A Century of Market Reversals: Resurrecting Volatility

Vincent Bogousslavsky, Blake LeBaron, and Jeffrey Pontiff*

December 7, 2023

ABSTRACT

Inventory models posit that return autocorrelation is affected by collateral, volume, and expected volatility. We show that daily market autocorrelations are lower on negative return days, consistent with collateral concerns. Unlike previous literature, we document a strong role of volatility on autocorrelation. Puzzlingly, anticipated volume, not volume shocks, drive reversals. Sparked by these findings, we construct a liquidity risk factor in accordance with Pastor-Stambaugh (2003) that is volatility, not volume, based. The volatility-based factor is more robust and has a higher risk premium than the volume-based factor.

Keywords: Market Liquidity, Volatility, Serial Correlation, Collateral, Liquidity Risk.
JEL Code: G00, G12, G14

---

*Bogousslavsky and Pontiff are at Boston College. LeBaron is at Brandeis. We thank Raj Agarwal, Neil Pearson, David Solomon and seminar participants at Boston College, Brandeis, and the 2023 Conference on Derivatives and Volatility for useful feedback.

I. Introduction

Liquidity providers buy when there is an influx of sell orders and sell when there is an influx of buy orders. These liquidity providers expect compensation—when they buy securities they expect higher returns than when they sell securities. Thus, negative return autocorrelation reflects compensation for providing liquidity. Inventory models such as Ho and Stoll (1981) and Grossman and Miller (1988) formalize this intuition.[1] Liquidity providers are risk averse. As such, when expected volatility is higher, more compensation is required and thus, autocorrelations will be lower. Moreover, since trades are exogenously initiated by noise or liquidity traders, returns associated with high volume are more likely to be reversed.

Numerous studies consider the extent to which return autocorrelation is consistent with theory. Using daily data, Campbell, Grossman, and Wang (1993), hereafter CGW, find mixed evidence that volume is associated with lower market autocorrelation before 1950, but strong evidence from 1950 to 1987. Conrad, Hameed, and Niden (1994), using weekly returns on individual stocks over a sample period of 1983 to 1990, find a strong negative relation between volume and autocorrelation. These early findings of a relation between volume and autocorrelation spawned Pastor and Stambaugh's (2003) introduction of a market-wide liquidity factor.

The literature is mixed regarding the relation between volatility and autocorrelation. All volatility studies are hampered by the fact that, unlike volume, volatility is unobservable. It must be estimated from data, resulting in measurement error. Using daily, market-level data LeBaron (1992) and Sentana and Wadhwani (1992) find evidence consistent with such a link, while CGW find neither a statistically nor economically significant relation. LeBaron (1992) and Sentana and Wadhwani (1992) do not consider a role for volume. Thus, their estimation may suffer from an omitted correlated variable bias. In the cross-section, Nagel (2012) shows that the return of short-term reversal strategies is predictable with the VIX. Collin-Dufresne and Daniel (2015), however, find that cross-sectional volatility dominates the VIX. These papers do not consider volume. The lack of resolution in this literature, in particular at the market level, is puzzling since the assumption of risk aversion plays a fundamental role in inventory models, as it does in a vast number of economic and financial models.

[1] Examples of recent works that emphasize inventory effects are Bogousslavsky and Collin-Dufresne (2023); Boyarchenko, Whelan, and Larsen (2023); and Hazelkorn, Moskowitz, and Vasudevan (2023).

Regarding the role of collateral and capital constraints, an early study, Atkins and Dyl (1990) examine stocks with extremely high or low daily returns, and finds a reversal effect that is much stronger following large declines. More recently, empirical support of the importance of collateral and margin constraints is highlighted by Hameed, Kang and Viswanathan (2010) who show that market declines have a pronounced impact on bid-ask spreads and returns on volume-weighted winner and loser portfolios.

We deviate from the previous literature in two critical ways. First, using a time-series of returns on the Dow Jones Index (1933 to 2022) from Global Financial Data (GFD), we contribute a high-power test to the market return autocorrelation and liquidity provision literature. On the average day, this data provides 8.04 observations of return and volume. We estimate that this provides volatility estimates that are 86% less noisy than a series of daily observations. Market movements triggered by public information frustrate liquidity tests. Boudoukh et al. (2019) show that public news accounts for four times as much return volatility at night than during the trading day. Previous studies use daily returns—which are influenced by the overnight news. The frequency of our data enables us, for the first time, to more precisely estimate market liquidity by discarding overnight returns and focusing on intraday returns. Second, our estimation disentangles the impact of predicted volume and volatility versus shocks to volume and volatility.

We estimate the relation between daily market autocorrelation and volatility and volume. CGW find a consistent, negative relation between volume and autocorrelation and an inconclusive relation between volatility (estimated from a GARCH) and autocorrelation. Our intraday results, show a diminished, albeit still negative, volume effect, and a strong negative volatility effect. Our estimation therefore resurrects the role of volatility for market return autocorrelation. The results line up with recent evidence from the cross-section of individual stocks that document an important role of volatility for return reversal, albeit ignoring volume.

To gain more intuition, we decompose both volume and volatility into a shock and a predicted component. The negative relation between volume and return autocorrelations is driven by predicted volume, not volume shocks. This distinction is not considered in most inventory models that treat trader demand as a shock. CGW measure contemporaneous volatility with a GARCH estimate. Liquidity providers incur inventory risk in the period following the volume shock. As such, we improve upon CGW by using contemporaneous information to forecast volatility over the next day. This result is stronger than the aforementioned contemporaneous volatility effect. The general effect is consistent with risk-averse liquidity providers forming expectations about future volatility. Our methodology allows us to ascertain the impact of the temporary volatility shock in the current period while controlling for forecasted volatility. The volatility shock might contribute/detract to the value of collateral in the current period. Consistent with theory, we find that volatility shocks tend to decrease return autocorrelation. This effect is, however, statistically significant in only one subsample period.

The collateral and capital constraints literature suggests a more direct test. Models in which negative returns are associated with tighter funding constraints for liquidity providers (Danielsson, Shin, and Zigrand, 2009; Brunnermeier and Pedersen, 2009) predict asymmetric return autocorrelation. We find daily market return autocorrelation displays persistent asymmetries. Positive market returns are associated with higher autocorrelation than negative returns, consistent with collateral constraints inhibiting liquidity provision. With nearly a century of data, this finding reinforces a finding from a 10-year sample by Chordia, Roll, and Subrahmanyam (2002).

We investigate the extent to which volume and volatility contribute to the asymmetric market return autocorrelation that we document. We find some evidence that predicted volume is related to the asymmetry, while the impact of volume shocks, forecasted volatility, and volatility shocks is roughly symmetric.

Finally, we explore the cross-sectional implications of volatility-based liquidity measures by extending the study of Pastor and Stambaugh (2003) with a volatility inspired measure of liquidity. Using the exact specification of Pastor and Stambaugh, we replace volume with a proxy for expected volatility. This produces annualized long-short returns that are over 3 percentage points greater than the PS volume-based estimation that is ubiquitous in the finance literature. This finding is not driven by portfolio volatility, since the Sharpe-ratio of the volatility-based risk portfolio is also higher than the volume-based risk portfolio. Volatility-based risk portfolio returns remain significant after consideration of four previously proposed specification modifications that render volume-based risk portfolio returns insignificant.

2. Data and Variables Construction

We use four datasets: Global Financial Data (GFD), ISSM, TAQ, and CRSP. Some of our estimation focuses on the time series of market returns, for these we use GFD and TAQ. Some of our estimation constructs a long-short liquidity risk factor following Pastor and Stambaugh (2003). For this, we use CRSP data.

GFD provides intraday prices of the Dow Jones Industrial Index. Using the composition of the Dow, we compute Dow daily yields, which is combined with GFD data to construct overnight returns and total returns. GFD reported opening prices are often inconsistent. Index providers often use previous closing prices to report opening prices, and opening prices can be noisy (for instance, Stoll and Whaley, 1990, and Bogousslavsky, 2021). As such, we use the first reported GFD price after the opening for our overnight return measure. That is, we do not use the GFD opening price. Our timing is detailed in figure 1. Our returns for day t-1, r_{t-1}, end at the close, and our overnight return, $r_t^{overnight}$, goes from this closing price to one intraday period (h) into day t. This price is the first recorded price after the open in our dataset. Intraday returns for day t, $r_t^{intraday}$, are then calculated from the price at t+h through the close on day t. We use similar timing conventions for daily, overnight, and intraday volume. Because of our timing conventions, even if there is not trading activity overnight, our overnight volume can be nonzero since it includes the first intraday subperiod on a given day. GFD reports Dow Jones levels, but not dividends. To construct accurate overnight returns and total returns, we use CRSP data on Dow stocks to include dividend payments on ex-dividend days in our Dow overnight returns.

Starting in 1988, we use ISSM and TAQ data to calculate higher frequency Dow returns than are possible with GFD—half hourly. The GFD data is missing several dates after 1988 and switches back to a lower frequency in 2018. Again, our overnight returns use the first Dow level following the opening price (i.e., the level at 10am). Table 1 details the frequency of our series. 57.6% of our returns have a duration of a half of an hour. 28.8% of our returns have a duration of one hour. 8.4% of our returns are overnight and have a duration of greater or equal to than 18 hours. The mean (median) trading day is comprised of a series of 8.20 (6) returns.

(Table 1 goes here)

We use the intraday data to estimate realized volatility as our measure of volatility. We begin by considering a variance and standard deviation volatility measure. For the variance measure, we divide the squared return over the period by the duration in hours. We then sum these components of the longer interval to get our variance estimate (equation 1). For our standard deviation volatility measure, we take the square root of this sum. For daily volatility, the sum uses all periods in a day, while for intraday returns the sum does not include the overnight period (equation 2). Our weekly (monthly) volatility measure is the sum of the previous 5 (21) daily volatility measures, multiplied by the square root of 5 (21).

$$\sigma_t^2 = \frac{r_t^{2,overnight}}{h_{overnight}} + \sum_{k=1}^{K} \frac{r_{t,k}^2}{h} \quad (1)$$

$$\sigma_t^{2,\text{intraday}} = \sum_{k=2}^{K} \frac{r_{t,k}^2}{h} \quad (2)$$

To ascertain the statistical power of our series, we calibrate a Monte-Carlo simulation of log normal returns with a mean annual return of 10%, sampled from online Oxford/Man realized volatility series. Mean squared errors are calculated using realized variance and the true variance. Sampling 8 observations per day (a little shy of our average day) produces mean squared errors that are 85.9% lower than one observation per day.

For each period, the measure of Dow Jones volume is calculated as the sum of shares traded divided by the sum of shares outstanding. Consistent with CGW and Gerety and Mulherin (1992), our primary volume measure can be considered a turnover measure. As CGW note, volume is non-stationary and has trended higher over time. Following CGW, we create a detrending variable that is the average of the natural log daily volume in the last 253 calendar days. A daily detrended volume measure is calculated as the natural log of daily turnover minus the detrending variable. Our weekly volume measure is the sum of the daily measure over the past 5 trading days, and our monthly volume measure is the sum of the daily measure over the past 21 trading days.

The Dow is a price-weighted index of 30 stocks, which could proxy poorly for the overall market. Even though this is a valid theoretical concern, Shoven and Sialm (2000) show that the Dow's performance is not significantly different from that of other indices over 1928 to 1999. The correlation between the CRSP value-weighted index daily return and the Dow daily total return is

0.95 over our sample period. Furthermore, the Dow's restricted investment set of 30 liquid stocks is an advantage in our study of short-term price fluctuations. A broader index may better capture the overall market, but this comes at the cost of increased nonsynchronous trading issues, which can induce spurious return autocorrelations. For example, the reported prices of thinly-traded stocks can fail to immediately incorporate a relevant piece of market news. This leads their return to lag that of other, more actively traded, stocks in the index, hence creating spurious positive return autocorrelation for the index.

Table 2 reports descriptive statistics for detrended volume, volatility, and return measured over the full day and intraday. Like CGW, we exclude the period surrounding Black Monday from our main tests. While not the primary focus of this paper, Table 2 reveals that the average intraday Dow return is only about 0.003%, which contrasts to the average full-day return of 0.047%. This supports, over a much longer sample period, the finding of Cliff, Cooper, and Gulen (2008) over 1993 to 2006 that the equity premium is solely due to overnight returns. At the same time, intraday return volatility is almost as large as daily volatility, 0.66% vs 0.65%.

(Table 2 goes here)

3. Market Return Autocorrelation Estimation

Conceptual framework. We briefly lay out the conceptual framework that underlines our empirical tests. Consider a risk-averse liquidity provider that absorbs a liquidity shock every period. In a setting like CGW with exponential utility and normally distributed shocks, the expected return in the next period is given by

$$E_t[R_{t+1}] = \gamma Var_t[R_{t+1}] \frac{\overline{P_t} - P_t}{P_\theta} \tag{3}$$

In this equation, γ is the risk aversion of the liquidity provider. However, it can also reflect the effect of collateral constraints. In that case, γ is directly proportional to the Lagrange multiplier on the collateral constraint (Brunnermeier and Pedersen, 2009; Danielsson, Shin, and Zigrand, 2009). In this interpretation, γ is naturally time-varying with the shadow cost of capital. An adverse shock to that tightens the liquidity providers' constraint and increases the required compensation for providing liquidity. The second term in (3) is the expected variance of next-period's return. Since the liquidity provider must hold some inventory between time *t* and *t+1*, she will require a higher return the more volatile this inventory is expected to be. The final term is the "non-fundamental" price move (scaled by price impact, P_θ). That is, the deviation of the current price, P_t from the fundamental price $\overline{P_t}$, which reflects the present value of future dividends. Thus, any change in the present value of dividends that is incorporated into the price today cancels out in (3), which leaves only the non-fundamental component of the price change. In this framework, volume helps identify this non-fundamental component. Therefore, greater volume is associated with stronger reversal.

Volatility, Volume and Return Autocorrelation. The previous literature (for example, LeBaron, 1992, Sentana and Wadhani, 1992, and Campbell et al., 1993) focuses on stochastic volatility (SV) models such as generalized autoregressive conditional heteroskedasticity (GARCH). Although we are able to replicate results in the earlier literature, our estimation focuses on realized volatility (RV). In summarizing a large literature, Andersen et al. (2011) write, "The realized variation forecasts generally dominate traditional SV model forecasts based on daily data and they perform roughly on par with the options-based forecasts." The model-free nature of our estimation allows us to study both expected volatility as well as shocks to volatility. This bifurcation is essential since volatility shocks are important to collateral and margin-based models—a negative return shock can cause forced liquidation (or fear of forced liquidation), which increases the required compensation for liquidity provision. The standard stochastic volatility models recognize the persistent nature of volatility, thus a volatility shock results in a higher expected volatility forecast. If, as predicted by the collateral and margin-based models, volatility shocks result in higher compensation for liquidity provision, volatility forecasts from a stochastic volatility model will not conflate compensation for risk and collateral concerns.

We begin by considering a variance and standard deviation volatility measure, which we construct as described in Section 2. At the core of liquidity provision models, are risk-averse investors with expectations of volatility (for example, Grossman and Miller, 1988, and CGW, 1993) since order flow causes liquidity providers to be subject to fluctuations in the value of the inventory that they carry into the next period. Volatility is not directly observable for a particular point of time. Rather, it must be estimated. CGW (1993) estimate current volatility with a Q-GARCH model and use these estimates to ascertain how market auto-correlation is affected by volatility. CGW use estimates of current volatility, not future volatility. This decision seems reasonable since volatility is persistent (see for example, Engle and Bollerslev, 1986, Schwert, 1989, LeBaron, 1992. On the other hand, Nagel (2012) uses estimates of future volatility that are implied from S&P 500 index options (VIX). Our focus is on realized volatility, measured as detailed above. Recent literature (e.g., Andersen et al., 2013; Bogousslavsky and Collin-Dufresne, 2023) note the benefits of volatility estimation with realized volatility.

We start by considering estimation that is very similar to CGW, except we use realized volatility and our sample is from 1933 to 2022 and CGW's main sample is between 1962 and 1988. They consider a secondary sample (using Dow returns) between 1926 and 1998. Like CGW, we start by considering full day returns. We estimate,

$$r_{t+1} = \alpha + \left(\sum_{i=1}^{6} \beta_i D_i + \gamma_1 V_t \ + \gamma_2 \sigma_t \ + \gamma_3 \sigma_t^2\right) r_t, \tag{4}$$

where r_t is the Dow Jones return on day t. α is the regression intercept. D_i is an indicator variable for the day of the week (Monday through Saturday). V_t is the log detrended turnover on day t, and σ_t^2 is the realized return variance on day t. (In untabulated results, we follow CGW and include squared detrended turnover. Inclusion of this variable, for most specifications, is associated with a slightly more negative slope on detrended volume.) β_i, γ_1, γ_2, and γ_3 are least squares slope coefficients. The bracketed term is the time-varying autocorrelation. We model the residuals as following 5th order autoregressive process. If well specified, as it seems from inspection of residual correlations, this produces unbiased standard errors and more efficient slope coefficients.

The results are reported in Table 3. Over our full sample, γ_1 is statistically significant and negative. For both subsamples after the end of the CGW data, γ_1 is insignificant. On the other hand, the impact of volatility is unequivocal. Whether volatility is measured as a standard deviation or variance, it has negative and statistically significant slope in every subperiod. γ_3 is statistically significant and negative. These results are roughly consistent with CGW, who report a negative and statically significant coefficient on volume in both of their samples. Importantly, in both of their samples, the coefficient on volatility is insignificant. In untabulated results, we follow the GARCH used by CGW and closely replicate their results. Thus, a more precise estimation of volatility resurrects the role of volatility for market return autocorrelation. This also makes the results more strongly in line with recent evidence from the cross-section of individual stocks that document an important role of volatility for return reversal (Nagel, 2012; Collin-Dufresne and Daniel, 2015).

(Table 3 goes here)

As mentioned earlier, a fundamental advantage of the GFD data is that we can eliminate overnight market movements and focus on returns, volatility, and volume during the trading day. Doing so enables a cleaner test of market liquidity since nighttime movements are disproportionately affected by public information (for example, Boudoukh et al., 2019). Inventory models make predictions about trading that is liquidity induced, not information induced. Table 4 presents intraday results for both realized standard deviation and variance specifications. Table 4 is consistent with Table 3. The slope coefficients on standard deviation are negative and statistically significant for all subperiods. The slope on variances is always negative, but it loses significance in the 1933 to 1952 subperiod. The coefficient on standard deviation doubles, while the coefficient on variance is negative and statistically significant. Volume remains insignificant in the 1990 to 2000 subperiod, and its significance in the 2001 to 2022 subperiod is specification dependent. Overall, these results are consistent with the fundamental implication of inventory models: Volatility is associated with a higher expected return to liquidity provision.

(Table 4 goes here)

Shocks to volume and volatility. Predicted volume and volatility. Risk-averse agents provide liquidity based on anticipated marginal risk. Past empirical research focuses on contemporaneous measures of risk since volatility is persistent. Volatility also contains a short-lived, shock component. The shock component might be related to pressure on collateral, so differentiating between these components allows inference on the role of risk aversion and collateral concerns in markets. The distinction between anticipated volume and volume shocks is also important. If liquidity providing capital is slow moving (Duffie, 2010), then it will move less effectively to volume shocks than to longer-term predicted volume. For example, an unexpected, abrupt high-volume event such as a natural disaster will be afforded with less liquidity capital, than a pre-scheduled earnings announcement. This thinking is consistent with the decision of stock index providers to pre-announce additions and deletions from the index. It is also consistent with the finding that prices react more intensely to the announcement, rather than the occurrence of index additions and deletions (for example, Greenwood and Sammon, 2023).

Note that we decompose volume into an expected and unexpected component as opposed to order flow itself, which is signed. In the standard Grossman and Miller (1988) setup, an anticipated supply shock has no impact on the stock price at the time of the shock since it is anticipated. Thus, it does not affect return autocorrelation. In a setting with non-myopic liquidity providers, however, an anticipated supply shock can have price impact at the time of the shock through a hedging demand effect. This happens when the anticipated shock correlates with a change in the investment opportunity set for the liquidity provider (Vayanos and Woolley, 2013).

We use a specification akin to an augmented Corsi (2009) estimation to tease out shocks from anticipated levels. This estimation uses a rolling window of three years of daily data. For each day, we regress either realized volatility or detrended volume on predetermined right-hand side variables for the preceding 759 trading days (3 x 253). For each time period, this produces an anticipated value of volatility and detrended volume as well as shocks to volatility and volume. We estimate this model for three variables—realized standard deviation for the entire day and within day, and detrended volume within day. The estimations that utilize within day variables are necessary to ascertain shocks that are contemporaneous with our within-day returns. For volume, the within day also estimation provides the expected volume forecast that market makers could have forecasted with our data. For expected volatility, liquidity providers must hold inventory over an entire day, thus the entire day estimation is needed to forecast forward-looking risk. We describe our forecasting strategy with equations (5)-(7). Equations (5) and (7) represent standard predictors using all information available at the start of our intraday(t) period. These are used for our volume predictions, and volume and volatility shocks. Equation (6) is slightly different since it is building a forecasting using only information through the close at time t-1. This is used for our volatility forecast only.

$$x_t^{P,\text{intraday}} = E[x_t \mid I(x_{t-1}, x_t^{overnight})] \tag{5}$$

$$x_t^{P} = E[x_t \mid I(x_{t-1})] \tag{6}$$

$$x_t^{S} = x_t - x_t^{P,\text{intraday}} = x_t - E[x_t \mid I(x_{t-1}, x_t^{overnight})] \tag{7}$$

For illustrative purposes, Table 5 forgoes the rolling nature of the Corsi estimation, and presents three OLS regressions that utilize the same specification as the Corsi over the entire sample. The table heading describes the entirety of right-hand side variables. Table 5 does not report estimated coefficients on dummy variables for the day of the week. All three variables exhibit significant persistence at the daily, weekly, and monthly levels. Previous Dow returns are inversely related to volatility and volatility is more persistent following negative return days. Volatility in the previous day and in the previous night/contemporaneous morning portends higher within day volume. The opposite is not true. Volume has little relation to future volatility.

(Table 5 goes here)

All three models explain a good deal of variation. Despite the fact that volume is already detrended, the estimation explains nearly 70% of the within-day volume variation. Certainly, our model omits valuable information—earnings release dates, macro announcements, religious holiday, etc. So, 70% is a lower bound on the amount variation in volume that is predictable. The day of the week indicators alone explain 23.6% of detrended volume's variation. Clearly, most variation in volume should be predictable by rational liquidity providers. The volatility models also explain a good deal of variation of volatility—58% to 59%. Unlike the volume specification, day of the week indicators only absorb 2% of the variation. Another takeaway from the table is that past volatility helps predict volume beyond the lagged volume components, whereas the reverse is not true. Finally, the coefficient estimates on lagged returns confirm the presence of the well-documented leverage effect. Our specification adds to the literature by showing the negative impact of overnight returns on within-day volatility.

For the 2001 to 2002 subsample, VIX data is available. We consider separate Corsi estimation for this period that is enhanced with the level of the previous day's VIX and the average level of the VIX over the last 5 trading days. In untabulated results, we find that during this period, a detrended within-day volume specification with VIX, has minimal impact, increasing the adjusted R^2 by 0.0023. The volatility specifications are more substantial. Considering VIX increase the adjusted R^2 on the standard deviation estimation by 0.031, and by 0.046 on the within-day standard deviation estimation.

One advantage of the Corsi estimation over the Table 5 estimation, is that "rolling" enables slope coefficients to adjust over time to reflect difference in data frequency, exchange hours, and trends in institutional trading (for example, the recent preponderance of orders at the close, see Bogousslavsky and Muravyev, 2023). We determine the usefulness of our Corsi estimation by regressing our time-series of forecasted volatility and volume, on realized volatility and volume (Mincer-Zarnowitz regressions). The rolling nature of the Corsi estimation ensures that the forecasts are only calculated with information known before the comparison period. The adjusted

R^2 for our volume forecast is 79.0%. While the adjusted R^2 for our within-day and entire entire-day volatility specifications are, respectively, 61.3% and 59.9%. Thus, our Corsi specification, using information that is available to market participants, generates useful forecasts.

The VIX-enhanced Corsi estimation in the 2001 to 2022 subsample improves the fit of Mincer-Zarnowitz regressions. The intra-day volume adjusted R^2 improves by 0.004, while the standard deviation and within-day standard deviation R^2's improve by, respectively, 0.031 and 0.027.

Table 6 examines autocorrelation of intraday returns as a function of the current detrended volume shock and the anticipated detrended value (both based on the information before the start of the day), the shock to volatility (based on information before the start of day), and anticipated volatility for the next day (based on today's information). In contrast to liquidity providers being compensated for absorbing volume shocks, the coefficient on volume shocks is positive for all subsamples except 1953 to 1989. The coefficient on anticipated volume is negative and statistically significant over the entire sample and in the 1953 to 1989 subsample and the 2001 to 2022 subsample. Thus, the relation between volume and reversals is driven by anticipated volume, not shocks to the volume. The coefficient on anticipated volatility is negative and statistically significant over the entire sample, and for all subsamples except 1990-2000, for which the coefficient is negative, but insignificant. Volatility shocks tend to have negative coefficients (significant only in the 1953 to 1989 subsample).

(Table 6 goes here)

The stronger impact of anticipated volume over unanticipated volume on return reversal is difficult to explain from the point of view of extant liquidity provision theories. One hypothesis is that predicted volume proxies for a component of risk faced by market makers, thus leading to stronger reversal. But day-to-day fluctuations in volume may only be noisily related to price moves once controlling for anticipated volume and volatility. The weaker connection between volume and price moves arises naturally in models with investor disagreement (e.g., Kandel and Pearson, 1995). Disagreement among investors has been shown to be crucial to generate trading volume that is remotely close to that observed in actual markets.

Asymmetric autocorrelation and collateral. The negative (but often insignificant) effect of volatility shocks on market autocorrelation is suggestive of a collateral channel. However, the collateral constraint literature suggests a more direct test. Negative returns could be associated with tighter funding constraints, effectively increasing the risk aversion (or shadow cost of capital) in Equation (3) and thus leading to stronger reversals (Brunnermeier and Pedersen, 2009). One possibility is that liquidity providers tend to be net long. In this case, negative returns lower their capital. For example, Comerton-Forde et al. (2010) document that NYSE specialists tend to be net long 94% of the time over 1994-2004. Thus, return shock asymmetries may be indirect evidence of collateral effects. We are aware of only one paper that finds market return-based autocorrelation asymmetries (Chordia, Roll, and Subrahmanyam, 2002). Using a sample from 1988 to 1998, they show that the autocorrelation of the S&P 500 tends to be higher following positive return days than negative return days. If this result is robust in a broader time period, it provides a starting point for understanding how market return autocorrelation is affected by margin constrains and collateral.

Table 7 estimates autocorrelations from the daily CRSP value-weighted index return over a sample from 1926 to 2022. The first set of results shows that when the entire CRSP VWRET series is considered, autocorrelations when the last day's return was negative are much lower than when the last day's return was positive. To guard against the influence of bid-ask bounce, we report autocorrelations for 5 lags of VWRET. Again, when the return two days beforehand is negative the autocorrelation is lower than when it is positive. The correlations from negative days continue to be significantly lower than positive days using 2 lags. The direction continues with 3 lags, although the difference is insignificant. The fourth and fifth lags show evidence of a reversal—positive lagged returns have lower autocorrelation than negative lagged returns.

(Table 7 goes here)

Perhaps the signed-return autocorrelation asymmetry is driven by market crashes or very extreme market returns. The second set of results in Table 2 considers this by eliminating all days for which the lagged return is either greater than 5% or less than negative 5%. Although the estimates of specific autocorrelations change, the difference between negative and positive return-day autocorrelation remains—negative return-day autocorrelations are lower than positive return day autocorrelations. Unlike the first set of results, there is not a reversal of the result until the fifth lag.

Index-level autocorrelation may be influenced by bid-ask spread effects. Since small market capitalization stocks have higher proportional spreads, index autocorrelation may occur from lead-lag effects between large and small stocks (Mech, 1993). The third and fourth set of results use our Dow data. Stocks in the Dow tend to have the lowest relative bid-ask spreads and are frequently traded. Non-synchronous trading issues are much less of a concern. The difference in negative and positive day autocorrelations at the first lag are larger and more statistically significant than the results using the CRSP value-weighted index, while the second and third lag results are similar.

The last set of results examines Dow returns, but the initial return is calculated during the trading day. Thus, variation in this return should reflect a higher proportion of trading shocks. The difference between negative and positive day autocorrelations is more striking than in the previous 3 panels. The magnitudes of the differences for the first three lags is larger, as is the statistical significance. The third lag results are now significant at the 1% level.

Table 7 presents evidence that is consistent with collateral concerns—liquidity provision improves on up-market days and deteriorates on down-market days. Table 8 considers whether or not volume and volatility play a role in this asymmetry. For each period, we consider the Table 6 estimation, but instead of relying on the current intraday market return, we conduct two estimations—one with maximum of the current market return and zero (positive specification), and one with the minimum of the current market return and zero (negative specification). Comparing these results, for volume shocks and volatility shocks there are no consistent patterns between the specifications. For anticipated volume, for all specifications except the 1990 to 2000 subsample, the negative estimation produces slope coefficients that are lower than the positive estimation. The differences are all statistically significant. This is consistent with anticipated volume playing a role in amplifying collateral-based asymmetry in liquidity. Again, interpretation of this result, is hampered by the current lack of theory regarding the role of anticipated volume in market liquidity. The role of anticipated return volatility is less clear. Contrary to a collateral channel, the full-sample estimation shows that anticipated volatility's impact on illiquidity is more pronounced for positive, rather than negative returns. For all subsamples except 2001 to 2022, this relation is reversed.

(Table 8 goes here)

4. Estimation of an Anticipated Volatility Liquidity Risk Factor

The previous section shows, consistent with the simplest inventory models, that anticipated volatility reduces liquidity provision as is evidenced in daily market return autocorrelation. The role of volume is less clear. Influenced by the findings of CGW, Pastor and Stambaugh (2003) introduce a liquidity risk factor. The keystone of the factor is time-series variation in how volume impacts return autocorrelation at the stock level. In this section we construct a new liquidity risk factor precisely following Pastor and Stambaugh, except we replace volume with anticipated volatility.

Using daily return and volume data, Pastor and Stambaugh estimate the following,

$$r^e_{i,d+1,t} = \theta_{i,t} + \emptyset_{i,t} r_{i,d,t} + \gamma_{i,t} sign\left(r^e_{i,d,t}\right) \cdot v_{i,d,t} + \epsilon_{i,d+1,t} \quad d = 1, \ldots D, \tag{8}$$

This regression is estimated for each firm-month. *d* denotes the day in month *t*. $r^e_{i,d+1,t} = r_{i,d,t} - r_{m,d,t}$, where $r_{i,d,t}$ and $r_{m,d,t}$ are the returns on stock *i* and the CRSP value-weighted index. $v_{i,d,t}$ is the dollar volume. $\epsilon_{i,d+1,t}$ is the residual of stock *i* on day *d* in month *t*. The above expression is equation 1 in Pastor and Stambaugh. The OLS regression produces the coefficients, $\theta_{i,t}$, $\emptyset_{i,t}$, and $\gamma_{i,t}$. The coefficient of interest is $\gamma_{i,t}$, which communicates the impact of volume on return autocorrelation. Pastor and Stambaugh construct an index from the $\gamma_{i,t}$'s by averaging the coefficients every month, and adjusting the coefficients for changes in the aggregate market value of all stocks. They create a time-series of shocks to the index from the residuals from an autoregressive process. This series is their liquidity factor. They show that stocks with high betas with their liquidity factor have higher average returns than stocks with lower beta, which they interpret as compensation for liquidity risk. Readers that are interested in more details on the estimation are encouraged to read Pontiff and Singla (2020) and Pastor and Stambaugh (2020).[2]

[2] Pontiff and Singla (2020) provide code on the *Critical Finance Review* website that perfectly replicates Pastor and Stambaugh (2003), and is used as the source for the estimation in this section.

We create an anticipated volatility measure at the daily-level. To do so, we use CRSP daily data starting in 1962 (the beginning of the Pastor-Stambaugh sample) through 2021, for securities with share codes of 11 or 12, on NYSE or AMEX, with prices greater than $5 but less than $1000. This exclusion follows PS. For stocks with non-zero trading volume in the current and previous day, we estimate a pooled, cross-sectional time-regression, using absolute values of excess daily returns of each stock with CRSP equal weighted index. We regress this value on the previous trading day's absolute excess return for that stock, the sum of absolute excess return from two days to 6 days before, and the sum of absolute excess returns from 7 days before to 11 days before. This estimation has an R^2 of 12.6%. The respective slope coefficients are, 0.170, 0.058, and 0.041. Our anticipated volatility measure is the sum of the appropriate product of each slope with each series of absolute excess returns.

We follow the PS methodology exactly with one exception--the magnitude of volume changes over time with changes in the market capitalization. As such, PS scale their index and changes in their index in consideration of this. Since volatility is not subject to this concern, our estimation eliminates this step.

Over the entire sample, the innovations to the volatility liquidity risk index and the innovations to Pastor-Stambaugh's volume liquidity risk index have a correlation of 0.268. The correlations between the long-short high and low decile portfolio returns is 0.246. Table 9 presents returns, standard deviations, and t-statistics for both portfolios. The average annual return for the volatility liquidity risk long-short portfolio commands an annual return of 7.79% is over 3% greater than the PS volume annual return. The *t*-statistic is also higher, implying that the Sharpe ratio is high.

(Table 9 goes here)

Pontiff and Singla (2020) propose three changes to the construction of the PS volume liquidity risk factor that they argue should improve the factor, and Pastor and Stambaugh (2020) dispute. Pontiff and Singla note that the estimation of equation (8) is noisy. A typical month contains 20 or 21 trading days that are used to estimate three parameters: $\theta_{i,t}$, $\emptyset_{i,t}$, and $\gamma_{i,t}$. Pontiff and Singla argue that theoretically $\theta_{i,t}$ should be very close to zero. So, restricting it to zero should reduce estimation error of the crucial parameter $\gamma_{i,t}$. They argue that asset pricing is inherently concerned with pricing the market value of assets, not a particular number of assets. As such, the Pastor Stambaugh index would be improved if instead of being an equal weighted average of $\gamma_{i,t}$, it was a value-weighted average. Pastor and Stambaugh omit stocks with prices less than \$5 and greater than \$1,000 from their index. Pontiff-Singla argue that these stocks are probably more likely to be sensitive to liquidity, so including them should improve the risk factor. Pastor and Stambaugh also omit zero volume day observations from their sample. Pontiff and Singla show that this decision reduces the amount of data used to construct the volume risk factor by over 9%.

Pontiff and Singla re-estimate Pastor and Stambaugh's volume liquidity risk index (using data from 1962 to 2017). All four adjustments result in risk premia that fail to reject the null at the 5% level. For 3 of the 4 changes (value-weighting, including all volume days, and including all stocks regardless of price level) lead to dramatic (over 75%) reductions in the factor returns. All three resulting *t*-statistics are less than 0.6.

We re-estimate the volume liquidity risk factor making the Pontiff and Singla adjustments. All specifications lead to factor returns that are less volatile. All adjustment specifications produce *t*-statistics that are higher than the Pastor and Stambaugh volume liquidity factor. For the specification that includes all stocks regardless of price, the annual long-short return is higher than the original specification. For the three remaining adjustment specifications, the average return is lower than the original volatility risk specification, although all *t*-statistics remain greater than 3.

5. Conclusions

Using a century of high frequency data, we revisit market return autocorrelations through the lens of inventory liquidity models We find that autocorrelations are lower on negative return days, which is consistent with collateral constraints that market-long liquidity providers. Our preferred test shows that this asymmetry persists for three trading days.

We reconsider previous literature by estimating the relation between daily market autocorrelation with volume and volatility. Our daily volatility estimates contain 86% less estimation error than inferences from a sole daily return realization. In contrast to the previous literature, we find weaker relations between autocorrelation and volume, and stronger relations between autocorrelations and volatility. We bifurcate volume and volatility into anticipated levels and shocks. Volume's negative relation with autocorrelation is related to anticipate volume, not shocks to volume. This result is puzzling since theory argues that shocks to volume should dominate. Consistent with liquidity provision from risk-averse agents, anticipated volatility drives the negative autocorrelation-volatility result.

Although we find evidence for liquidity effects from collateral constraints and varying anticipated volatility, we fail to find evidence of anticipated volatility having a role in exacerbating autocorrelation asymmetry. We find some evidence that asymmetries may be related to anticipated volume.

We revisit Pastor and Stambaugh's (2003) liquidity risk factor. The source of risk in this factor stems from variation in liquidity proxied through volume. We reconstruct this factor assuming that variation in liquidity stems from variation in anticipated volatility. The resulting liquidity volatility risk factor commands a higher risk premium and a higher Sharpe ratio than the original liquidity risk factor. The new factor is robust to specification changes that Pontiff and Singla (2020) show result in the deterioration of the original factor.

References

Andersen, T. G., T. Bollerslev, P. F. Christoffersen and F. X. Diebold, 2013, "Financial Risk Measurement for Financial Risk Management", in *Handbook of the Economics of Finance*, editors, G. Constantinedes, M. Harris, and R. Stulz, vol 2, pp 1127-1220.,

Bogousslavsky, V. 2021. "The cross-section of intraday and overnight returns," *Journal of Financial Economics* 141. 172-194.

Bogousslavsky, V. and P. Collin-Dufresne, 2023. "Liquidity, Volume, and Order Imbalance Volatility," *Journal of Finance*78. 2189-2232.

Bogousslavsky, V. and D. Muravyev. 2023. "Who Trades at the Close? Implications for Price Discovery and Liquidity." *Journal of Financial Markets*, forthcoming.

Boudoukh, J., R. Feldman, S. Kogan, and M. Richardson. 2019. "Information Trading, and Volatility: Evidence from Firm-Specific News." *The Review of Financial Studies* 32. 992–1033

Boyarchenko, N., Larsen, L.C. and P. Whelan. 2023. "The Overnight Drift." *Review of Financial Studies* 36. 3502–3547.

Brunnermeier, M.K., and L. H. Pedersen. 2009. "Market Liquidity and Funding Liquidity," *The Review of Financial Studies* 22. 2201–2238.

Campbell, J. Y., S. J. Grossman, and J. Wang. 1993. "Trading Volume and Serial Correlation in Stock Returns." *Quarterly Journal of Economics*. 108. 905–939.

Chordia, T., Roll, R., and A. Subrahmanyam. 2002. "Order Imbalance, Liquidity, and Market Returns." *Journal of Financial Economics*. 65. 111–130.

Cooper, M.J., Cliff, M.T. and H. Gulen. 2008. "Return Differences between Trading and Non-Trading Hours: Like Night and Day." Working paper available at SSRN 1004081.

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

Conrad, J.S., Hameed, A. and C. Niden. 1994. "Volume and Autocovariances in Short-Horizon Individual Security Returns." *Journal of Finance*. 49. 1305–1329.

Danielsson, J., Shin, H. S., and Zigrand, J. 2009. “Risk Appetite and Endogenous Risk.” Working Paper.

Engle, R. F. and T. Bollerslev, 1986, “Modelling the Persistence of Conditional Variances”, vol 5, pp 1-50.

Gerety, M.S. and J.H. Mulherin. 1992. “Trading halts and market activity: An analysis of volume at the open and the close.” *The Journal of Finance 47*. 1765-1784.

Greenwood, R., and M. C. Sammon. 2022. “The Disappearing Index Effect.” Working Paper No. w30748. National Bureau of Economic Research.

Gromb, D. and D. Vayanos. 2002. “Equilibrium and welfare in markets with financially constrained arbitrageurs,” *Journal of Financial Economics*, 66. 361-407.

Grossman, S.J. and Miller, M.H. 1988. “Liquidity and Market Structure.” *Journal of Finance,* 43, 617-633.

Hameed, A., W. Kang, and S. Viswanathan. 2010. “Stock Market Declines and Liquidity.” *Journal of Finance.* 65. 257–293.

Hazelkorn, T.M., Moskowitz, T.J. and K. Vasudevan. 2023. “Beyond Basis Basics: Liquidity Demand and Deviations from the Law of One Price.” *Journal of Finance* 78. 301–345.

Kandel, E. and N.D. Pearson. 1995. Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy* 103: 831–872.

LeBaron, B. 1992. “Some Relationships between Volatility and Serial Correlations in Stock Market Returns.” *Journal of Business*, 65, 199-219.

Pastor, L. and R. Stambaugh. 2003. “Liquidity Risk.” *Journal of Political Economy* 111: 642–685.

Mech, T.S., 1993. “Portfolio return autocorrelation.” *Journal of Financial Economics* 34. 307-344.

Nagel, S. 2012. “Evaporating Liquidity,” *Review of Financial Studies* 25, 2005-2039

Pontiff, J. and R. Singla, 2019, “Liquidity Risk?,” *Critical Finance Review 8. 257–276*

Schwert, G. W. 1989. “Why Does Stock Market Volatility Change Over Time?” *Journal of Finance,* 44(5), 1115-1153.

Sentana, E. and Wadhwani, S.B. 1992. “Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data.” *Economic Journal*, 102, 415-425.

Shoven, J.B. and C. Sialm. 2000, “The Dow Jones Industrial Average: The impact of fixing its flaws,” *Journal of Wealth Management* 3, 9-18.

Stoll, H.R., 1985, *The Stock Exchange Specialist System: An Economic Analysis,* Monograph series in finance and economics 1985-2, New York University.

Stoll, H.R., and R.E. Whaley, 1990, “Stock Market Structure and Volatility,” *Review of Financial Studies* 3. 37–71.

Vayanos, D. and P. Woolley. 2013. “An Institutional Theory of Momentum and Reversal.” *Review of Financial Studies* 26. 1087–1145.

Figure 1

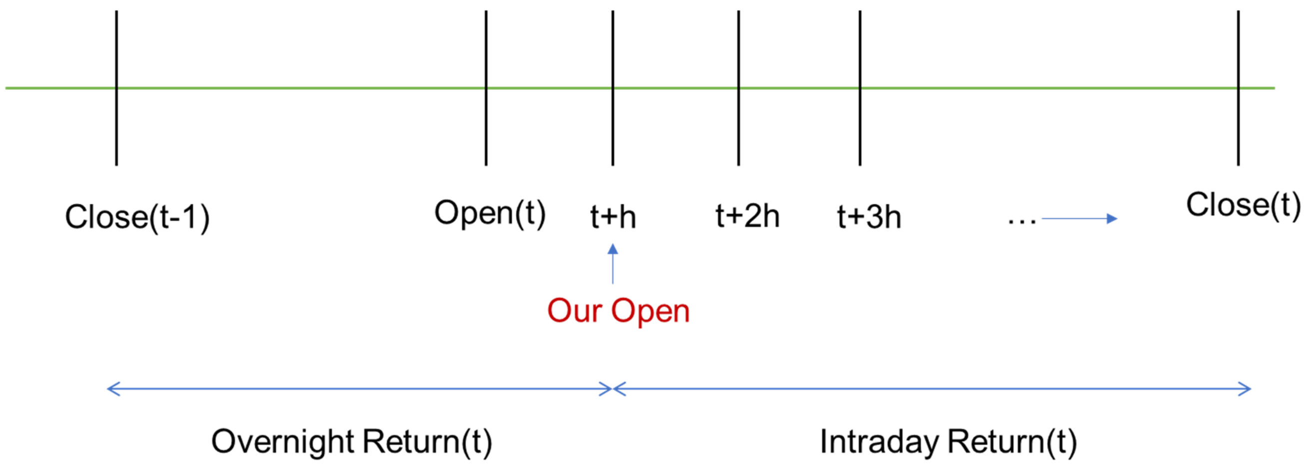
Close(t-1)
Open(t)
t+h
t+2h
t+3h
…
Close(t)
Our Open
Overnight Return(t)
Intraday Return(t)

Table 1

Frequency of Return Series

Exchange opening hours and properties of the data over the sample period. Part of the information in this table is obtained from Gerety and Mulherin (1992). Selected open price indicates the open price that we use in the analysis to compute overnight returns. It is always the second price available in the GFD data series, and the 10am price after 1987.

Period	Hours	Frequency	Selected Open	Source
1/4/1933-9/26/1952	10am-3pm M-F +10am-12pm S[a]	Hourly	11am	GFD
9/29/1952-1/19/1968	10am-3:30pm M-F	Hourly[b,c]	11am	GFD
9/29/1952-1/19/1968	10am-3:30pm M-F	Hourly[b,c]	11am	GFD
1/22/1968-3/1/1968	10am-2pm M-F	Hourly	11am	GFD
3/2/1968-1/1/1969	10am-3:30pm M-F[d]	Hourly	11am	GFD
1/2/1969-7/3/1969	10am-2pm M-F	Hourly	11am	GFD
7/7/1969-9/26/1969	10am-2:30pm M-F	Hourly	11am	GFD
9/29/1969-5/1/1970	10am-3pm M-F	Hourly	11am	GFD
5/4/1970-9/30/1974	10am-3:30pm M-F[e]	Hourly	11am	GFD
10/1-1974-9/26/1985	10am-4pm M-F	Hourly	11am	GFD
9/30/1985-12/31/1987	9:30am-4pm M-F	Half-hourly[f]	10am	GFD
1/1/1988-12/31/2022	9:30am-4pm M-F	Half-hourly	10am	ISSM/TAQ[g]

[a]The NYSE closed on Saturday in the Summer months of 1945-52.
[b]From 9/29/1952 to 11/1/1963, the last return and volume are from 2pm to 3:30pm.
[c]From 11/4/1963 to 12/31/1968, the last return and volume are from 3pm to 3:30pm.
[d]The NYSE was closed on Wednesdays in the latter half of 1968.
[e]From 5/4/1970 to 9/30/1974, the last return and volume are from 3pm to 3:30pm.
[f]Data frequency switches from 1 hour to 30 minutes on 12/2/1986.
[g]Replicated Dow series using midquote returns. This series misses the ticker COKE Data frequency switches from 1 hour to 30 minutes on 12/2/1986.

Table 2

Descriptive Statistics

This table reports descriptive statistics for Dow Jones detrended volume, volatility, and return for the full day and intraday periods. The Crash of 1987 is excluded (10/15 to 10/21/1987). The sample is from 01/04/1933 to 12/31/2022.

Variable	Mean	Std Dev	Min	25th	Median	75th	Max	N
Volume	0.01	0.37	-2.23	-0.19	0.00	0.21	2.13	23202
Volume intraday	-0.23	0.40	-2.83	-0.43	-0.22	0.00	1.81	23202
Volatility (%)	0.660	0.560	0.000	0.308	0.524	0.838	10.063	23455
Volatility intraday (%)	0.650	0.559	0.000	0.298	0.515	0.831	10.020	23455
Return (%)	0.047	0.993	-12.684	-0.404	0.059	0.520	15.621	23455
Return intraday (%)	0.003	0.758	-9.489	-0.341	0.017	0.361	7.957	23455

Table 3

Full Day Returns, Volume, Return Standard Deviation and Variance, and Autocorrelation

Specification:

$$r_{t+1} = \alpha + \left(\sum_{i=1}^{6} \beta_i D_i + \gamma_1 V_t \quad + \gamma_2 \sigma_t \quad + \gamma_3 \sigma_t^2\right) r_t$$

Full day returns are used. The Crash of 1987 is excluded (10/15 to 10/21/1987). Estimation models a 5th order error autoregressive process. The sample is from 01/04/1933 to 12/31/2022.

Sample	γ_1	γ_2	γ_3
1933-2022	-0.10		-98.74
	(-5.81)		(-14.00)
	-0.06	-7.82	
	(-3.16)	(-14.86)	
1933-1952	-0.06		-147.73
	(-2.36)		(-3.34)
	-0.04	-8.69	
	(-1.39)	(-4.85)	
1953-1989	-0.20		-87.60
	(-5.83)		(-4.80)
	-0.15	-7.67	
	(-4.21)	(-6.65)	
1990-2000	-0.98		-142.79
	(-1.21)		(-3.42)
	-0.08	-7.51	
	(-0.88)	(-3.18)	
2001-2022	-0.07		-78.86
	(-1.70)		(-7.05)
	-0.05	-5.72	
	(-1.21)	(-5.87)	

Table 4
Intraday Volume, Return Standard Deviation and Variance, and Autocorrelation,
Specification:

$$r_{t+1} = \alpha + \left(\sum_{i=1}^{6} \beta_i D_i + \gamma_1 V_t^{intraday} + \gamma_2 \sigma_t^{intraday} + \gamma_3 \sigma_t^{2,intraday} \right) r_t^{intraday}$$

Variable are described in the header to Table 3. Full day returns are used. The Crash of 1987 is excluded (10/15 to 10/21/1987). Estimation models a 5th order error autoregressive process. The sample is from 01/04/1933 to 12/31/2022.

Sample	γ_1	γ_2	γ_3
1933-2022	-0.08	-6.94	
	(-3.13)	(-9.68)	
	-0.13		-74.06
	(-5.88)		(-7.74)
1933-1952	-0.01	-6.18	
	(-0.22)	(-2.96)	
	-0.05		-31.83
	(-1.54)		(-0.71)
1953-1989	-0.19	-6.92	
	(-4.16)	(-5.05)	
	-0.25		-66.71
	(-5.84)		(-2.94)
1990-2000	-0.02	-5.58	
	(-0.17)	(-2.22)	
	-0.04		-89.95
	(-0.40)		(-2.24)
2001-2022	-0.12	-3.63	
	(-1.90)	(-2.61)	
	-0.14		-44.27
	(-2.52)		(-2.85)

Table 5
Regression estimation of daily Dow-Jones detrended volume (V_t) and return volatility (σ_t).

Regressions using the entire sample (01/04/1933 to 12/30/2022), with the same specification as the rolling Corsi estimation that is used to estimated shocks and predicted volatility and volume. The superscript *morn* denotes the time period from the last close to the current day selected open. daily denotes and entire day. *weekly,* with the subscript *w-1* denotes the last 5 trading days. monthly with subscript *m-1* denotes the last 21 trading days. *ret* denotes the log return of Dow Jones Index. $I_{\text{Dow Neg}}$ is an indicator variable for whether the Dow Jones index return was negative for the past day. Day of the week indicator variables are included as independent variables.

Independent Variables	**Dependent Variables**		
	Detrended Volume within day V_d^{intraday}	Volatility (x 100) within day $\sigma_d^{\text{intraday}}$	Volatility (x 100) entire day σ_d
σ_d^{morn}	34.15 (17.43)	0.58 (18.43)	
σ_{d-1}^{daily}	4.14 (7.00)	0.24 (25.72)	0.26 (26.91)
σ_{d-1}^{daily} x $I_{\text{Dow Neg}}$	0.62 (1.11)	0.04 (4.53)	0.03 (3.57)
σ_{w-1}^{weekly}	-1.90 (-5.34)	0.13 (23.47)	0.15 (25.24)
$\sigma_{m-1}^{monthly}$	0.65 (4.38)	0.05 (22.71)	0.06 (24.36)
V_d^{morn}	0.10 (25.40)	0.00 (0.21)	
V_{d-1}^{daily}	0.28 (36.20)	0.02 (1.64)	0.01 (1.22)
V_{w-1}^{weekly}	0.08 (30.58)	0.00 (0.59)	0.01 (1.43)
$V_{m-1}^{monthly}$	0.01 (11.98)	-0.00 (-2.26)	-0.00 (-2.84)
Ret_d^{morn}	0.69 (2.65)	-9.21 (-21.99)	
Ret_{d-1}^{daily}	0.61 (2.43)	-4.40 (-10.99)	-5.41 (-13.40)
Adjusted R^2	0.698	0.605	0.596

Table 6
Shocks to Volume and Volatility, Anticipated Volume and Volatility, and Autocorrelation

Specification:

$$r_{t+1} = \alpha + \left(\sum_{i=1}^{6} \beta_i D_i + \gamma_1 V_t^{P,intrday} + \gamma_2 V_t^S + \gamma_3 \sigma_t^P + \gamma_4 \sigma_t^S \right) r_t^{intraday}$$

r_{t+1} is the log return of the Dow from the next period to the next trading day. The other variables are described in the header to Table 3. The Crash of 1987 is excluded (10/15 to 10/21/1987). Estimation models a 5th order error autoregressive process.

Sample	γ_1	γ_2	γ_3	γ_4
1933-2022	-0.14 (-5.01)	0.07 (1.70)	-9.52 (-10.24)	-0.37 (-0.34)
1933-1952	-0.04 (-0.95)	0.04 (0.59)	-16.56 (-3.22)	1.14 (0.32)
1953-1989	-0.23 (-4.59)	-0.14 (-2.11)	-7.60 (-4.46)	-3.54 (-2.16)
1990-2000	-0.04 (-0.30)	0.12 (0.86)	-11.71 (-1.82)	-2.36 (-0.51)
2001-2022	-0.15 (-2.32)	0.26 (2.16)	-4.88 (-2.75)	-0.17 (-0.08)
2001-2022, VIX Enhanced Corsi	-0.08 (-1.13)	0.22 (1.80)	-7.77 (-4.40)	4.39 (1.93)

Table 7
Market Return Autocorrelation Depending on Return Direction

Autocorrelation of returns on the CRSP daily value-weighted index and the Dow-Jones Index using returns on the next five trading days. Autocorrelations are calculated depending on whether the initial return is positive or negative. The last set of results calculates Dow-Jones autocorrelations for which the initial return is intraday. The sample is from 01/02/1926 to 12/31/2022 (from 01/04/1933 for the Dow-Jones). Observations between 10/15 and 10/21/1987, "Black Monday," are omitted.

	Initial Return <0	Initial Return ≥0	Difference	Difference z -statistic	p-value
		VWRET			
$\rho(VWRET_0, VWRET_1)$	-0.016	0.036	-0.052	-4.11	0.00
$\rho(VWRET_0, VWRET_2)$	-0.039	-0.024	-0.014	-1.17	0.12
$\rho(VWRET_0, VWRET_3)$	-0.009	0.014	-0.023	-1.80	0.04
$\rho(VWRET_0, VWRET_4)$	0.042	-0.010	0.052	4.12	0.00
$\rho(VWRET_0, VWRET_5)$	0.016	-0.005	0.021	1.69	0.05
		Only trading days for which $\lvert VWRET_0 \rvert \leq 5\%$			
$\rho(VWRET_0, VWRET_1)$	-0.013	0.015	-0.027	-2.20	0.01
$\rho(VWRET_0, VWRET_2)$	-0.014	-0.022	0.008	0.65	0.26
$\rho(VWRET_0, VWRET_3)$	0.014	0.021	-0.007	-0.53	0.30
$\rho(VWRET_0, VWRET_4)$	0.024	0.011	0.013	1.05	0.15
$\rho(VWRET_0, VWRET_5)$	0.000	-0.026	0.026	2.07	0.02
		Dow Returns			
$\rho(DowRet_0, DowRet_1)$	-0.046	0.011	-0.056	-4.30	0.00
$\rho(DowRet_0, DowRet_2)$	-0.012	0.006	-0.018	-1.37	0.09
$\rho(DowRet_0, DowRet_3)$	0.010	0.019	-0.009	-0.67	0.25
$\rho(DowRet_0, DowRet_4)$	-0.022	0.005	-0.027	-1.42	0.08
$\rho(DowRet_0, DowRet_5)$	-0.014	-0.013	-0.001	-0.05	0.48
		Dow Returns, initial return, $DowRet_0^{intra}$, is intraday			
$\rho(DowRet_0^{intra}, DowRet_1)$	-0.027	0.027	-0.054	-4.13	0.00
$\rho(DowRet_0^{intra}, DowRet_2)$	-0.037	0.024	-0.061	-4.67	0.00
$\rho(DowRet_0^{intra}, DowRet_3)$	-0.004	0.037	-0.041	-3.13	0.00
$\rho(DowRet_0^{intra}, DowRet_4)$	-0.006	-0.008	0.002	0.16	0.44
$\rho(DowRet_0^{intra}, DowRet_5)$	-0.017	-0.001	-0.016	-1.23	0.11

Table 8
Autocorrelation Asymmetries and the Role of Shocks to Volume to Volatility, and Anticipated Volume and Volatility

Two speciation are considered. A "positive" and "negative" specification. Both take the form

$$r_{t+1} = \alpha + \left(\sum_{i=1}^{6} \beta_i D_i + \gamma_1 V_t^{P,intraday} + \gamma_2 V_t^S + \gamma_3 \sigma_t^P + \gamma_4 \sigma_t^S \right) r_t^{intraday} + \left(\Delta_1 V_t^{P,intrday} + \Delta_2 V_t^S + \Delta_3 \sigma_t^P + \Delta_4 \sigma_t^S \right) I\left(r_t^{intraday} < 0 \right) r_t^{intraday}$$

$I\left(r_t^{intra} < 0\right)$is an indicator variable that is equal to one when r_t^{intra} is negative, and zero otherwise. r_{t+1} is the log return of the Dow from the next period to the next trading day. The other variables are described in the header to Table 3. The Crash of 1987 is excluded (10/15 to 10/21/1987). Estimation models a 5th order error autoregressive process.

Sample	Δ_1	Δ_2	Δ_3	Δ_4
1933-2022	-0.24	0.38	-0.74	-2.16
	(-4.67)	(0.25)	(-0.56)	(-0.98)
1933-1952	-0.16	0.12	-20.65	-9.52
	(-2.04)	(0.87)	(-2.87)	(-1.30)
1953-1989	-0.61	-0.31	-8.48	-4.50
	(-6.73)	(-2.22)	(-3.09)	(-1.32)
1990-2000	0.01	0.26	-5.22	-14.77
	(0.04)	(0.90)	(-0.83)	(-1.70)
2001-2022	-0.17	0.62	1.62	12.38
	(-1.35)	(2.51)	(-0.67)	(2.57)
2001-2022, VIX	-0.09	0.73	-2.41	9.15
Enhanced Corsi	(-0.72)	(2.94)	(-1.00)	(1.84)

Table 9

Performance of Liquidity Risk Indices

Returns to the liquidity beta top decile portfolio minus the return of the bottom decile portfolio: August 1962 to December 2021

	Annualized Return	Monthly Standard Deviation	t-statistic
Pastor and Stambaugh	4.58%	3.48%	2.79
Volatility Risk, PS Estimation	7.79%	4.31%	3.84
Volatility Risk Robustness			
$\theta_{i,t}$ restricted to zero	6.11%	4.21%	3.08
Value Weighted	5.78%	3.73%	3.30
All Price Levels	8.04%	4.07%	4.19
Zero Volume Days Included	6.95%	4.09%	3.60