5$, the profit of this reversal strategy actually falls when ϕ rises. The findings in Hasbrouck (1991) and more recent evidence from Hendershott and Menkveld (2010) suggest that unexpected order flow explains about $1/3$ of the variance of permanent ("efficient") price changes. In addition, Hendershott and Menkveld (2010) show that order flow also exerts substantial transitory price pressure. Taken together, these findings suggest values for ρ^2 that are likely close to or greater than 0.5. Thus, the profits of this alternative "autocorrelation" reversal strategy should be relatively insensitive, or even inversely related to changes in ϕ.

Thus, compared with these two alternative reversal strategies, the reversal strategy in (9) that is used in the empirical analysis below strikes a balance between insensitivity to ϕ and insensitivity to changes in the volatility of the public information component of returns. The reversal strategy formed according to (9) has the added benefit of a clear interpretation as a \$1 long/\$1 short strategy. But, as shown in the online appendix, all the predictability results below also hold if one replaces the reversal strategy with these alternative ones based on cross-sectional autocovariance or autocorrelation estimates. Time variation in ϕ or in the volatility of public information shocks is therefore unlikely to provide an explanation of the predictability patterns reported in this article.

1.4 Empirical implementation and data

The empirical implementation of the reversal strategies uses returns of NYSE, AMEX, and Nasdaq stocks calculated from daily closing transaction prices from CRSP. For Nasdaq stocks, CRSP also reports closing bid and ask quotes, which I use to calculate quote-midpoint returns (see Appendix B for further details). The sample period runs from January 1998 to December 2010. Mapping the model to the empirical data requires some adjustments to take into account complexities that the model abstracts from for the sake of clear intuition.

Individual stocks or portfolios. Most of the analysis employs reversal strategy portfolios constructed from individual stocks. This is the proper approach to evaluate the expected returns of liquidity providers overall. However, anecdotally, it seems that transitory price pressure from order imbalances also affects entire sectors of the market in a correlated way during times of financial turmoil (e.g., because mutual funds concentrated in certain sectors face outflows), and market makers may, at the same time, be averse to absorbing these correlated imbalances. For this reason, I also examine reversal strategies constructed with industry portfolios as basis assets. The industry portfolios are constructed by classifying stocks into forty-eight industries as in Fama and French (1997).[7] I am not aware of evidence in the literature that a reversal strategy based on industry portfolios is profitable unconditionally, but I investigate here whether it is profitable conditional on high levels of the VIX index.

Return measurement horizon. It is not obvious how one should interpret empirically the period length in the model. While analyses of microstructure models often focus on intraday data, inventory imbalances, and their associated price effects, are likely to persist beyond a daily horizon. For example, Hansch, Naik, and Viswanathan (1998) report that the average half-life of

[7] I thank Ken French for providing the industry classification on his website.

dealer inventory positions on the London Stock Exchange is roughly two days. Hendershott and Menkveld (2010), using NYSE data, find half-lives ranging from half a day for the largest stocks to two days for the smallest stocks. These findings suggest that data at daily frequency may allow us to capture much of the effects of imperfect liquidity provision.[8] A related issue arises from the model's omission, for the sake of simplicity, of features that can cause positive serial correlation in returns. As shown, for example, in Wang (1994) and Llorente et al. (2002), long-lived private information can induce positive serial correlation at short horizons. Conditioning reversal strategy day t portfolio weights only on day $t-1$ returns could understate the returns from supplying liquidity in this case. To address this, I calculate the returns of the reversal strategies as an overlay of the returns of five substrategies: One with portfolio weights conditioned on day $t-1$ returns, one conditioned on day $t-2$ data, … , one conditioned on $t-5$ data. I then take the simple average of these five substrategies' returns as the overall reversal strategy return. Adding lags beyond the first lag helps in case of short-run continuation and delayed reversal, but does not introduce distorting effects in case these additional lags of returns do not predict future returns. With the exception of the industry portfolio results, which do exhibit some return continuations at a daily horizon, the results in the empirical analysis are not sensitive to the choice of lags (see the online appendix).

Bid-ask spreads. If calculated based on transaction prices, the reversal strategy returns represent the returns of a hypothetical representative liquidity supplier whose limit orders or quotes always get executed at the closing transaction price. To assess the returns from liquidity provision earned by the market-making sector as a whole, including all designated and de facto market makers, this perspective makes sense, as the market-making sector does not pay the bid-ask spread, but instead earns the non-adverse selection component of the bid-ask spread—that is, the part that induces negative serial correlation in transaction-price returns.[9] However, it would also be interesting to see how much of the returns from liquidity provision arise from this bid-ask bounce in transaction prices, and how much is attributable to negative serial correlation in quote-midpoint changes. For this reason, I calculate reversal strategy returns both with returns based on daily closing transaction prices (for all stocks) as well

[8] Algorithmic trading systems operated by hedge funds and broker-dealers have recently taken over much of the liquidity provision business from designated market makers. Those with a high-frequency trading focus often try to avoid holding overnight inventory (see, e.g., Menkveld 2011). This does not mean, however, that the returns from overnight or multiday liquidity provision are zero. If order imbalances from the public do not perfectly cancel out on a given day, some liquidity providers must hold overnight inventory. The analysis of daily returns in this article captures the returns earned by these low-frequency liquidity suppliers, but the analysis does not capture the returns that high-frequency traders earn from supplying liquidity intraday.

[9] The existence of positive bid-ask spreads need not necessarily imply negative serial correlation in transaction price changes. If adverse selection was the only reason for the existence of bid-ask spreads, transaction prices would follow a martingale (Glosten and Milgrom 1985). Only the part of the bid-ask spread in excess of the adverse selection component, which compensates market makers for taking on inventory or reflects market power of market makers, generates negative serial correlation and positive reversal strategy profits.

as returns based on the midpoints of bid and ask closing quotes as recorded (for Nasdaq stocks only) by CRSP. In each case, the portfolio weights are calculated with the same type of return (on days $t-1$ to $t-5$) as the type used to calculate portfolio returns (on day t).

Common factors in returns. Reversal strategies of the sort analyzed in this article have a rather mechanical time-varying exposure to common factors. For example, consider a return-reversal strategy that buys stocks with negative market-adjusted returns on day $t-1$ and shorts those with positive market-adjusted returns on day $t-1$. If the market index went up on day $t-1$, this strategy tends to be long low-beta stocks and short high-beta stocks, resulting in a negative conditional beta for the strategy on day t. Similarly, the strategy tends to have a positive conditional beta following days on which the market went down. Along the same lines, time-varying factor exposures can arise with respect to other common factors in stock returns. Market makers might hedge some of these common factor exposures, as the factor loadings are straightforward to predict based on the sign of lagged factor realizations. Hedging market factor risk would also be relatively simple in practice—for example, with S&P 500 futures contracts. For this reason, I focus on the returns of hedged reversal strategies after eliminating time-varying market factor exposure. I first estimate a regression

$$L_t^R = \beta_0 + \beta_1 f_t + \beta_2 (f_t \times \mathrm{sgn}(f_{t-1})) + \varepsilon_t, \tag{18}$$

where f_t is the return on the CRSP value-weighted index and L_t^R is the reversal strategy return. The time-varying beta is $\beta_{t-1} = \beta_1 + \beta_2 \mathrm{sgn}(f_{t-1})$, which is then used to calculate hedged returns as $L_t^R - \beta_{t-1} f_t$.

Heterogeneity in scale. In the model, all stocks have the same size. In reality, there is enormous dispersion in size. Market-maker inventory portfolios and their profits are likely to be dominated by large stocks. For this reason, the online appendix reports results for an alternative value-weighted reversal strategy where portfolio weights are proportional to the negative of market-adjusted return times the lagged market capitalization of the stock. These results convey a similar message about time variation in the expected returns from liquidity provision as those reported in the main part of the article. Section 2.4 constructs reversal strategies for subgroups of stocks sorted by several stock characteristics, including size.

Sample period and institutional change. The sample period runs from the beginning of 1998 to the end of December 2010. The start of the sample period is set in 1998 because a substantial change in order-handling rules on Nasdaq was phased in throughout 1997. This institutional change, together with Department of Justice investigations and public scrutiny following the Christie and Schultz (1994) findings, resulted in a dramatic decrease in bid-ask spreads and trading costs on Nasdaq in the pre-1998 period (Barclay et al. 1999). These changes are also likely to affect the returns from liquidity provision and the serial correlation properties of price changes for many stocks. The presence of these institutional regime changes in the sample could therefore obscure the time-series relation between the expected returns from liquidity provision and market turmoil factors (as proxied for by VIX) that are the focus of this article. Even the post-1998 period saw some institutional changes, though. The likely most important change was the introduction of decimalization in 2001. Bessembinder (2003) finds that while this change was associated with a substantial decline in quoted bid-ask spreads, it did not reduce effective bid-ask spreads, and so it may not have a big effect on reversal strategy profitability. Nevertheless, to control for possible effects, the empirical analysis below employs a dummy for the pre-decimalization period.

2. Time Variation in Expected Returns from Liquidity Provision

Table 1 reports summary statistics of the reversal strategy returns. Panel A presents statistics for the raw returns of these strategies, while Panel B shows similar statistics for hedged returns, which are obtained by eliminating conditional market factor exposure. These hedged returns are the focus of the empirical analysis that follows. Comparing Panels A and B, the mean returns are almost identical, but the standard deviations of the hedged strategy returns are moderately smaller. This reflects the fact that conditional market factor exposure constitutes a significant contribution to the total volatility of reversal strategy returns, and this component is eliminated in Panel B. Moreover, while unconditional betas in Panel A are close to 0.10, unconditional betas are virtually exactly zero in Panel B, as one would expect.

Whether the calculation of returns is done with quote-midpoints or transaction prices makes a substantial difference. While return standard deviations are similar with the two approaches, the mean returns are only about half as big when quote-midpoints are used to calculate returns. This indicates that a substantial portion, although by far not all, of the reversal strategy returns with transaction prices arise from the bid-ask bounce. For the industry return-reversal strategy, however, there is virtually no difference between the transaction-price and quote-midpoint returns, and so I report only the transaction-price returns here and in the analysis below.[10]

Focusing on mean returns, it is apparent that the reversal strategies constructed from individual stocks earn very high returns with relatively low volatility (for comparison, the mean return per day of the CRSP value-weighted index during the sample period is 0.02% with a standard deviation of 1.35%). This is also reflected in the enormous Sharpe ratios of the reversal strategies at the bottom of Panels A and B (for comparison, the CRSP value-weighted index has a realized Sharpe ratio of 0.26 during the sample period). Thus, the

[10] At the end of each day, some stocks' closing prices are at the bid, some are at the ask, and so averaging transaction-price returns across all stocks within an industry portfolio yields virtually the same result as averaging the quote-midpoint returns.

Table 1
Summary statistics of reversal strategy returns

	Indiv. stock reversal		Industry
	Transact. prices	Quote-midpoints	portfolio reversal
Panel A: Raw returns			
Mean return (% per day)	0.30	0.18	0.02
Std. dev. (% per day)	0.56	0.61	0.52
Skewness	3.02	2.74	1.06
Kurtosis	38.21	40.50	17.93
Worst day return (%)	−3.88	−4.76	−3.93
Worst 3-month return (%)	2.56	−2.13	−9.28
Beta	0.11	0.11	0.09
Annualized Sharpe ratio	8.44	4.50	0.56
Panel B: Returns hedged for conditional market factor exposure			
Mean return (% per day)	0.29	0.17	0.01
Std. dev. (% per day)	0.48	0.54	0.47
Skewness	2.45	2.26	0.88
Kurtosis	31.26	34.51	15.97
Worst day return (%)	−2.26	−3.92	−3.12
Worst 3-month return (%)	2.27	−1.28	−7.87
Beta	0.00	0.00	0.00
Annualized Sharpe ratio	9.58	4.91	0.44

The daily reversal strategy return is calculated as the average of the returns, on day t, of five substrategies that weight stocks (or industries) proportional to the negative of market-adjusted returns on days $t-1$, $t-2$, …, $t-5$, with weights scaled to add up to \$1 short and \$1 long. Transaction-price returns are calculated from daily CRSP closing prices. Quote-midpoint returns are calculated from bid-ask midpoints of daily CRSP closing quotes (with Nasdaq stocks only). The industry return-reversal strategy is calculated with transaction prices. The sample period runs from January 1998 to December 2010.

volatility of the reversal strategy returns by itself is unlikely to be the main impediment that deters investors from investing more aggressively in these kinds of strategies and supplying liquidity. The industry return-reversal strategy is different. It earns much lower mean returns than the individual-stock reversal strategies, leading to a much lower Sharpe ratio (but one that is still higher than the Sharpe ratio of the CRSP value-weighted index). Thus, unconditionally at least, the evidence indicates that inventory-induced reversals of price changes are less prevalent at the industry portfolio level than at the individual stock level.

The statistics in the table also indicate that exposure to asymmetric downside risk can be ruled out as a potential explanation for the high Sharpe ratios. Reversal strategy returns have positive skewness, and while there are instances of losses of several percents on a given day, there is no three-month period in the sample period in which the individual-stock reversal strategy lost money in terms of transaction-price returns. Even with quote-midpoint returns, the worst three-month loss is only a few percents (the corresponding number for the CRSP value-weighted index is –52%).

Fixed costs for high-speed market access and technological requirements for successful placement of orders that capture order flow probably play an important role in preventing more aggressive entry into the liquidity provision business. After accounting for these fixed costs, Sharpe ratios would likely be much less extreme. In any case, the focus of this article is on the relative variation over time in the expected returns and conditional Sharpe ratios of these reversal strategies, rather than the level of unconditional mean returns and Sharpe ratios.

2.1 Predicting returns from liquidity provision with VIX

Turning to time variation in the expected returns from liquidity provision, I focus on the VIX index as a "market turmoil" state variable to predict the returns of reversal strategies. Table 2 presents predictive regressions of the form

$$L_t^R = a + bVIX_{t-5} + c'g_{t-5} + e_t, \tag{19}$$

where L_t^R is the reversal strategy return on day t. VIX is lagged by five days to account for the fact that the portfolio weights of the day t reversal strategy are conditioned on returns from days $t-1$ to $t-5$. In these regressions, the VIX is normalized to a daily volatility measure by dividing it by $\sqrt{250}$. To control for effects of the institutional changes associated with decimalization, the control variable vector g_{t-5} includes a dummy variable that takes a value of one prior to decimalization (April 9, 2001) and a value of zero thereafter. Furthermore, I also include R_M, the lagged four-week return on the value-weighted CRSP index up until the end of day $t-5$ to capture the dependence of reversal strategy profits on lagged market returns documented in Hameed, Kang, and Viswanathan (2010).

As column (1) of Table 2 shows, reversal strategies constructed from individual stocks have returns that are strongly predictable with the VIX. The magnitude of the coefficient (0.22) is big relative to the standard error shown in parentheses (0.02). An increase of one percentage point in the normalized VIX (corresponding to an increase of $\sqrt{250} \approx 16$ percentage points in the annualized VIX) is associated with an increase of 0.22 percentage points in the daily returns of the return-reversal strategy. The sizeable economic magnitude of the effect is evident from the adjusted R^2 of 0.07, which is extremely high for a predictive regression with daily returns. Column (2) adds the pre-decimalization dummy as a control, which reduces the coefficient on VIX only marginally. Adding the lagged market return as an explanatory variable in column (3) also has only a weak effect, and VIX remains a strong predictor. Columns (5) to (7) repeat the same regressions, but now with reversal strategy returns calculated from quote-midpoint returns. The magnitude of the coefficient is about two-thirds of the coefficient obtained with transaction-price returns, but everything else is similar.

Columns (9) to (11) examine the predictability of reversal strategy returns using industry portfolios as basis assets. Even though the industry reversal strategy is unconditionally not profitable (the fitted value with normalized VIX at the sample mean of 1.4% is close to zero), its returns vary substantially with VIX. An increase of one percentage point in the normalized VIX raises the

Table 2
Predicting reversal strategy returns with VIX

	Individual stocks Transaction-price returns				Individual stocks Quote-midpoint returns				Industry portfolios			
	Daily			Monthly	Daily			Monthly	Daily			Monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	−0.03	−0.05	−0.02	0.02	−0.06	−0.07	−0.04	−0.01	−0.08	−0.09	−0.06	−0.05
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
VIX	0.22	0.20	0.18	0.15	0.16	0.16	0.13	0.10	0.07	0.07	0.05	0.04
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Pre-decim.		0.22	0.22	0.23		0.08	0.09	0.09		0.00	0.01	0.01
		(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)		(0.02)	(0.02)	(0.02)
R_M			−0.60	−0.03			−0.59	−0.16			−0.42	−0.05
			(0.19)	(0.26)			(0.21)	(0.28)			(0.17)	(0.16)
Adj. R^2	0.07	0.11	0.11	0.56	0.03	0.03	0.04	0.25	0.01	0.01	0.01	0.07

In the daily regressions, the dependent variable is the reversal strategy return on day t (in percents), and the predictor variables are measured at the end of day $t-5$. In the monthly regressions, the dependent variable is the monthly average of daily reversal strategy returns, and the predictor variables are measured five days before the end of the month preceding the return measurement month. VIX, the CBOE S&P 500 implied volatility index, is normalized to a daily volatility measure by dividing it by $\sqrt{250}$. The control variables include a dummy for the time period prior to decimalization (April 9, 2001) and R_M, the lagged four-week return on the value-weighted CRSP index. Newey-West HAC standard errors (with twenty lags for daily data and three lags for monthly data) are reported in parentheses. Quote-midpoint returns are calculated from bid-ask midpoints of daily CRSP closing quotes (with Nasdaq stocks only). The industry reversal strategy is calculated with transaction prices. The sample period runs from January 1998 to December 2010.

expected daily return by 0.07 percentage points. The fitted value corresponding to VIX levels of 60% reached during the height of the financial crisis (which corresponds to roughly 4% for the normalized VIX used in the regression) is a conditional expected return of about 0.20% per day. This indicates that either there is unusual industry-level liquidity demand from the public (e.g., because of greater commonality of within-industry order imbalances), or that market makers are particularly averse to absorbing correlated order imbalances in times of high VIX.

Columns (4), (8), and (12) explore monthly regressions in which the daily reversal strategy returns are averaged within each calendar month, and the predictor variables are measured five days before the end of the prior month. The magnitude of the coefficient on VIX is very close to the coefficient in the corresponding daily regression, which indicates that the predictable component in reversal strategy returns persists far beyond one day. As a consequence, the monthly adjusted R^2 is enormous, reaching 56% for transaction-price returns, 25% for quote-midpoint returns, and a still sizeable 7% for the industry portfolio reversal strategy, which underscores the economic significance of the predictability associated with VIX.

The high degree of predictability is also apparent in Figure 2. The plots on the left-hand side average the dependent variable (solid line) and the fitted values from the predictive regressions in Table 2, columns (1), (5), and (9) (dotted line), within three-month rolling windows. Focusing on the first row, which shows the transaction-price returns of the reversal strategy constructed from individual stocks, the in-sample fit (in terms of these three-month moving averages) of these regressions is extremely good.

However, the VIX is quite persistent, and so a natural concern is how well this in-sample fit extends out of sample.[11] An out-of-sample analysis would also be an interesting check of the extent to which the enormous increase in reversal strategy returns during the financial crisis could have been predicted conditional on pre-crisis estimates of the predictive regression coefficients and conditional on the time path of VIX realized during the crisis. For these reasons, the plots on the right-hand side look at an out-of-sample experiment. The predictive regressions are estimated with data leading up to June 2007—that is, until just before the onset of the financial crisis of 2007–09. The plot then compares the three-month moving averages of realized reversal strategy returns with the out-of-sample prediction based on the pre-June 2007 coefficient estimates. As the plot in the top row shows, the out-of-sample fit for transaction-price returns is remarkably good. In other words, the increase in reversal strategy profitability during the financial crisis corresponds closely to what one would have expected conditional on the rise in VIX, given the relationship between

[11] The persistence of the predictor does not lead to a noticeable predictive regression bias in this case, though; see the online appendix.

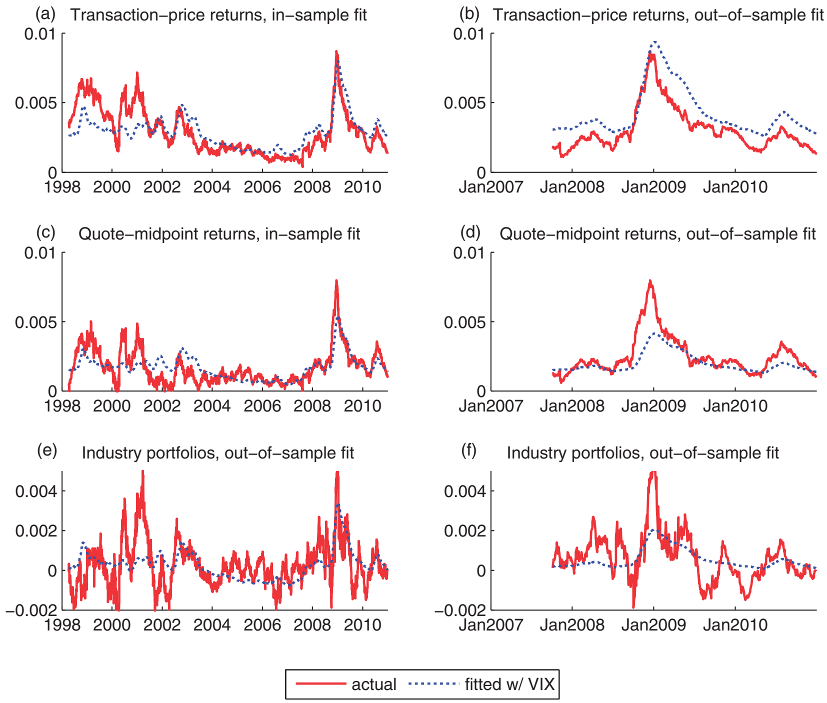

Figure 2
In-sample and out-of-sample predicted reversal strategy returns
The figure shows three-month moving averages of daily reversal strategy returns and of fitted values from predictive regressions on lagged VIX as in columns (1), (5), and (9) of Table 2. The left-hand side plots show the in-sample fitted values, and the plots on the right-hand side show the out-of-sample fitted values when the predictive regression is estimated with data up to the end of June 2007.

VIX and reversal strategy profits that was apparent before the crisis. For quote-midpoint returns, the out-of-sample fit is good, too, but the out-of-sample predictions underestimate to some extent the reversal strategy returns during the height of the crisis. For the industry-portfolio reversal strategy in the bottom row, the out-of-sample fit also picks up a substantial part of the increase in reversal strategy profits during the financial crisis, but the fit is not as good as for the individual-stock reversal strategies, which partly simply reflects the fact that even in-sample, the returns of the industry-portfolio reversal strategy are less predictable.

2.2 Time variation in compensation for risk

The volatility of individual-stock reversal strategy returns is generally low relative to the mean returns earned by these strategies, but it is possible that periods of financial market turmoil could also produce bursts of substantially higher volatility of reversal strategy returns. To interpret the predictability of reversal strategy returns, it would be useful to know whether the rise in expected reversal strategy returns with VIX is just commensurate with a rise in their volatility, or whether the compensation per unit of risk increases as well. In Grossman and Miller (1988), a rise in the volatility of returns would increase the expected return from liquidity provision, but not the Sharpe ratio, unless market makers' participation costs or their risk aversion rose as well. Thus, if Sharpe ratios from liquidity provision are higher in times of high VIX, this would indicate that additional impediments to liquidity provision such as funding constraints (Gromb and Vayanos 2002; Brunnermeier and Pedersen 2009) may be relevant.

For this reason, I now investigate to what extent the conditional Sharpe ratios of reversal strategies vary with VIX. I specify the conditional mean of the reversal strategy return as

$$E[L_t^R | VIX_{t-5}] = \sigma_t \theta_t, \tag{20}$$

where $\sigma_t \equiv \mathrm{Var}(L_t^R | VIX_{t-5})^{1/2}$, and θ_t is the Sharpe ratio conditional on VIX_{t-5}. Both σ_t and θ_t are assumed to be linear in VIX_{t-5} and a pre-decimalization dummy d_{t-5},

$$\sigma_t = a_0 + a_1 VIX_{t-5} + a_2 d_{t-5} \tag{21}$$

$$\theta_t = b_0 + b_1 VIX_{t-5} + b_2 d_{t-5}. \tag{22}$$

The earlier evidence of a positive relationship between VIX and reversal strategy returns could be explained by either $a_1 > 0$ or $b_1 > 0$.

To estimate σ_t conditional on lagged VIX, I run predictive regressions

$$|\tilde{L}_t^R| \kappa = a_0 + a_1 VIX_{t-5} + a_2 d_{t-5} + u_t, \tag{23}$$

where $\tilde{L}_t^R$ is the residual from the regression of daily reversal strategy returns on VIX_{t-5} and d_{t-5}, and it is scaled by

$$\kappa = \frac{\left(T^{-1} \sum_{t=1}^{T} (\tilde{L}_t^R)^2\right)^{1/2}}{T^{-1} \sum_{t=1}^{T} |\tilde{L}_t^R|} \tag{24}$$

to account for the difference between standard deviation and expected absolute value.[12] The fitted value is used as an estimate of σ_t. I then proceed to run predictive regressions

$$\frac{L_t^R}{\sigma_t} = b_0 + b_1 VIX_{t-5} + b_2 d_{t-5} + e_t. \tag{25}$$

The fitted value from (25) represents the conditional Sharpe ratio of the reversal strategy return.

12 In a large sample drawn from a (mean zero) normal distribution, κ would equal $\sqrt{\pi/2}$, the ratio of the standard deviation to the expected absolute value.

Table 3
Conditional Sharpe ratios of reversal strategies

	Indiv. stocks		
	Transact. prices (1)	Quote- midpoints (2)	Industry portfolios (3)
Intercept	0.33	0.10	−0.12
	(0.04)	(0.04)	(0.04)
VIX	0.13	0.13	0.08
	(0.03)	(0.03)	(0.02)
Pre-decim.	0.23	0.02	0.02
	(0.04)	(0.04)	(0.03)
Adj. R^2	0.02	0.01	0.00

The dependent variable is the reversal strategy return on day t standardized by its conditional volatility, which is estimated by regressing (scaled) absolute unexpected reversal strategy returns on lagged VIX. The VIX is measured at the end of day $t-5$, and it is normalized to a daily volatility measure by dividing it by $\sqrt{250}$. The regressions include a dummy for the time period prior to decimalization (April 9, 2001). Newey-West HAC standard errors (with twenty lags) are reported in parentheses. The sample period runs from January 1998 to December 2010.

Table 3 presents the results. The regressions show that the VIX still has strong explanatory power after scaling returns with the reciprocal of their conditional volatility. The point estimates of the coefficient on VIX are far larger than the standard errors, and the economic magnitudes are big. For the individual-stock reversal strategy with transaction-price returns in column (1), a one-percentage-point increase in the VIX corresponds to an increase in the conditional (annualized) Sharpe ratio by 0.13.[13] With quote-midpoint returns in column (2), a one-percentage-point increase in VIX is associated with a similar increase in the conditional Sharpe ratio of 0.13. As in the previous unscaled regressions in Table 2, the coefficients on VIX for the industry portfolio reversal strategy are somewhat smaller, but still economically big.

To illustrate the time variation in the magnitudes of conditional Sharpe ratios, Figure 3 plots the fitted values from the regressions in Table 3. To focus on the variation in conditional Sharpe ratios associated with variation in VIX, the pre-decimalization dummy is set to zero for the whole sample in the calculation of the fitted values. The solid line represents transaction-price returns, quote-midpoint returns are shown as a dotted line, and conditional Sharpe ratios for industry-portfolio reversal strategy returns as a dashed line. The plots clearly show the substantial increase in conditional Sharpe ratios during times of financial market turmoil, such as the LTCM crisis in late 1998, and, much more dramatically, the financial crisis of 2007–09. The plots also show a pronounced spike in the second quarter of 2010 in which the European sovereign debt crisis leads to elevated levels of the VIX index. The volatility of reversal strategy returns is higher in times of high VIX, which dampens the rise in conditional Sharpe ratios compared with the rise in conditional expected returns. For example, the conditional expected return of the individual-stock

[13] Both the dependent variable and the VIX must be multiplied by $\sqrt{250}$ to get annualized numbers, and hence the coefficients in the table directly provide the effect of annualized VIX on annualized Sharpe ratios.

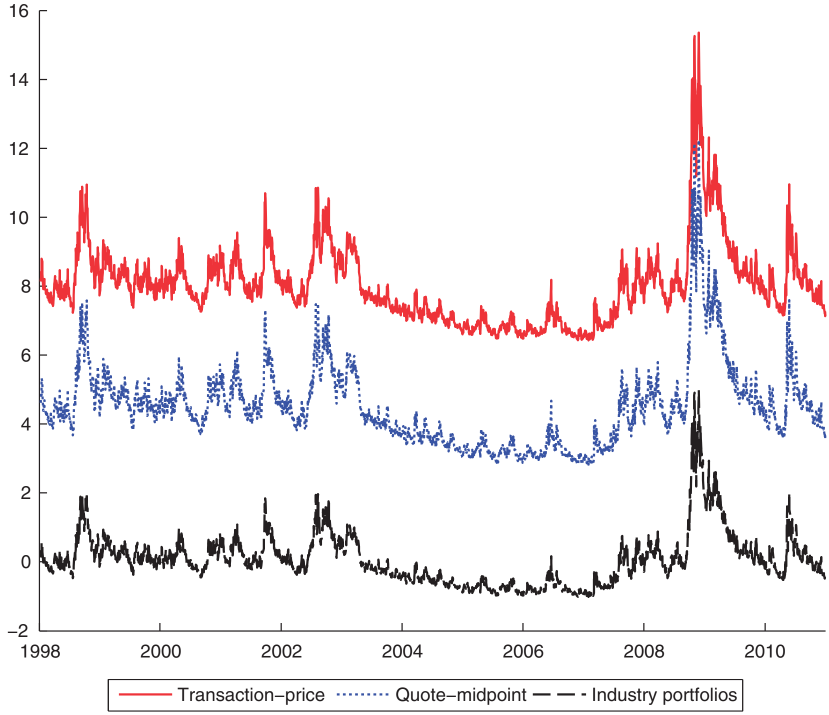

Figure 3
Annualized conditional Sharpe ratios of reversal strategy returns

reversal strategy calculated from transaction prices rose almost tenfold from the pre-crisis period to the fourth quarter of 2008, while the conditional Sharpe ratio only doubled. As the figure shows, the variation in conditional Sharpe ratios is still substantial, though. This indicates that liquidity providers earn a higher compensation per unit of risk in times of high VIX.

2.3 Exploring the role of the VIX

The results so far show that the VIX captures very well the time variation in the expected returns and the risk premium from providing liquidity. This does not necessarily mean that the VIX index itself is the state variable driving expected returns from liquidity provision. More likely, the VIX proxies for the underlying state variables that drive the willingness of market makers to provide liquidity and the public's demand for liquidity. Uncovering these underlying state variables is difficult, as they are likely highly correlated with VIX and among one another. For example, the severity of funding constraints, the level of risk, and perhaps also risk aversion on the part of market makers might all have spiked simultaneously during the financial crisis, and hence a time-series analysis will have a hard time disentangling these effects. Nevertheless, this section attempts to shed some light on potential underlying drivers of the predictability associated with VIX.

Given that VIX represents the square root of the risk-neutral expectation of variance, a natural question to ask first is whether the expectation of future variance under the physical measure or the variance risk premium drive the predictability of reversal strategy profits. If the variance risk premium captures option market makers', and perhaps more generally financial intermediaries', aversion to absorbing inventory, as argued by Gârleanu, Pedersen, and Poteshman (2009), then not only the expected variance component but also the variance risk premium component might be related to the returns from supplying liquidity.[14]

Table 4 repeats the regressions from Table 2, but with the VIX broken up into its two components. In column (1), the regression includes σ_M, the square root of a GARCH(1,1) forecast of the variance of the S&P 500 index return over a twenty-one-trading-day horizon. This horizon corresponds to the approximately one-calendar-month maturity of the options that are underlying the VIX index. The GARCH(1,1) model is estimated with daily S&P 500 returns over the full sample period from 1998 to 2010. Conditional volatility σ_M is then constructed as a multiperiod forecast from these estimates. The volatility risk premium is represented by VIX – σ_M.

As column (1) shows using transaction-price returns, both components of the VIX contribute roughly equally, in terms of the magnitude of their coefficients, to the individual-stock reversal strategy profitability. Including lagged market returns in column (2) has only a minor effect on the coefficient estimates. Both components are also significant predictors in the monthly regressions in column (3). With quote-midpoint returns in columns (5) to (7), however, most of the predictability is driven by the expected variance component and not by the variance risk premium. The same tends to be true for the industry-portfolio reversal strategy.

To the extent that the volatility forecast σ_M contains errors due to imprecision in estimation or omission of relevant conditioning information beyond the information captured in the GARCH model, it is also possible that the $VIX - \sigma_M$ variable picks up an expected volatility component missed by the GARCH forecast. The VIX is calculated from market prices of options and therefore may contain information about future volatility above and beyond the GARCH forecast. To check robustness, columns (4), (8), and (12) report monthly regressions that use an alternative volatility forecast in constructing σ_M. I obtain a monthly realized variance series for the S&P 500 index from

[14] In a simple affine jump-diffusion model with constant prices of risk, the volatility risk premium is a linear function of spot volatility, which would imply that expected variance and the volatility risk premium can be collinear (see, e.g., Chernov 2007). However, stochastic volatility of volatility or time-varying prices of risk break this collinearity. Empirically, estimates of the two components of VIX are positively correlated, but far from perfectly so. Nevertheless, their role may be difficult to disentangle with relatively short time series.

Table 4
Predicting reversal strategy returns: Separating conditional volatility and the volatility risk premium

	Individual stocks Transaction-price returns				Individual stocks Quote-midpoint returns				Industry portfolios			
	Daily		Monthly		Daily		Monthly		Daily		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	−0.06	−0.02	0.02	0.02	−0.08	−0.05	−0.01	−0.03	−0.09	−0.06	−0.06	−0.07
	(0.02)	(0.02)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)	(0.02)	(0.03)
VIX − σ_M	0.18	0.16	0.12		0.07	0.05	0.05		0.06	0.04	−0.01	
	(0.04)	(0.04)	(0.06)		(0.05)	(0.05)	(0.06)		(0.03)	(0.03)	(0.03)	
σ_M	0.21	0.18	0.16		0.17	0.15	0.12		0.07	0.05	0.05	
	(0.02)	(0.02)	(0.02)		(0.03)	(0.03)	(0.03)		(0.02)	(0.02)	(0.01)	
VIX − $\sigma_M(RV)$				0.15				0.08				0.01
				(0.04)				(0.05)				(0.02)
$\sigma_M(RV)$				0.15				0.13				0.07
				(0.05)				(0.06)				(0.03)
Pre-decim.	0.22	0.23	0.23	0.23	0.09	0.10	0.10	0.10	0.01	0.01	0.02	0.02
	(0.22)	(0.03)	(0.03)	(0.03)	(0.09)	(0.03)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)
R_M		−0.60	−0.05	−0.07		−0.58	−0.19	−0.13		−0.42	−0.08	−0.02
		(0.18)	(0.27)	(0.29)		(0.20)	(0.29)	(0.33)		(0.17)	(0.17)	(0.18)
Adj. R^2	0.11	0.11	0.56	0.56	0.04	0.04	0.25	0.26	0.01	0.01	0.08	0.07

In the daily regressions, the dependent variable is the reversal strategy return on day t (in percent), and the predictor variables are measured at the end of day $t-5$. The regression includes σ_M, the square root of a GARCH(1,1) forecast of the variance of the S&P 500 index return over a twenty-one-trading-day horizon, corresponding to the approximately one-calendar-month maturity of the options underlying VIX. The forecast is obtained by estimating the GARCH model with daily data, and then constructing multiperiod forecasts from these estimates. VIX – σ_M represents an estimate of the volatility risk premium. VIX is normalized to a daily volatility measure by dividing it by $\sqrt{250}$. In the monthly regressions, the dependent variable is the monthly average of daily reversal strategy returns, and the predictor variables are measured five days before the end of the month preceding the return measurement month. The monthly regression includes $\sigma_M(RV)$, the square root of an ARMA(1,1) variance forecast constructed from a monthly series of realized variances from Bollerslev, Gibson, and Zhou (2011). The monthly realized variances are the sum of squared five-minute returns of the S&P 500 within each month. Both the GARCH model for σ_M and the ARMA model for $\sigma_M(RV)$ are estimated in sample over the full sample period. The control variables include a dummy for the time period prior to decimalization (April 9, 2001) and R_M, the lagged four-week return on the value-weighted CRSP index. Newey-West HAC standard errors (with twenty lags for daily data and three lags for monthly data) are reported in parentheses. The sample period runs from January 1998 to December 2010, except for columns (4), (8), and (12), where the sample period ends in February 2010 due to limited availability of the realized volatility series.

Bollerslev, Gibson, and Zhou (2011),[15] where each monthly observation is the within-month sum of squared five-minute returns. I estimate an ARMA(1,1) model, the preferred model in Bollerslev, Gibson, and Zhou (2011), from these monthly realized variance observations; I use the ARMA(1,1) forecast at the end of each month as the expected variance, and the square root of this expected variance is denoted $\sigma_M(RV)$. Using this alternative measure of expected variance yields a slightly stronger effect for the variance risk premium for all three types of reversal strategies.

Overall, the results suggest that both the expected volatility component and the variance risk premium embedded in the VIX help forecast the returns from supplying liquidity. However, the bid-ask bounce component of reversal strategy returns (transaction price returns minus quote-midpoint returns) seems to be explained mostly by the variance risk premium, while the quote-midpoint reversal component is explained mostly by the expected variance component. This difference is intriguing, but theory does not yet provide much guidance on potential causes for this difference. The models in Ho and Stoll (1981) and Hendershott and Menkveld (2010) predict that the strength of quote-midpoint reversals depends on the magnitude of inventory imbalances absorbed by market makers, while the size of the bid-ask spread and the strength of the bid-ask bounce effect do not depend on inventory positions.[16] Thus, interpreted through the lens of these models, the findings above suggest the possibility that the variance risk premium might be correlated more strongly with liquidity supply factors (market power and risk-bearing capacity of market makers), which drive the bid-ask bounce, while expected volatility may be more strongly related to liquidity demand factors (variance of inventory imbalances) which, in addition to liquidity supply factors, influence the strength of quote-midpoint reversals. A further evaluation of this hypothesis is beyond the scope of this article, but it would be interesting to investigate this further in future research.

Table 5 looks at predictor variables that should proxy for liquidity supply factors. These alternative predictors include the level of idiosyncratic volatility (measured as the cross-sectional standard deviation of individual stock returns during the prior month) as a proxy for the level of risk faced by imperfectly diversified liquidity providers, the TED spread (the three-month Eurodollar deposit rate minus the three-month Treasury Bill rate) as a proxy for funding costs of financial intermediaries (see, e.g., Gârleanu and Pedersen 2011), and the thirteen-week growth rate in primary dealer repurchase agreements (repo) based on weekly data from the Federal Reserve Bank of New York. Repo is one of the main funding sources of broker-dealers, and Adrian and Shin (2010) show that expansion and contraction of broker-dealer balance sheets happens largely via expansion and contraction of repo. Times of high repo growth appear

[15] I thank Hao Zhou for providing the data on his website.

[16] In these models, the bid-ask spread does not have an adverse selection component, and hence a greater bid-ask spread introduces stronger negative serial correlation into transaction price changes.

Table 5
Predicting reversal strategy returns: Liquidity supply proxies

	Indiv. stocks Transaction price returns				Indiv. stocks Quote-midpoint returns				Industry portfolios			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	−0.09	0.16	0.23	−0.06	−0.11	0.06	0.14	−0.05	−0.09	−0.01	0.01	−0.07
	(0.04)	(0.02)	(0.01)	(0.03)	(0.05)	(0.02)	(0.01)	(0.04)	(0.03)	(0.01)	(0.01)	(0.02)
VIX				0.12				0.05				0.03
				(0.02)				(0.03)				(0.02)
Idio. Vol.	8.80			2.95	7.02			2.39	2.71			0.88
	(1.20)			(1.35)	(1.46)			(1.53)	(0.80)			(1.02)
TED		12.08		2.24		14.22		8.53		4.50		1.73
		(2.87)		(3.07)		(2.82)		(3.30)		(2.29)		(2.24)
Repo Growth			−0.71	−0.10			−0.86	−0.32			−0.01	0.18
			(0.27)	(0.29)			(0.27)	(0.29)			(0.36)	(0.37)
Pre-decim.	0.11	0.24	0.25	0.18	−0.01	0.10	0.11	0.05	−0.03	0.01	0.01	−0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
R_M				−0.64				−0.59				−0.43
				(0.17)				(0.18)				(0.17)
Adj. R^2	0.09	0.08	0.05	0.12	0.03	0.03	0.01	0.04	0.00	0.00	0.00	0.01

The dependent variable is the reversal strategy return on day t (in percents), and the predictor variables are measured at the end of day $t-5$. VIX, the CBOE S&P 500 implied volatility index, is normalized to a daily volatility measure by dividing it by $\sqrt{250}$. Idiosyncratic volatility is measured as the cross-sectional standard deviation of individual stock returns on day $t-5$. TED is the spread between three-month Eurodollar deposit rates and three-month Treasury Bill rates. Repo growth is the thirteen-week growth rate in primary dealer repo outstanding calculated from weekly data reported by the Federal Reserve Bank of New York. A dummy for the time period prior to decimalization (April 9, 2001) is included as a control variable. Newey-West HAC standard errors (with twenty lags) are reported in parentheses. Quote-midpoint returns are calculated from bid-ask midpoints of daily CRSP closing quotes (with Nasdaq stocks only). The industry-portfolio reversal strategy is calculated with transaction prices. The sample period runs from January 1998 to December 2010.

to be associated with high intermediary risk appetite and therefore, presumably, aggressive liquidity provision.[17]

The results in Table 5 show that when these alternative predictors are the only explanatory variable (in addition to the pre-decimalization dummy variable), they do indeed capture some of the predictable variation in reversal strategy returns, and they do so with the expected sign. High idiosyncratic volatility and high TED spread should be associated with lower liquidity supply and higher expected returns from liquidity provision, which is consistent with the positive coefficients in Table 5. For repo growth, too, the sign is as expected: high repo growth predicts low future returns from liquidity provision. With the exception of columns (10) and (11) for the industry portfolio reversal strategy, the point estimates are also more than two standard errors away from zero. These results provide some support for the notion that the time variation in expected reversal strategy returns is driven at least partly by liquidity supply factors.

The regressions reported in columns (4), (8), and (12) show, however, that these alternative predictors do not fully subsume the predictive power of the VIX and the lagged market return. Including the liquidity supply proxies jointly with the VIX leads to a substantial drop in their slope coefficients, while the coefficient on VIX does not drop as much compared with the earlier estimates in Table 2. Statistically, the coefficient on VIX remains highly significant for transaction-price returns and marginally significant for quote-midpoint returns and the industry portfolio reversal strategy, while the liquidity supply proxies are mostly insignificant in the joint regression. The VIX seems to contain additional information regarding the current state of market liquidity provision that is not fully captured by the liquidity supply proxies.

2.4 Exploring cross sectional heterogeneity

In this section, I examine the expected return from liquidity provision and its time variation for subgroups of stocks sorted by stock characteristics. The motivation for this analysis is twofold. First, there is reason to believe that in times of financial market turmoil the expected return from liquidity provision increases particularly strongly among “low quality” assets. For example, in the model of Brunnermeier and Pedersen (2009), high-volatility assets have higher margin requirements. When market makers face a lack of capital, they focus their liquidity provision activities on low-volatility assets and withdraw liquidity supply from high-volatility assets. Furthermore, Naik and Yadav (2003) find that individual dealers on the London Stock Exchange are averse to risk that would be diversifiable at the dealership firm level. To the extent that

[17] Adrian, Etula, and Muir (2011) show that a risk factor constructed from broker-dealer leverage can help explain a variety of asset pricing facts. For the purposes of the analysis in this article, repo growth is preferable because it is available at weekly frequency, while the broker-dealer balance sheet variables are from Flow of Funds Accounts data, which are available only quarterly.

high-volatility assets also experience the strongest increases in volatility during periods of turmoil, one would therefore expect a more pronounced withdrawal of liquidity supply from high-volatility assets. Second, Avramov, Chordia, and Goyal (2006) show that reversal strategy returns are highest among illiquid stocks, as measured by the Amihud (2002) illiquidity ratio. This raises the question of whether all of the reversal strategy return in the previous analysis, and its predictable variation, is driven entirely by illiquid stocks.

To analyze cross-sectional heterogeneity of this kind, I sort stocks into decile groups based on three characteristics: market capitalization at the end of the prior month, the Amihud (2002) illiquidity ratio computed as the average of the daily ratio of absolute returns and dollar trading volume during the prior month, and the volatility of daily returns during the prior month. To account for the fact that trading volume is counted differently on Nasdaq, the assignment of Amihud illiquidity ratio decile ranks is done separately for NYSE/AMEX and Nasdaq stocks.

Figure 4 presents fitted values from regressions of the subgroup reversal strategy returns on VIX and a pre-decimalization dummy, as in Table 2. The fitted values are evaluated at the 5th (circles) and 95th percentile (crosses) of the distribution of VIX, with the pre-decimalization dummy set to zero. The error bars indicate 95% confidence intervals. For comparison, the dashed line shows the high-VIX fitted value from a reversal strategy that uses all stocks, as in Table 2.

The figure clearly shows that the “lowest-quality” stocks (small, illiquid, high volatility) generally offer the highest reversal strategy returns, consistent with Avramov, Chordia, and Goyal (2006). Even in times of low VIX, reversal strategies among these stocks offer daily returns up to roughly 0.40% per day in transaction-price returns (top row) and 0.20% per day in quote-midpoint returns (bottom row). This is consistent with the flight-to-quality hypothesis discussed above.

In contrast, for large, liquid, low-volatility stocks, reversal strategy profits are very close to zero when VIX is low. In low-volatility times, liquidity providers are apparently sufficiently aggressive that the expected return from liquidity provision is close to zero for all but the lowest-quality stocks. In times of high VIX, however, even the largest, most liquid, lowest-volatility stocks exhibit statistically and economically significant reversal strategy returns. The magnitude of the return is on the order of about 0.1% per day for both transaction-price and quote-midpoint returns. This may seem small compared with the much bigger magnitudes for the lowest-quality stocks in times of high VIX, but one has to keep in mind that 0.1% per day represents an annualized return of about 25%. This is clearly economically significant, especially for a strategy that uses only the largest stocks.

Overall, the evidence suggests that flight to quality in times of high VIX leads to a particularly pronounced increase in the expected returns from liquidity provision among small, illiquid, high-volatility stocks. But the evaporation of

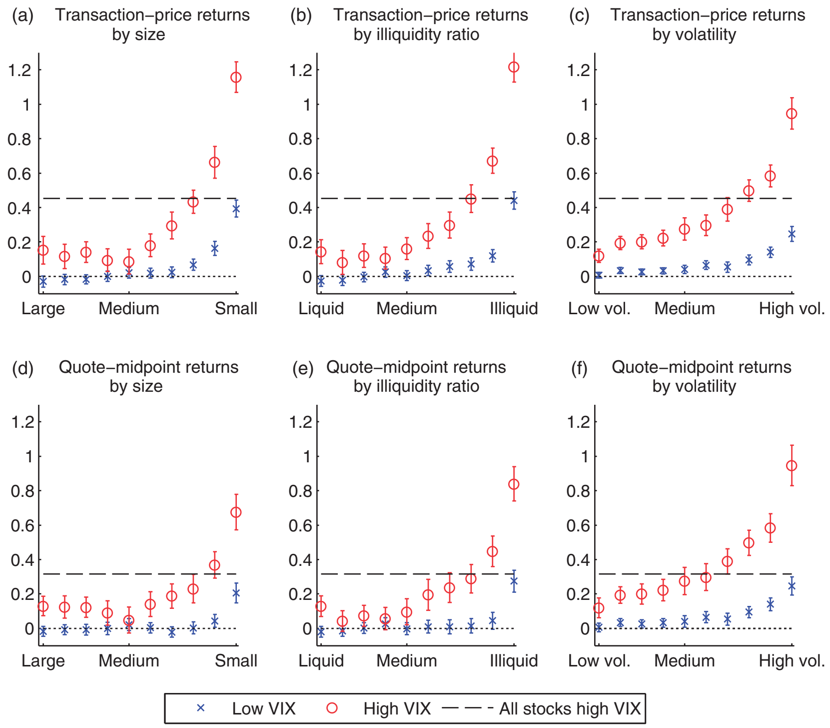

Figure 4
Predicted daily reversal strategy returns within size-, illiquidity-, and volatility-sorted subgroups evaluated at low (5th percentile) and high (95th percentile) VIX level
Fitted values from regression of each subgroup's reversal strategy returns on VIX and a pre-decimalization dummy as in Table 2. Error bars indicate 95% confidence intervals. The dashed line shows the corresponding high-VIX fitted value from the reversal strategy in Table 2 that uses all stocks.

liquidity is not confined to these types of stocks. It is a pervasive phenomenon that affects the largest, most liquid, lowest-volatility stocks, too.

3. Conclusion

This article shows that short-term reversal strategy returns can be interpreted as proxies for the returns from liquidity provision earned by the market-making sector. In times of financial market turmoil, as indicated by elevated levels of the VIX index, the expected returns of these reversal strategies rise predictably and dramatically. For example, during the financial crisis of 2007–09, expected returns of reversal strategies formed with individual stocks rose almost tenfold from their levels in 2006 in close lockstep with a corresponding increase in the VIX index. Even reversal strategies formed with industry portfolios as basis assets, which are not profitable in "normal" times, earn substantial returns during times of high VIX. The volatility of reversal strategy returns is less sensitive to the VIX than expected returns. As a result, conditional Sharpe ratios of reversal strategies are elevated in times of high VIX.

These findings suggest that the expected return and the risk premium earned by liquidity providers are highly time-varying and closely related to the level of the VIX index. The same factors that drive time variation in the VIX index appear to drive time variation in the returns from liquidity provision.

Thus, at least part of the reason for the evaporation of market liquidity during periods of financial market turmoil seems to be that liquidity providers demand a higher expected return from liquidity provision. Potential explanations for this phenomenon are provided by Adrian and Shin (2010), who argue that variations in financial intermediaries' risk appetite are driven by risk-management constraints, which are more likely to be binding when VIX is high, and Brunnermeier and Pedersen (2009), who show that the funding of liquidity suppliers can dry up when volatility is high.

Appendix A: Proofs

Informed trader demand. Informed traders take as given their joint aggregate demand and the demand function of the market maker, and CARA utility implies that their demand function is linear in the expected dollar return of the asset,

$$y_t = \tilde{\beta}(E[P_{t+1}|\mathcal{I}_t] - E[P_t|\mathcal{I}_t]), \tag{A1}$$

where $\mathcal{I}_t$ is the informed traders' information set and the slope $\tilde{\beta}$ represents the aggregate risk-bearing capacity of informed traders divided by the variance of the asset perceived by informed investors. Given the IID nature of the shocks in the model, we have $E[P_{t+1}|\mathcal{I}_t] = v_t + s_t$. Informed traders conjecture (confirmed below) that their aggregate price impact per unit of order flow will be $1/\gamma + \phi$, and that their aggregate demand is linear in their signal, $y_t = \beta s_t$, which implies

$$E[P_t|\mathcal{I}_t] = v_t + \left(\frac{1}{\gamma} + \phi\right)\beta s_t. \tag{A2}$$

Substituting back into (A1),

$$y_t = \tilde{\beta}\left(s_t - \left(\frac{1}{\gamma} + \phi\right)\beta s_t\right), \tag{A3}$$

which is consistent with the conjecture that $y_t = \beta s_t$, with

$$\beta = \frac{\tilde{\beta}}{1 + \tilde{\beta}\left(\frac{1}{\gamma} + \phi\right)}. \tag{A4}$$

Equilibrium. The joint normality of δ_{t+1} and z_t implies

$$E[\delta_{t+1}|\mathcal{M}_t] = \frac{\beta\sigma_\delta^2}{\beta^2\sigma_\delta^2 + \sigma_z^2} x_t. \tag{A5}$$

Writing $E[\delta_{t+1}|\mathcal{M}_t] = \phi x_t$, with ϕ defined accordingly,[18] substituting into the market maker's demand function, and imposing the market-clearing condition $x_t + m_t = 0$ yields the equilibrium

[18] Note that, as shown above, β is a function of ϕ, and so the definition of ϕ is implicit. The explicit expression of ϕ is rather complicated, and does not provide further essential intuition other than that the aggressiveness of the informed traders' demand, β, is moderated by the price impact that the informed traders expect to have in aggregate.

price

$$P_t = v_t + \left(\frac{1}{\gamma} + \phi\right) x_t. \tag{A6}$$

Using the definition of (dollar) returns $R_{t+1} \equiv P_{t+1} - P_t$, we obtain

$$R_{t+1} = \xi_{t+1} + \delta_{t+1} + \left(\frac{1}{\gamma} + \phi\right)(x_{t+1} - x_t). \tag{A7}$$

Here, δ_{t+1} can be decomposed into a predictable (based on x_t) and an unpredictable component as $\delta_{t+1} = \phi x_t + \eta_{t+1}$, which yields

$$R_{t+1} = \xi_{t+1} + \eta_{t+1} + \left(\frac{1}{\gamma} + \phi\right) x_{t+1} - \left(\frac{1}{\gamma}\right) x_t, \tag{A8}$$

as stated in the text.

Aggregate Market-maker Profits. Returns per dollar invested for the market maker are

$$q_t = -\left(\frac{1}{2}\sum_{i=1}^{N} |x_{it-1}|\right)^{-1} \sum_{i=1}^{N} x_{it-1} R_{it}. \tag{A9}$$

Since δ_{it} and z_{it} are cross-sectionally jointly normal IID, x_{it} is also cross-sectionally normal IID, which implies that we can find the probability limit of the term in the inverse in (A9) from the properties of the half-normal distribution. We obtain

$$\operatorname*{plim}_{N\to\infty} \frac{1}{2N} \sum_{i=1}^{N} |x_{it-1}| = \frac{\sigma_x}{\sqrt{2\pi}}, \tag{A10}$$

where $\sigma_x \equiv \mathrm{Var}(x_{it})^{1/2}$, while

$$\operatorname*{plim}_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} x_{it-1} R_{it} = -\frac{\sigma_x^2}{\gamma}. \tag{A11}$$

Taking the negative of the ratio (A11) and (A10) yields the result stated in the text.

Reversal strategy profits. Focusing first on the inverse term in the expression for the reversal strategy weights (9), and taking probability limits, it follows from the (cross-sectionally IID) normal distribution of $R_{it-1} - R_{mt-1}$ that

$$\operatorname*{plim}_{N\to\infty} \frac{1}{2N} \sum_{i=1}^{N} |R_{it-1} - R_{mt-1}| = \frac{\sigma_R}{\sqrt{2\pi}}, \tag{A12}$$

where σ_R is defined as the cross-sectional standard deviation of R_{it-1}. Further,

$$\operatorname*{plim}_{N\to\infty} \frac{1}{N} \sum_{i=1}^{N} R_{it-1} R_{it} = E[R_{it-1} R_{it}] \tag{A13}$$

$$= -\left(\frac{1}{\gamma} + \phi\right)\left(\frac{1}{\gamma}\right)\sigma_x^2. \tag{A14}$$

Taking the negative of the ratio of (A14) and (A12) yields the result stated in the text.

Appendix B: Data

The stock-return data used in this article are from the CRSP daily returns file. The sample period runs from January 1998 to December 2010. Reversal strategy returns based on transaction prices are calculated from daily closing prices, and the reversal strategy returns based on quote-midpoints are calculated from averages of closing bid and ask quotes, as reported in the CRSP daily returns file (for Nasdaq stocks only), adjusted for stock splits and dividends using the CRSP adjustment factors and dividend information. To enter into the sample, a stock needs to have share code 10 or 11. In addition, it must have a closing price of at least \$1 on the last trading day of the previous calendar month.

In a few instances, the closing bid and ask data for Nasdaq stocks on CRSP have some data-recording errors, such as increases of bid or ask by a factor of 100 or digits that are cut off. To screen out these corrupted records, I require that the ratio of bid to quote-midpoint is not smaller than 0.5, and the one-day return based on quote-midpoints minus the return based on closing prices is not less than -50% and not higher than 100%. If a closing transaction price is not available, the quote-midpoint is used to calculate transaction-price returns.

References

Admati, A. R., and P. Pfleiderer. 1988. A Theory of Intraday Patterns: Volume and Price Variability. *Review of Financial Studies* 1:3–40.

Adrian, T., E. Etula, and T. Muir. 2011. Financial Intermediaries and the Cross-section of Asset Returns. Working Paper, Northwestern University and Federal Reserve Bank of New York.

Adrian, T., and H. S. Shin. 2010. Liquidity and Leverage. *Journal of Financial Intermediation* 19:418–37.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets* 5:31–56.

Ang, A., S. Gorovyy, and G. B. van Inwegen. 2011. Hedge Fund Leverage. *Journal of Financial Economics* 102:102–26.

Avramov, D., T. Chordia, and A. Goyal. 2006. Liquidity and Autocorrelations in Individual Stock Returns. *Journal of Finance* 61:2365–394.

Bao, J., J. Pan, and J. Wang. 2011. The Illiquidity of Corporate Bonds. *Journal of Finance* 66:911–46.

Barclay, M. J., W. G. Christie, J. H. Harris, E. Kandel, and P. H. Schulz. 1999. Effects of Market Reform on the Trading Costs and Depths of Nasdaq Stocks. *Journal of Finance* 54:1–34.

Ben-David, I., F. Franzoni, and R. Moussawi. 2012. Hedge Fund Stock Trading in the Financial Crisis of 2007–2008. *Review of Financial Studies* 25:1–54.

Bessembinder, H. 2003. Trade Execution Costs and Market Quality After Decimalization. *Journal of Financial and Quantitative Analysis* 38:747–77.

Bollerslev, T., M. Gibson, and H. Zhou. 2011. Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-implied and Realized Volatilities. *Journal of Econometrics* 160:102–18.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen. 2008. Carry Trades and Currency Crashes. In *NBER Macroeconomics Annual 2008*, ed. D. Acemoglu, K. Rogoff, and M. Woodford. University of Chicago Press, pp. 313–47.

Brunnermeier, M. K., and L. H. Pedersen. 2009. Market Liquidity and Funding Liquidity. *Review of Financial Studies* 22:2201–38.

Brunnermeier, M. K. 2009. Deciphering the Liquidity and Credit Crunch 2007–2008. *Journal of Economic Perspectives* 23:77–100.

Chernov, M. 2007. On the Role of Risk Premia in Volatility Forecasting. *Journal of Business and Economic Statistics* 25:411–26.

Chordia, T., A. Sarkar, and A. Subrahmanyam. 2005. An Empirical Analysis of Stock and Bond Market Liquidity. *Review of Financial Studies* 18:85–129.

Christie, W. G., and P. H. Schultz. 1994. Why Do NASDAQ Market Makers Avoid Odd-eighth Quotes? *Journal of Finance* 49:1813–40.

Comerton-Forde, C., T. Hendershott, C. M. Jones, P. C. Moulton, and M. S. Seasholes. 2010. Time Variation in Liquidity: The Role of Market Maker Inventories and Revenues. *Journal of Finance* 65:295–331.

Deuskar, P. 2008. Extrapolative Expectations: Implications for Volatility and Liquidity. Working Paper, University of Illinois Urbana-Champaign.

Fama, E. F., and K. R. French. 1997. Industry Costs of Equity. *Journal of Financial Economics* 43:153–93.

Gârleanu, N., L. H. Pedersen, and A. M. Poteshman. 2009. Demand-based Option Pricing. *Review of Financial Studies* 22:4259–99.

Gârleanu, N., and L. H. Pedersen. 2011. Margin-based Asset Pricing and Deviations from the Law of One Price. *Review of Financial Studies* 24:1980–2022.

Glosten, L. R., and P. R. Milgrom. 1985. Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders. *Journal of Financial Economics* 14:71–100.

Gorton, G., and A. Metrick. 2010. Haircuts. *Federal Reserve Bank of St. Louis Review* 92:507–19.

Gromb, D., and D. Vayanos. 2002. Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs. *Journal of Financial Economics* 66:361–407.

Grossman, S. J., and M. H. Miller. 1988. Liquidity and Market Structure. *Journal of Finance* 43:617–33.

Hameed, A., W. Kang, and S. Viswanathan. 2010. Stock Market Declines and Liquidity. *Journal of Finance* 65:257–93.

Hansch, O., N. Y. Naik, and S. Viswanathan. 1998. Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange. *Journal of Finance* 53:1623–56.

Hasbrouck, J. 1991. The Summary Informativeness of Stock Trades: An Econometric Analysis. *Review of Financial Studies* 4:571–95.

Hendershott, T., C. M. Jones, and A. J. Menkveld. 2011. Does Algorithmic Trading Improve Liquidity? *Journal of Finance* 66:1–33.

Hendershott, T., and A. J. Menkveld. 2010. Price Pressures. Working Paper, University of California–Berkeley.

Hendershott, T., and M. S. Seasholes. 2007. Market Maker Inventories and Stock Prices. *American Economic Review Papers and Proceedings* 97:210–14.

Ho, T., and H. R. Stoll. 1981. Optimal Dealer Pricing Under Transactions and Return Uncertainty. *Journal of Financial Economics* 9:47–73.

Kaniel, R., G. Saar, and S. Titman. 2008. Individual Investor Trading and Stock Returns. *Journal of Finance* 63:273–310.

Khandani, A. E., and A. W. Lo. 2007. What Happened to the Quants in August 2007? *Journal of Investment Management* 5:5–54.

Kyle, A. S. 1985. Continuous Auctions and Insider Trading. *Econometrica* 53:1315–35.

Lehman, B. N., 1990. Fads, Martingales, and Market Efficiency. *Quarterly Journal of Economics* 105:1–28.

Llorente, G., R. Michaely, G. Saar, and J. Wang. 2002. Dynamic Volume-return Relation of Individual Stocks. *Review of Financial Studies* 15:1005–47.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton. 2010. How Sovereign Is Sovereign Credit Risk? *American Economic Journal: Macroeconomics* 3:75–103.

Lo, A. W., and A. C. MacKinlay. 1990. When Are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies* 2:175–205.

Menkveld, A. J. 2011. High-frequency Trading and the New Market Makers. Working Paper, Vrije Universiteit Amsterdam.

Naik, N. Y., and P. K. Yadav. 2003. Do Dealer Firms Manage Inventory on a Stock-by-stock or a Portfolio Basis? *Journal of Financial Economics* 69:325–53.

Pástor, Ľ., and R. F. Stambaugh. 2003. Liquidity Risk and Expeced Stock Returns. *Journal of Political Economy* 111:642–85.

Wang, J. 1994. A Model of Competitive Stock Trading Volume. *Journal of Political Economy* 102:127–68.