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EVAPORATING LIQUIDITY

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ABSTRACT

Evaporating Liquidity*

The returns of short-term reversal strategies in equity markets can be interpreted as a proxy for the returns from liquidity provision. Analysis of reversal strategies shows that the expected return from liquidity provision is strongly time-varying and highly predictable with the VIX index. Expected returns and conditional Sharpe Ratios increase enormously along with the VIX during times of financial market turmoil, such as the financial crisis 2007-09. Even reversal strategies formed from industry portfolios (which do not yield high returns unconditionally) produce high rates of return and high Sharpe Ratios during times of high VIX. 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 Classification: G01 and G12
Keywords: financial crisis, liquidity and return reversals

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1 Introduction

Liquidity evaporated in many sectors of financial markets during the financial crisis 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 paper studies this second channel using data from equity markets. The main objective is to estimate the extent by which the expected return from liquidity provision rises in times of financial market turmoil. The notion of "liquidity providers" adopted in this paper 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

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

(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. Effectively, reversal strategies 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 paper 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&P500 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 (2011) 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 literature that finds the VIX to be related to various asset-pricing phenomena that may be related to risk-taking of financial intermediaries, 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, Pan, Pedersen, and Singleton (2010)).

Figure 1 illustrates some of the key findings of the paper. The solid line plots a three-

[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.

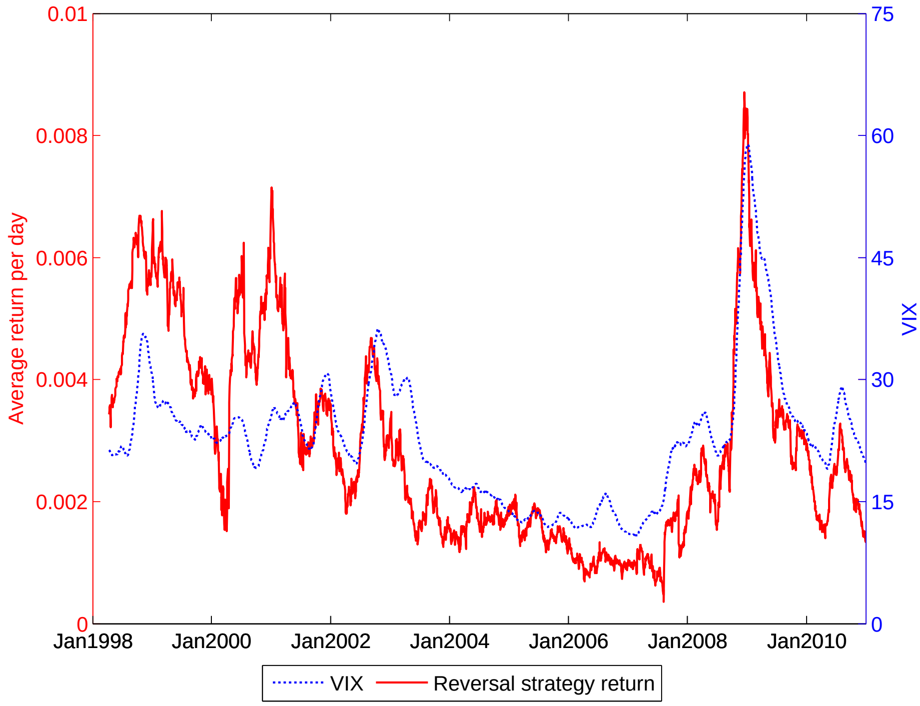

Figure 1: 3-month moving averages of daily return-reversal strategy returns and the CBOE S&P500 implied volatility index (VIX). Each day t, the reversal strategy returns are calculated as the average of returns from five reversal strategies that weight stocks proportional to the negative of market-adjusted 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.

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 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 exceed 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 almost perfectly.

Predictive regressions confirm that the correlation between VIX and reversal strategy returns is predictive, i.e., 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 paper 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 paper 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 each other, 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 paper 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, Hendershott, Jones, Moulton, and Seasholes (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 paper 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 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 papers 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 paper 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 paper, 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 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.

2 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 understand which reversal strategy specification approximates best 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.

2.1 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, 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]

[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.

Informed traders submit market orders, i.e., 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).

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 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 for both 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 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 earns positive expected profits.

2.2 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

[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.

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 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

[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.

thought of as changing the demand for liquidity.

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 non-degenerate 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 endogenizing the limited risk-bearing capacity of market makers implied by the assumption of a finite γ.

2.3 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 Eq. (7). Some researchers have obtained proprietary data sets on designated market maker inventory positions (e.g., Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (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 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 of 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 market place.

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 dollar 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 to 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: (a) 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}; (b) high values of L_t^R might reflect high ϕ (which raises ρ towards one) rather than high L_t^{MM}.

With regards to (a), 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

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

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 regards to (b), 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 $0 \leq \rho \leq 1$, 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

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

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 Appendix C, 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 paper.

2.4 Empirical Implementation and Data

The empirical implementation of the reversal strategies uses daily data on NYSE, AMEX, and Nasdaq stocks from CRSP (see Appendix B). 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 affect 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 48 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 dealer inventory positions on the London Stock Exchange is roughly two days.

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

Hendershott and Menkveld (2010), using NYSE data, find half-lifes 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 to capture much of the effects of imperfect liquidity provision. 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, Michaely, Saar, and Wang (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 sub-strategies: 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 sub-strategies' 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 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 Appendix C).

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, i.e., the part that induces negative serial correlation in transaction-price returns.[8] However, it would also interesting to see how much of the returns from liquidity

[8]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

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 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 paper 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, e.g. 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

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

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 $\beta_{t-1} = \beta_1 + \beta_2 \operatorname{sgn}(f_{t-1})$, 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

market power of market makers, generates negative serial correlation and positive reversal strategy profits.

be dominated by large stocks. For this reason, Appendix C 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 paper. Section 3.4 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, Christie, Harris, Kandel, and Schulz (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 paper. 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.

3 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.[9]

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

[9]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

The daily reversal strategy return is calculated as the average of the returns, on day t, of five sub-strategies 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.

	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

index has a realized Sharpe Ratio of 0.26 during the sample period). Thus, the 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 percent 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 percent (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 paper 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.

3.1 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 parenthesis (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 adj. 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 only has 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

Table 2: Predicting Reversal Strategy Returns with VIX

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 $t-5$. 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&P500 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 20 lags for daily data and 3 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.

	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

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 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 there is either 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 adj. 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.[10] An out-of-sample analysis would also be an interesting check of

[10]The persistence of the predictor does not lead to a noticeable predictive regression bias in this case, though; see Appendix C

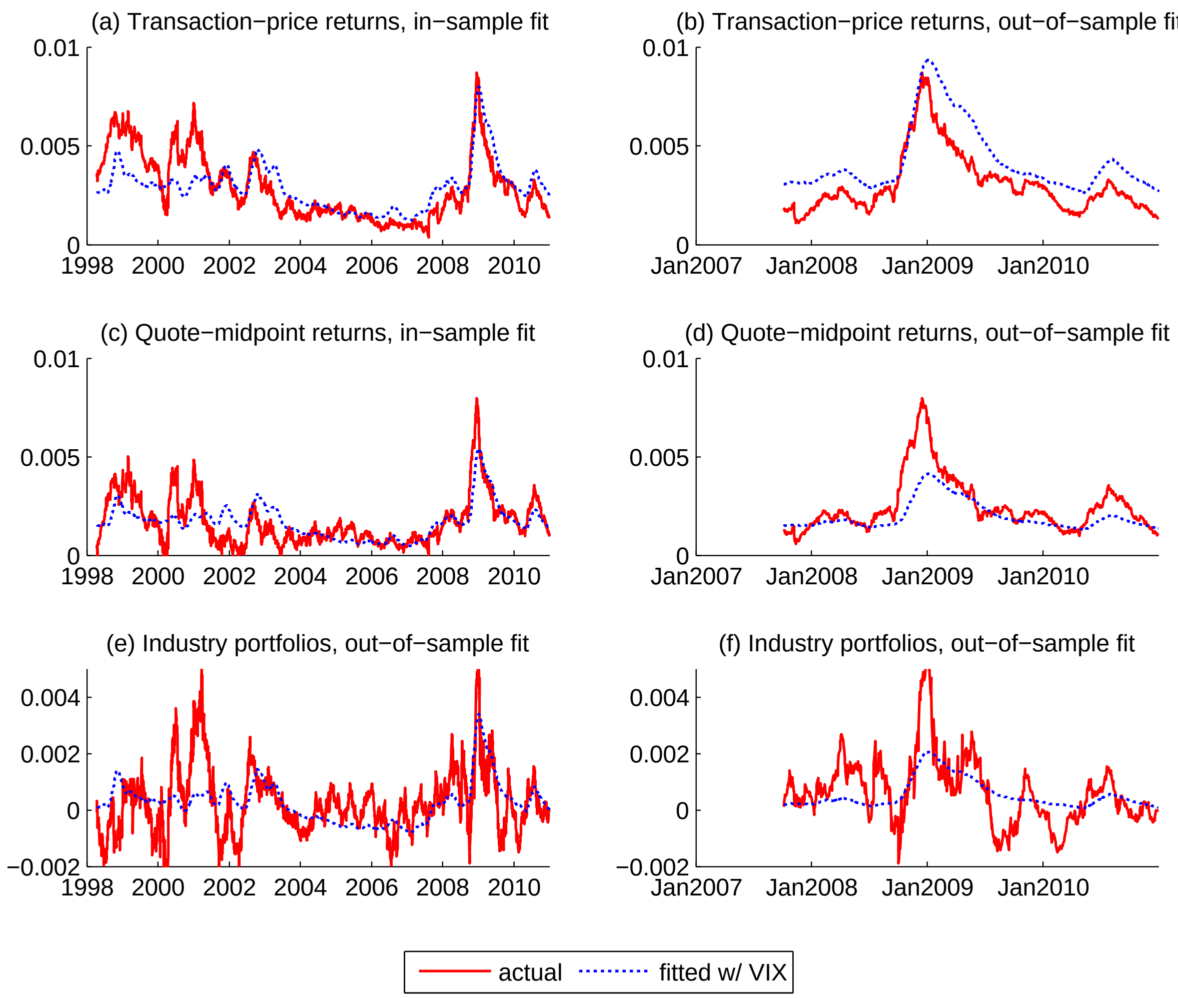

Figure 2: In-sample and out-of-sample predicted reversal strategy returns. The figure shows 3-month moving averages of daily reversal strategy returns and of fitted values from predictive regressions on lagged VIX as in columns (1), (5), and (9) of Table 2. The left-hand side plots show the in-sample fitted values, 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.

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, i.e. until just before the onset of the financial crisis 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 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.

3.2 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 $\sigma_t \equiv \text{Var}\,(L_t^R|VIX_{t-5})^{1/2}$, 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 either by $a_1 > 0$ 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.[11] The

[11]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

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 20 lags) are reported in parentheses. The sample period runs from January 1998 to December 2010.

	Indiv. stocks		Industry
	Transact. prices	Quote-midpoints	portfolios
	(1)	(2)	(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

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.

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

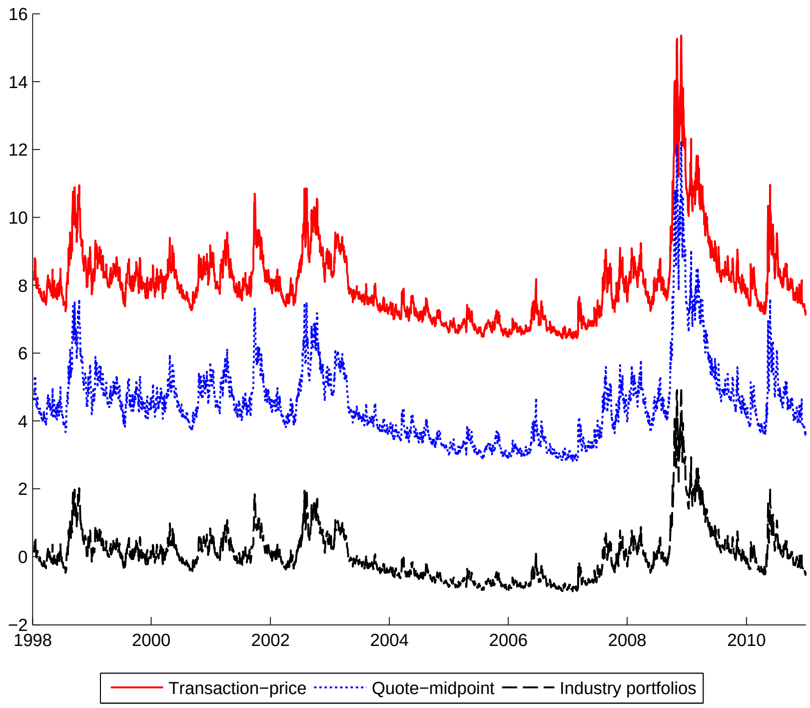

Figure 3: Annualized conditional Sharpe Ratios of reversal strategy returns

conditional (annualized) Sharpe Ratio by 0.13.[12] 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 lines represent transaction-price returns, quote-midpoint returns are shown as dotted lines, and conditional Sharpe Ratios for industry-portfolio reversal strategy returns as dashed line. The plots clearly show the substantial increase in conditional Sharpe Ratios during times of financial market

[12]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.

turmoil, such as the LTCM crisis in late 1998, and, much more dramatically, the financial crisis in 2007-09. The plots also show a pronounced spike in the second quarter of 2010 in which the European sovereign debt crisis lead 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 reversal strategy calculated from transaction prices rose almost ten-fold 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.

3.3 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 each other. 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.[13]

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&P500 index return over a 21 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&P500 returns over the full sample period from 1998 to 2010. Conditional volatility σ_M is then constructed as a multi-period forecasts 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) only has 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

[13] 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

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&P500 index return over a 21 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 multi-period 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 5-minute returns of the S&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 20 lags for daily data and 3 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.

	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

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&P500 index from Bollerslev, Gibson, and Zhou (2011),[14] where each monthly observation is the within-month sum of squared 5-minute returns. I estimate an ARMA(1,1) model, the preferred model in Bollerslev, Gibson, and Zhou (2011), from these monthly realized variance observations, and 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.[15] 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

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

[15] 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.

this paper, 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 3-month Eurodollar deposit rate minus the 3-month Treasury Bill rate) as a proxy for funding costs of financial intermediaries (see, e.g., Gârleanu and Pedersen (2011)), and the 13-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 to be associated with high intermediary risk appetite and therefore, presumably, aggressive liquidity provision.[16]

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 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 alterna-

[16] 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 paper, 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 is available only quarterly.

Table 5: Predicting Reversal Strategy Returns: Liquidity Supply Proxies

The dependent variable is the reversal strategy return on day t (in percent), and the predictor variables are measured at the end of day $t-5$. VIX, the CBOE S&P500 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 3-month Eurodollar deposit rates and 3-month Treasury Bill rates. Repo growth is the 13-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 20 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.

	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

tive 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.

3.4 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 is analysis is two-fold. 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 high-volatlity 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 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 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

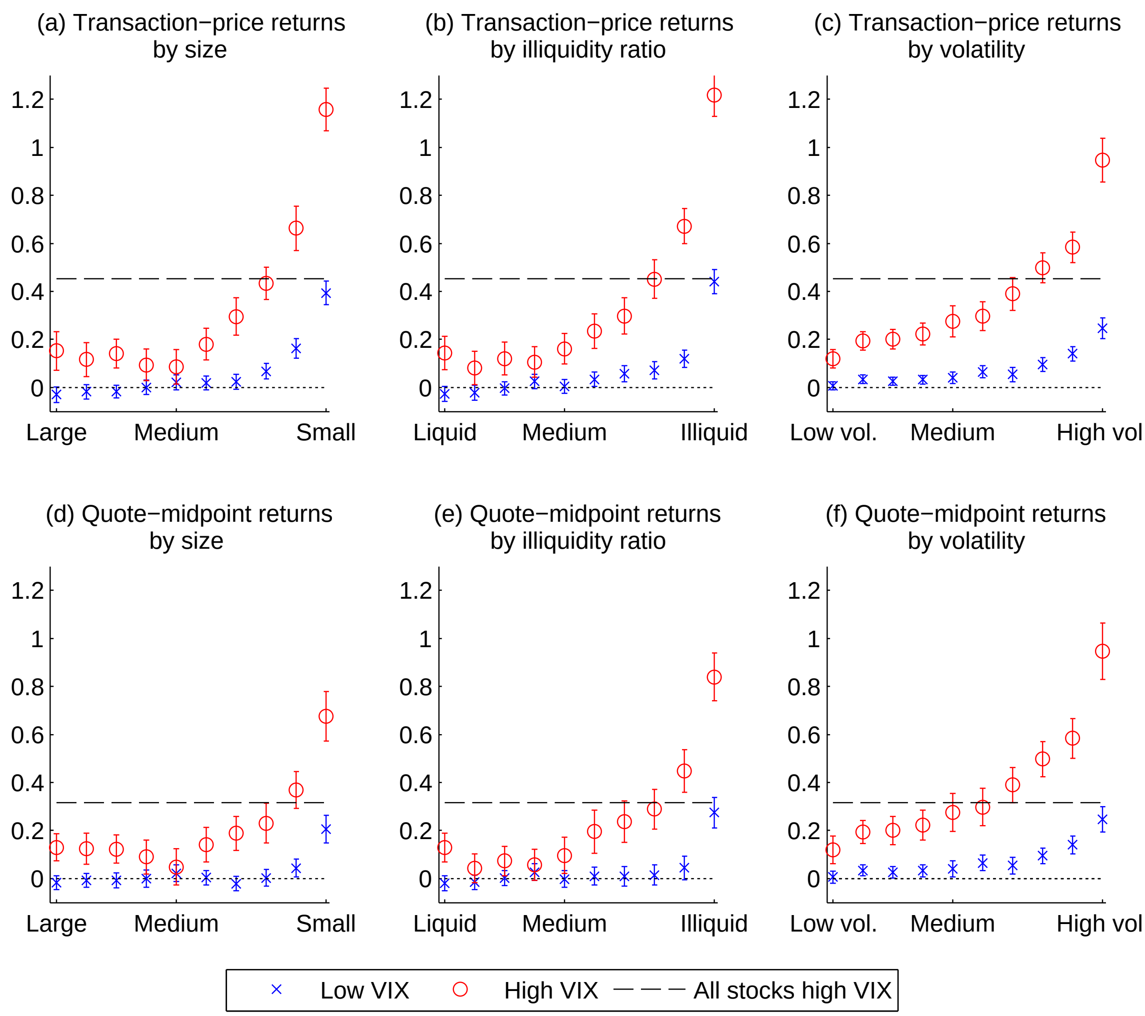

Figure 4: Predicted daily reversal strategy returns within size-, illiquidity-, and volatility-sorted subgroups evaluated at low (5th percentile) and high (95th percentile) VIX level. Fitted values from regression of each subgroups reversal strategy returns on VIX and a pre-decimalization dummy as in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

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

4 Conclusion

This paper 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 2007-09, expected returns of reversal strategies formed with individual stocks rose almost ten-fold 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 is 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.

Appendices

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,

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

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

$$E[P_t|\mathcal{I}_t] = v_t + \left(\frac{1}{\gamma} + \phi \right) \beta s_t. \tag{A.2}$$

Substituting back into (A.1),

$$y_t = \tilde{\beta} \left(s_t - \left(\frac{1}{\gamma} + \phi \right) \beta s_t \right), \tag{A.3}$$

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

$$\beta = \frac{\tilde{\beta}}{1 + \tilde{\beta} \left(\frac{1}{\gamma} + \phi \right)}. \tag{A.4}$$

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

$$E[\delta_{t+1}|\mathcal{M}_t] = \frac{\beta \sigma_\delta^2}{\beta^2 \sigma_\delta^2 + \sigma_z^2} x_t. \tag{A.5}$$

Writing $E[\delta_{t+1}|\mathcal{M}_t] = \phi x_t$, with ϕ defined accordingly,[17] substituting into the market maker's demand function, and imposing the market clearing condition $x_t + m_t = 0$ yields the equilibrium price

$$P_t = v_t + \left(\frac{1}{\gamma} + \phi\right) x_t. \tag{A.6}$$

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

$$R_{t+1} = \xi_{t+1} + \delta_{t+1} + \left(\frac{1}{\gamma} + \phi\right)(x_{t+1} - x_t). \tag{A.7}$$

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

$$R_{t+1} = \xi_{t+1} + \eta_{t+1} + \left(\frac{1}{\gamma} + \phi\right) x_{t+1} - \left(\frac{1}{\gamma}\right) x_t, \tag{A.8}$$

as stated in the text.

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

$$q_t = -\left(\frac{1}{2}\sum_{i=1}^{N} |x_{it-1}|\right)^{-1} \sum_{i=1}^{N} x_{it-1} R_{it}. \tag{A.9}$$

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 (A.9) from the properties of the half-normal distribution. We obtain

$$\operatorname*{plim}_{N\to\infty} \frac{1}{2N} \sum_{i=1}^{N} |x_{it-1}| = \frac{\sigma_x}{\sqrt{2\pi}}, \tag{A.10}$$

[17]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.

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

$$\underset{N\to\infty}{\mathrm{plim}}\,\frac{1}{N}\sum_{i=1}^{N} x_{it-1}R_{it} = -\frac{\sigma_x^2}{\gamma}. \tag{A.11}$$

Taking the negative of the ratio (A.11) and (A.10) 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

$$\underset{N\to\infty}{\mathrm{plim}}\,\frac{1}{2N}\sum_{i=1}^{N} |R_{it-1} - R_{mt-1}| = \frac{\sigma_R}{\sqrt{2\pi}}, \tag{A.12}$$

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

$$\underset{N\to\infty}{\mathrm{plim}}\,\frac{1}{N}\sum_{i=1}^{N} R_{it-1}R_{it} = E\left[R_{it-1}R_{it}\right] \tag{A.13}$$

$$= -\left(\frac{1}{\gamma} + \phi\right)\left(\frac{1}{\gamma}\right)\sigma_x^2. \tag{A.14}$$

Taking the negative of the ratio of (A.14) and (A.12) yields the result stated in the text.

B Data

The stock return data used in this paper is from the CRSP daily returns file. 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.

C Robustness Checks

Predictive regression bias. Given that VIX is quite persistent, one might worry that the predictive regressions with VIX as predictor could suffer from predictive regression bias. However, the bias-adjustment proposed by Stambaugh (1999) is virtually zero in this case here. The reason is that the time-t innovation in the predictor variable (VIX) has virtually zero correlation with the innovation in time-t reversal strategy returns. As a result, the bias-adjustment is also extremely close to zero. This is very different from the situation in typical stock market return prediction regressions with scaled price ratios as predictors, where the correlation of these innovations is far from zero. Thus, there is little reason to believe that the predictive regressions in the paper suffer from predictive regression bias.

Return horizon in construction of reversal strategy portfolio weights. The reversal strategies in the main analysis are constructed as an overlay of sub-strategies with portfolio weights conditioned on day $t-1$, $t-2$, ..., $t-5$ returns. Table A.1 shows that focusing on the reversal strategy with portfolio weights conditioned on day $t-1$ returns only delivers a similar relationship between reversal strategy returns and the VIX as in the main analysis in Table 2. Only for industry portfolios, the relationship with VIX becomes weak. For portfolios like the industry portfolios in this analysis, non-synchronous trading or lead-lag relationships between firms within an industry is a potential explanation for small short-run continuations in industry portfolio returns. Overlaying sub-strategies with portfolio weights conditioned on day $t-1$, $t-2$, ..., $t-5$ returns as in the main analysis helps to reduce the influence of these short-run continuations.

Alternative scaling of reversal strategy portfolio weights. The portfolio weights of the reversal strategies in the main analysis are scaled to sum up to \$1 long and \$1 short. Table A.2 repeats the regressions from Table 2 for a reversal strategy that is constructed with alternative portfolio weights $w_{it} = -\left(\sum_{i=1}^{N}(R_{it-1} - R_{mt-1})^2\right)^{-1}(R_{it-1} - R_{mt-1})$. In this case, the reversal strategy profit is the negative of the slope coefficient in a cross-sectional regression of market-adjusted returns on their own lag, and hence, effectively, the negative of a cross-sectional estimate of the autocorrelation. Table A.2 shows that VIX is a strong predictor of the profits from this alternative specification of reversal strategies. Table A.3 shows results for a reversal strategy with weights $w_{it} = -(1/N)(R_{it-1} - R_{mt-1})$, which yields, effectively, the negative of a cross-sectional estimate of the autocovariance of market-adjusted returns. VIX is again a strong predictor of reversal strategy profits for this alternative formulation.

Heterogeneity in scale. In the model, all stocks are of the same size. In reality, there are large differences in scale between stocks. A unit of unexpected order flow has less price impact for a large stock than for a small stock. Market maker inventory, and hence market maker's portfolios and profits are likely to be heavily dominated by large stocks. For this reason, Table A.4 explores value-weighted reversal strategies where the weights $w_{it} = -\left(\frac{1}{2}\sum_{i=1}^{N}|(R_{it-1} - R_{mt-1})M_{it-1}|\right)^{-1}(R_{it-1} - R_{mt-1})\,M_{it-1}$ have been multiplied with M_{it-1}, stock i's lagged market capitalization. The results are similar to those of Table 2. VIX is still strongly related to reversal strategy profits. This demonstrates that the results in the main paper are not driven just by small stocks. One notable difference, though, is that the reversal strategy profits in terms of transaction-price returns and quote-midpoint returns are now almost identical. This reflects the fact that large stocks have tiny bid-ask spreads, and hence there is hardly any difference between quote-midpoints and transaction prices.

Long and short components of reversal strategy. Table A.5 splits the reversal strategy (9) into long and short positions to check whether there is any asymmetry in the returns from liquidity provision between the long and short side. The reversal strategy portfolio in (9) is split into two components: stocks with positive portfolio weight (long) and stocks negative portfolio weights (short). The equal-weighted market return is subtracted from the long component and added to the short component, so that both components represent \$1 long/\$1short strategies. As Table A.5 shows, there is little difference in the results for the long and short components. Only for the industry reversal strategy, there is some evidence for a higher sensitivity to VIX on the long side which indicates that the industry reversals arise mostly from price impact of sell orders.

Table A.1: Predicting Reversal Strategy Returns with VIX: Reversal Strategies Formed Based on Day $t-1$ returns

This table repeats the regressions from Table 2, but with reversal strategies with portfolio weights formed based on day $t-1$ returns instead of the overlay of sub-strategies formed based on day $t-1$ to $t-5$ returns that is used in the main text. Predictor variables are measured on day $t-1$.

	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	-0.13	-0.21	-0.12	-0.06	-0.41	-0.38	-0.22	-0.13	-0.06	-0.06	-0.10	-0.08
	(0.13)	(0.10)	(0.09)	(0.08)	(0.11)	(0.11)	(0.10)	(0.12)	(0.06)	(0.06)	(0.06)	(0.05)
VIX	0.77	0.71	0.65	0.61	0.51	0.53	0.43	0.34	0.01	0.00	0.03	0.02
	(0.10)	(0.08)	(0.08)	(0.06)	(0.09)	(0.09)	(0.08)	(0.10)	(0.05)	(0.05)	(0.05)	(0.05)
Pre-decim.		0.70	0.72	0.70		-0.27	-0.25	-0.23		0.03	0.03	0.03
		(0.08)	(0.08)	(0.12)		(0.09)	(0.08)	(0.12)		(0.04)	(0.04)	(0.05)
R_M			-1.52	-1.30			-2.70	-1.59			0.62	-0.12
			(0.58)	(0.68)			(0.88)	(0.89)			(0.42)	(0.43)
Adj. R^2	0.14	0.21	0.21	0.63	0.05	0.05	0.06	0.18	-0.00	-0.00	0.00	-0.01

Table A.2: Predicting Reversal Strategy Returns with VIX: Reversal Strategies Scaled to Estimate Autocorrelation

This table repeats the regressions from Table 2, but with reversal strategies with portfolio weights $w_{it} = -\left(\sum_{i=1}^{N}(R_{it-1}-R_{mt-1})^2\right)^{-1}(R_{it-1}-R_{mt-1})$. The reversal strategy profits in this case correspond to the negative of a cross-sectional autocorrelation estimate.

	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	1.38	1.19	1.72	2.06	0.09	0.07	0.61	0.97	-3.43	-3.51	-2.60	-2.25
	(0.31)	(0.26)	(0.27)	(0.29)	(0.32)	(0.31)	(0.30)	(0.29)	(1.29)	(1.30)	(1.37)	(1.07)
VIX	1.88	1.73	1.38	1.08	1.50	1.48	1.13	0.78	2.66	2.60	2.00	1.64
	(0.22)	(0.20)	(0.20)	(0.18)	(0.24)	(0.25)	(0.23)	(0.20)	(0.86)	(0.87)	(0.88)	(0.62)
Pre-decim.		1.63	1.70	1.80		0.15	0.23	0.41		0.63	0.76	1.02
		(0.30)	(0.28)	(0.38)		(0.30)	(0.28)	(0.35)		(1.06)	(1.05)	(1.24)
R_M			-9.01	-2.28			-9.11	-5.30			-15.40	0.47
			(2.06)	(2.36)			(2.40)	(2.64)			(9.13)	(7.97)
Adj. R^2	0.03	0.05	0.05	0.36	0.02	0.02	0.02	0.14	0.00	0.00	0.00	0.01

Table A.3: Predicting Reversal Strategy Returns with VIX: Reversal Strategies Scaled to Estimate Autocovariance

This table repeats the regressions from Table 2, but with reversal strategies with portfolio weights $w_{it} = -(1/N)(R_{it-1} - R_{mt-1}) \times 100$. The reversal strategy profits in this case correspond to the negative of a cross-sectional autocovariance estimate of percentage market-adjusted returns.

	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	-0.66	-0.76	-0.59	-0.39	-0.62	-0.66	-0.50	-0.33	-0.14	-0.14	-0.11	-0.08
	(0.15)	(0.16)	(0.14)	(0.11)	(0.17)	(0.17)	(0.15)	(0.12)	(0.04)	(0.04)	(0.03)	(0.02)
VIX	1.05	0.98	0.87	0.72	0.79	0.76	0.65	0.53	0.11	0.11	0.09	0.07
	(0.12)	(0.13)	(0.12)	(0.09)	(0.14)	(0.15)	(0.13)	(0.11)	(0.03)	(0.03)	(0.03)	(0.02)
Pre-decim.		0.83	0.85	0.87		0.34	0.36	0.39		-0.00	0.00	0.01
		(0.12)	(0.12)	(0.15)		(0.14)	(0.14)	(0.15)		(0.03)	(0.03)	(0.03)
R_M			-2.85	-0.45			-2.72	-0.40			-0.54	-0.01
			(0.87)	(1.32)			(0.96)	(1.39)			(0.23)	(0.22)
Adj. R^2	0.10	0.13	0.14	0.53	0.04	0.05	0.05	0.27	0.01	0.01	0.01	0.13

Table A.4: Predicting Reversal Strategy Returns with VIX: Value-weighted Reversal Strategies

This table repeats the regressions from Table 2, but with value-weighted reversal strategies with portfolio weights $w_{it} = -\left(\frac{1}{2}\sum_{i=1}^{N} |(R_{it-1} - R_{mt-1})M_{it-1}|\right)^{-1} (R_{it-1} - R_{mt-1}) M_{it-1}$, where M_{it-1} is stock i's lagged market capitalization.

	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	-0.14	-0.15	-0.09	-0.05	-0.16	-0.18	-0.11	-0.06	-0.06	-0.06	-0.02	-0.01
	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
VIX	0.20	0.20	0.15	0.13	0.25	0.24	0.19	0.15	0.06	0.07	0.04	0.03
	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Pre-decim.		0.07	0.08	0.09		0.13	0.14	0.16		-0.02	-0.01	-0.01
		(0.04)	(0.04)	(0.04)		(0.06)	(0.06)	(0.06)		(0.04)	(0.03)	(0.03)
R_M			-1.14	-0.57			-1.18	-1.10			-0.62	-0.34
			(0.28)	(0.41)			(0.35)	(0.58)			(0.34)	(0.29)
Adj. R^2	0.03	0.03	0.03	0.27	0.02	0.02	0.02	0.25	0.00	0.00	0.00	0.03

Table A.5: Long and Short Components of Reversal Strategy

This table repeats the regressions from Table 2, but with reversal strategy portfolios split into those with positive portfolio weight (long) and negative portfolio weights (short). The equal-weighted market return is subtracted from the long component and added to the short component. The returns used in the regressions are hedged against conditional market factor exposure as in Table 2.

	Individual stocks Transaction-price returns				Individual stocks Quote-midpoint returns				Industry portfolios			
	Daily		Monthly		Daily		Monthly		Daily		Monthly	
	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.04	-0.02	0.01	0.01	-0.05	-0.03	-0.02	-0.00	-0.05	-0.03	-0.05	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
VIX	0.11	0.09	0.08	0.07	0.07	0.09	0.05	0.07	0.04	0.02	0.04	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Pre-decim.	0.12	0.09	0.13	0.10	0.04	0.03	0.04	0.03	-0.02	0.02	-0.02	0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
Adj. R^2	(0.05)	(0.04)	(0.46)	(0.27)	(0.01)	(0.01)	(0.06)	(0.06)	(0.01)	(0.00)	(0.10)	(0.01)

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