The Time-Varying Liquidity Premium:
Speculator Hesitation in Liquidity Shocks

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Abstract
This paper studies the effect of the time-varying liquidity premium on equities in both a short and long run framework. In the long run, we find changes in consumer confidence and expected volatility shift the liquidity premium. We show the time-varying liquidity premium drives some of the variation in two significant time series: The equal-weighted S&P 500 and the Fama-French “Small minus Big” pricing factor. In the short run, after a liquidity shock, we find speculators exacerbate the impact of the shock by checking their models, causing an additional increase in the price of liquidity.

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I. Introduction

We know land on the banks of the Mississippi River is “cheap;” are stocks that are exposed to “catastrophic events” cheap as well? In financial markets, a liquidity shock—defined as a sharp increase in the price of trading—can be catastrophic. Trading can become prohibitively expensive leading to financial gridlock and an inability to transact as occurred most recently after September 11, 2001. At times of less severe shocks, which occur frequently, investors may be forced to liquidate their holdings at a substantial cost. Liquidity is the ease with which an owner of an asset can sell at the current market price. For example, selling a pair of tickets to the Rolling Stones concert is much easier than selling a pair of tickets to an obscure opera. Even if the tickets have the same face value, there may be a website open to sell tickets for the Rolling Stones, but not for the opera. More music fans know the fair value of a Roll Stones ticket. There are fewer buyers who know the fair price for an opera ticket. There is a built in option to the Stones tickets: The holder can immediately sell them if for example he is sick the day of the show. The Rolling Stones tickets have higher liquidity than the opera tickets. The extent to which liquidity affects the price of an asset is called the liquidity premium.

The liquidity premium is the difference in price between assets identical except for their liquidity. When we think about owning an asset, a desirable property for that asset is the ability to sell it quickly for the current market price. In equilibrium, assets should yield equally after factoring out risk differences; otherwise, arbitrageurs would enter the market to eliminate these discrepancies. For example, many accept that investors prefer high expected returns, low risk, and high liquidity. This is by no means an exhaustive list. If one asset has higher liquidity than another, the liquid asset should have a lower return, higher risk, or a combination of both. If risk is equal, higher liquidity should lead to lower returns—this difference in returns due to
differences in the liquidity is called the liquidity premium. There is no reason for the price of liquidity to remain constant. We look for long run drivers of change in the liquidity premium and then track the short term effects of a liquidity shock when these long run drivers change sharply. Since some of this long run analysis has been done for bonds, we conduct the analysis with equities.\footnote{See Amihud and Mendelson (1991), Scholes (2000) and Longstaff (2002).} We find that investor sentiment affects the long-run price of liquidity, and, in the short run, shocks affect the price of liquidity as demanders are willing to pay more for liquidity and suppliers demand a much higher price to supply liquidity.

Any change in the price of liquidity must arise from net changes in preferences of liquidity demanders and providers. On the demand side are hedgers. These investors want the ability to opt out of any investment at their discretion at the market price. On the supply side are speculators. Speculators, by definition, buy an asset when the price is low enough and sell it when the price is high to cover their required return on capital. Understanding what motivates hedgers and speculators is paramount to understand why the price of liquidity changes over time.

Vayanos (2003) argues that investors have a time-varying liquidity preference arising from investing constraints. When volatility increases, many investors face an “implicit leverage” constraint. These investors may be forced to liquidate their positions in one period if performance is poor in the previous period. Mutual fund managers, pension fund managers, investment bank traders and hedge fund traders all may face this pressure. Fund managers observe fund outflows if performance is poor. Traders may be fired if performance is poor. Therefore, investors facing implicit leverage have strong incentives to buy liquid assets as liquidation increases in likelihood—and increases in volatility increase this likelihood. In other words, implicit leverage creates a link between volatility and the liquidity premium. Following Vayanos, we argue the implicitly levered “fly to liquidity” as expected and realized volatility.
increases. Crucially, the liquidity premium rises from changes in hedger preferences, not because of new asset pricing information.

A liquidity shock occurs if and only if suppliers for whatever reason cannot step in to supply liquidity profitably. Their business is to correct asset mispricings in markets they understand. However, as Scholes (2003) argues, if the shock is large enough and as hedging demands increase, the mispricing could become extreme because speculators withdraw capital for they may question whether their model is misspecified or the calibration of their existing model is wrong! This is a rational response to a sharp change in market prices as we will discuss. Since speculators sometimes hesitate exactly when their services are most needed and appear on the surface to be most profitable, there are many buyers and few sellers of liquidity. The price of liquidity spikes. Suppliers then check their models and evaluate the new information over time; consequently, the price of liquidity will stabilize and recover. Uncovering and detailing how this process evolves is central to our investigation of the short-term effects of a liquidity shock. We are interested in the “response function” of the liquidity market over time.

We find evidence of change in the price of liquidity after shocks for roughly a 2-week period. The reaction is also proportional to the size of the liquidity shock. Over the long term, the same kind of process occurs to change the price of liquidity where concerns of optimism and pessimism drive the premium.

The main motivation for this paper is to delve into the “size effect,” which is defined as the persistent over performance of small stocks over large stocks, as measured by market capitalization, on a risk-adjusted basis. While the economic basis for size being a true pricing factor is shaky, at best, liquidity has a solid theoretical foundation to become a true pricing

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2 See Banz (1981) and Reinganum (1981)
factor. Small stocks have, on average, lower liquidity than large stocks. We argue that the size effect proxies for a liquidity effect.

We test the theory in two well-known financial time series used in size effect analysis: Equal-weighted minus value-weighted S&P 500 and the Fama-French “Small minus Big” pricing factor. We find consumer confidence and implied volatility drive a liquidity premium in these portfolios which are both short liquidity. One true driver of higher returns for small stock is their illiquidity, which investors rationally trade-off for lower returns in liquid stocks. They are willing to pay for the right to liquidate quickly if need be.

An interesting view into this trade-off between expected returns and liquidity comes from a recent New York Times article. A mutual fund company, Dimensional Fund Advisors (DFA) has devised a way to take advantage of manager fears and the occasional flight to liquidity. Their advantage is to float a large stock order below the bid price. The bid price is the highest price a buyer is willing to pay to a security. According to John C. Siciliano, the company’s director of global institutional services, DFA looks “for a transaction that’s below the bid.” In short, they offer a trade: large liquidity for expected returns. By acting as a liquidity provider in a notoriously illiquid market, DFA is able to “charge” a service fee by buying below the bid. In fact, 40% of their small cap trades are done under bid. While the article offers no timetable for when these transactions occur, we certainly can imagine these under bid transactions occur when pessimism rises.

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4 See Roll (1981) for EW-VW and Fama and French (1993) for “Small minus Big”
5 Eisenstein, Howard, “Mutual Funds Report; Reading the Index To Beat the Index,” New York Times, January 11, 2004
The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 documents our theory of liquidity and liquidity shocks. Section 4 describes the data and carries out empirical tests. Section 5 concludes.

II. Literature Review

II.i Overview:

The study of the time-varying liquidity premium is linked to the size effect, one of the main puzzles in financial economics. In the Capital Asset Pricing Model (CAPM), size should not factor into asset returns in equilibrium. CAPM states that investors only care about risk and return and, that, in equilibrium, the risk/return trade-off should be consistently priced through the whole market. However, Banz (1981) showed that small capitalization was a very good predictor of expected returns after adjusting for risk. Reinganum (1982) confirmed the size effect and showed its predictive power subsumed P/E, which was previously shown by Basu (1979) to predict returns.

The debate of the small stock effect was subsumed by average liquidity measures as Amihud and Mendelson (1986) argued, both theoretically and empirically, that post-transaction cost returns should be equal on a risk-adjusted basis. Since small stocks tend to have higher bid-ask spreads, average liquidity subsumed the previously debated size effect. This result suggests that CAPM is misspecified; bid-ask spread should be another factor in predicting expected returns.

Shleifer and Vishney (1997) argue the size effect persists because arbitrageurs face investment constraints. Arbitrageurs may be forced to sell fundamentally good positions if performance lags as investors withdraw funds. Noise trader action may increase the difference between actual price and true price, so arbitrageurs may be forced to withdraw capital when
opportunities are greatest. Since noise trader impact is largest on equity positions and since modeling is relatively easier for fixed income markets, arbitrageurs tend to stay away from size effect trades.

Academic research is now moving towards studies of market-wide co-movements in liquidity. Chordia, Roll, and Subrahanyam (1999) show these movements do exist while others show that these movements can in fact move between markets. Pastor and Stambaugh (2002) argue that an asset’s sensitivity to these co-movements (its “liquidity beta”) is an undiversifiable risk inherent to the asset, so investor’s must price this characteristic.

II.ii Academic Literature

In the late 1970’s and early 1980’s a great deal of research discovered, examined, and debated the underlying causes of the so-called small stock effect.

Banz (1981) was the first author to show the inverse relationship between company size and stock performance. Over the period 1936-1975, he shows “the common stock of small firms had, on average, higher risk-adjusted returns than the common stock of large firms.” He notes that size by itself is not the likely driver of the over performance. Instead, size is likely well correlated with a true pricing factor. He also notes that any possible arbitrage profit may not be due to market inefficiency, but rather to hidden risk factor that is not priced.

Banz uses New York Stock Exchange (NYSE) stocks from the Center for Research in Securities Prices (CRSP) database. This introduces a slight large stock bias since other studies include AMEX stocks, which on average are smaller in size. Banz uses three difference market indices to see if results differ due to the baseline “market.” He uses a value-weighted, equal-weighted and value-weighted combination of the value-weighted with government and corporate
bond returns, following Ibbotson and Sinquefield (1977), to capture more accurately the CAPM market pricing factor. Reassuringly the results are relatively stable.

Banz estimates that on average, if we construct long-short portfolios of small stocks versus large stocks, rebalanced every month, and levered to make each have equal risk, produces excess returns of 20% annually. Banz argues that size is not a good proxy for the true beta of a portfolio; if CAPM is true, but we are using an inadequate measure of “the market,” we could misestimate expected returns. If size is correlated to the true beta, including it in predictions would lead to more accurate expected return predictions. Finally, Banz highlights the severe non-linearity of the size effect. He finds that the small stock effect affects the smallest firms only. Specifically, he breaks the NYSE into deciles and finds that only the smallest two groups significantly outperform their expectations. All other groups, on a risk-adjusted basis, perform as expected. From our point of view, this might hint that liquidity discounts are concentrated in the bottom 20% of the stocks in his sample.

Reinganum (1981) shows that low price/earnings (P/E) ratios and small firm size are positively correlated to risk-adjusted excess returns on stocks in New York Stock Exchange (NYSE) and America Stock Exchange (AMEX) over a long period of trading. Since AMEX stocks tend to be smaller than NYSE stocks, their addition imparts a small stock bias compared to Banz’s study. The P/E prediction method was first suggested in an earlier paper by Basu (1979). Reinganum uses more robust methods than the previous authors to confirm the existence these anomalies.

Reinganum is principally concerned with positive autocorrelation in small stock returns. Small stocks tend to have positive autocorrelation due to infrequent trading. Reinganum controls for autocorrelation using Scholes-Williams beta estimation, an econometric method that
Reinganum estimates that low P/E ratio firms outperform high P/E firms by 0.1% a day, which is both economically large and statistically different than 0.0%. He also uses different market measures to correct for risk and find stable results. He estimates small firms outperform large firm on an annual basis by nearly 30%.

Reinganum’s main innovation is to show that while low P/E and small firms are highly correlated, size subsumes the predictive effects of P/E when considered simultaneously. That is, low P/E and size seem to be a proxy for set of real underlying, priced variables, but that size more closely tracks these underlying variables than does P/E. In the end, Reinganum and Banz come to the same conclusion that size is a robust predictor of expected returns, but both offer no reason what size proxies for.

Some economists argue the small stock effect results from econometric problems arising from estimating returns and variances of infrequently traded (i.e. illiquid) stocks. Roll (1981) employs simple methods to achieve striking results showing that normal estimation methods on positively autocorrelated time series can lead to an underestimation of risk. In regression analysis, there is an explicit assumption of independent, identically distributed (I.D.D) variables. However autocorrelation violates this assumption; positive returns tend to follow positive returns, while negative returns tend to follow negative returns. Roll shows when I.D.D. is violated, estimation accuracy becomes biased. Since small stocks exhibit positive autocorrelation, standard estimations of small stock risks are biased.

He examines only 2 time series: Equal-weighted (EW) S&P 500 and the value-weighted (VW) S&P 500. His two series run from 1962-1977. Clearly, small stocks influence the EW portfolio more than the VW portfolio, so we can expect more autocorrelation in the EW portfolio. Roll then creates different holding periods: daily, weekly, bi-weekly, monthly, bi-
monthly, quarterly, and semi-annually. Over each holding period, the EW outperforms the VW by around 12% annually, with a correlation of 0.85. However, as the holding period is increased, the ratio of the standard deviations of EW divided by VW rises monotonically. That is, the longer the holding period, the higher the variance.

Roll argues that autocorrelation causes this shift in variance upwards. When variance is estimated from daily data, the autocorrelation biases the estimation downwards; as holding period is increased, the autocorrelated returns “unwind” themselves. Put another way, over a longer holding period, swings in autocorrelated data tend to be more pronounced, leading to a higher and more accurate estimation of risk.

Empirically, the lengthening of the holding period from daily to semi-annually increases the annual variance threefold. Now, on a risk-adjusted basis, the EW portfolio looks much less attractive than previously thought. Roll stresses that by compounding before averaging; the size effect is halved, leaving open the question of why academics continue to be so interested in this anomaly, given that much of its size is due to econometric estimation problems.

Roll approaches the problem in another fashion as well. Noting that “when shares are being regressed on an index which is composed of large companies and/or which is value-weighted, it is the lagged coefficients which are of importance” (p. 205). Using the Dimson beta estimation, another robust method to correct for autocorrelation, Roll finds the EW beta increases from the normal OLS estimator. This method has the particular advantage of increasing the sample size from semi-annual chunks to daily data, increasing the accuracy of the estimates.

The second econometric problem with small stock analysis exists because academics tend to use the arithmetic average for a particular stock instead of a buy-and-hold estimation of
returns. Compared the buy-and-hold or daily rebalancing methods of calculating returns, arithmetic means can be biased upward if the right conditions are persist. Roll (1983) first theoretically shows the differences in expected values of the arithmetic average (AR) return, the buy-and-hold (BH) return, and a daily rebalanced (RB) return as various assumptions of autocorrelation change. Daily rebalancing entails selling a portion of winning stocks and buying more of losing stocks to maintain equal dollar amounts in each stock. This procedure is prohibitively expensive since each rebalancing requires transaction costs. Roll first shows that if one assumes returns are generated from a stationary distribution with independent disturbances, then $E[AR] \geq E[RB]$ and if variance of the disturbance is greater than 0, then $E[BH] \geq E[RB]$.

However, comparing $E[BH]$ and $E[AR]$ is more complicated. Depending on the cross-sectional dispersion of expected returns and the dispersion of unexpected returns, $E[AR]/E[BH]$ can either be greater than, equal to, or less than 1.

Roll concludes with a few basic lessons. BH gives an unbiased estimate of the holding period return under normal investment conditions, since investors usually buy-and-hold, allowing for returns to compound for some time before examining them. RB gives an unbiased estimate as well, but is unrealistic due to high trading costs. AR gives a biased estimate of both RB and BH investments, except “under a fortuitous combination of circumstances.” Namely, an absence of the autocorrelation problems introduced above.

To test his theoretical calculations, Roll again utilizes a simple but effective test. He uses all stocks in either the NYSE/AMEX over the period 1963-1981. He then calculates AR, BH, and RB returns daily and over one year periods. When the holding period is daily, all the returns are the same by their mathematical definitions. However, when the holding period is extended to one year, AR gives an estimate of 14.9% return with a t-statistic of 3.07 while BH only give
7.45% return with a t-statistic of only 1.53 over the 19 year period. Therefore, the estimate of the small firm premium is cut in half by compounding before averaging, nearly identical to his results in the previous paper. Further, the second return is not statistically different from 0. That is, by a simple change in return calculation, the small firm premium becomes roughly half as attractive as an investment. Roll warns that one must be extremely careful in choosing one’s method of calculating returns.

Despite Roll’s econometric adjustments for both return and variance due to autocorrelation, a residual positive return for small firms remains. Roll admits “the investigation of the observed small firm premium in the context of a more general asset pricing model would be a worthwhile endeavor,” but adds, “estimation problems in expected returns and in simple risk parameters can explain much of the apparent anomaly.”

Blume and Stambaugh (1983) argue, like Roll, that computing returns with small stock data is fraught with danger; economists may introduce an upward bias on expected returns. Blume and Stambaugh argue for the existence of a “bid-ask” effect, which is defined as the difference in true price from closing price. Any traded security’s closing price is affected by the last trade of the day. If the last trade of the day was a purchase, the closing price will be the ask price, which is higher than the true price. Similarly, if the last trade of the day was a sale, the closing price will be the bid price, which is lower than the true price.

Blume and Stambaugh argue the bid-ask effect causes first-order negative autocorrelation in returns, as market participants view that last traded price and see it is too low (bid) or too high (ask) and trade to correct the imbalance. The major implication of negative first-order autocorrelation is that imparts an upwards bias in computed rates of return for stocks. That is, the expected return as computed using closing prices can be too high.
This effect becomes more pronounced as the spread increases, leading to an econometric explanation of the size effect. Expected returns are estimated to be much too high for high spread stocks, which tend to be small stocks, leading to misleading results. To remedy this misestimating, Blume and Stambaugh use the same buy-and-hold calculation Roll does and finds the same results; estimated returns for small stocks decrease as the holding period is increased. Like Roll, they find the full year size effect is halved.

However, even the skeptical economists (i.e. Roll, Blume, and Stambaugh) who argue for underestimated risk concede that even after they control for these estimation problems, some over performance persists, suggesting some underlying factor still drives a real difference in returns.

Other empirical anomalies further complicate the small stock effect. Keim (1983) shows the small stock effect mostly occurs in the month of January. This phenomenon is known as the “January effect.” Based on his calculations, roughly 50% of the average annual small stock over performance comes from January, and 27% of the over performance comes from the first week of trading of January. The remaining 50% of over performance is then documented to occur evenly over the February to December span. While January’s over performance is the largest, 7 of the 11 remaining months independently differ statistically from 0. Armed with these surprising results, Keim argues that the small stock effect should be decomposed into two parts—though clearly linked in spirit—the large premium in January and the smaller, yet on average positive risk-adjusted return over the February to December period. In his opinion, any theory that attempts to explain the small stock effect must take into account this pronounced seasonal effect. While Keim’s paper does not directly link to our paper, we think it belongs in
the literature review because of its prominence in small stock research and its implications for future work. For example, more shocks may have occurred in January by chance.

Keim is cognizant of Roll’s critique that autocorrelation in small stock returns may overstate returns and understate risk. Thus, he uses three different risk measurements to adjust for risk: CAPM beta, Scholes-Williams beta, and Dimson beta. Yet, after these corrections, small stock over performance persists. Keim notes the near monotonic relationship between firm size and Dimson beta. Thus, Keim argues that misestimating betas does not account for the anomaly. Keim reports 20.7% annual over performance than indicated by the small stock portfolio, an economically large result.

In January specifically, the excess returns on a portfolio combining a long position in small stocks and a short position in large stocks are measured to be 15%, but only 2.5% in the other months. Both of these returns are economically large, especially the January result.

Keim then offers some possible explanations for causes of the January effect. The first is tax-loss selling. In this model, investors sell small stocks to offset the capital gains of other stocks. Since small stocks tend to be more volatile than larger stocks, small stocks have more candidates for sale—i.e. small stocks have larger winners and losers than large stocks. Since the end of the tax year is December 31, small stock prices are temporarily depressed to reflect this selling, only to rebound after New Year’s Day. Keim argues this hypothesis cannot be true because of arbitrageurs and a lack of evidence as the tax structure has changed. Many market participants, most notably pension funds, do not pay capital gains taxes, so these investors could arbitrage away this imbalance due to their tax-exempt status. Second, if tax-loss selling is the cause of the January effect, the level of January over performance should respond to different levels of taxes. However, this is not the case empirically.
The second theory Keim offers is informational differences in January compared to other months. January marks a period of increased uncertainty. Many companies end their fiscal year on December 31st. Thus, in January, earnings are released, employees are hired and fired, and risk rises. Also, the impact of any released information may have a larger effect on the smaller firms because the costs of processing this year end information. This theory is possible, but as yet unproven. This theory is consistent with an increasing liquidity premium as volatility increases with higher information flow. The increase in volatility encourages hedging activity, leading to a higher price of liquidity.

Acknowledging Keim’s paper, Reinganum (1983) argues against tax-loss selling as the sole driver of the January effect. Reinganum creates a measure that, though imperfect, is a good proxy for a stock’s “potential tax-loss selling” (PTS). He measures the PTS as end of the year price divided by the maximum price in the last 6 months. Ideally, this measure would include price changes, volume, and institutional holdings. Since many institutional investors are exempt from capital gains taxes, they would have no incentive to sell to cover their gains. Nevertheless, this PTS measure fluctuates between 0 and 1 and seems to be a sensible proxy for true PTS.

Empirically, there are a lot of small stock losers, but a number of winners as well. So, Reinganum compares the performance of those stocks we expect to rebound in January (low PTS) with those we don’t expect to rebound (high PTS). In the first group of “expected to be sold” small stocks, there certainly is over performance. Over 1962-1980, these stocks averaged a 4.1% return in January and there is not one negative return in January for 17 years. However, the “unlikely to be sold” group of small stocks do well too, though not as spectacularly. Reinganum concludes that some of the size effect is due to taxes, but not all of it.
Reinganum also finds that when holding the PTS measure constant, its predictive power declines as size increases. So, the size effect still persists to some extent. This could be explained if institutions tended to own larger sized stocks, since PTS does not affect these investors. In a final analysis of the size effect, there remains a positive residual return that so far remains unexplained. Researchers then showed high transaction costs contribute substantially to small firm over performance in equilibrium.

Amihud and Mendelson (1986) offer compelling evidence that illiquidity is the primary driver behind the small stock effect. They construct a model explaining why assets with lower liquidity in equilibrium will yield higher returns, then test this hypothesis empirically.

Their theoretical model makes natural assumptions and comes to testable conclusions. Each asset in the economy has identical per period cash flow, but with increasing spreads. Investors are modeled to enter the economy stochastically, and hold their assets for a period of time also determined stochastically. Once the investor’s time is up, he liquidates his assets at the bid price and leaves. The investors try to maximize their net expected cash flows over their expected investment horizon. Crucially, the spread adjusted return on an asset is the gross return minus the expected liquidation costs. Thus, as the investment horizon increases, these expected liquidation costs are defrayed over time, resulting in higher returns for investors with long investment horizons.

Amihud and Mendelson report two main theoretical conclusions. First, called the “clientele effect” predicts that “assets with higher spreads are allocated in equilibrium to portfolios with (the same or) longer expected holding periods” or portfolios portioned such that a part is in less liquid assets. Second, they predict the “spread-return relationship,” which states that “in equilibrium, the observed market (gross) return is an increasing and concave piecewise-
linear function of the (relative) spread.” They predict that short-term traders hold low spread assets and that as the spread increases, expected returns will increase, but at a decreasing rate. Since an individual investor’s investment horizon is unknown from aggregate data, only the second theoretical result is testable.

To test their theory, Amihud and Mendelson use bid-ask spread as a natural liquidity measurement. After all, “the quoted ask (offer) price includes a premium for immediately buying, and the bid price similarly reflects a concession required for immediate sale.” They cite other papers that show bid-ask spread is correlated with other natural liquidity measures, like volume, number of shareholders, and price continuity, suggesting that the bid-ask spread is a good proxy for liquidity. We are aware, however, of the problem with using bid-ask spread as a pure measure of liquidity. The bid-ask spread is determined by the amount of traders who are willing to pay to trade and the information holders. That is, if the dealer suspects informational trading, the bid-ask spread will widen without a change in liquidity.

Amihud and Mendelson first determine the basic relations between stock returns, relative risk (as measured by a CAPM beta), and relative spread using NYSE data from 1961-1980. Relative spread is just the bid-ask spread divided by the average of the bid and ask prices (it is used for scaling purposes to remove spread differences due to individual stock price levels). Using individual stock analysis, portfolio creation, and cross-sectional testing similar to that of Black, Jensen, and Scholes (1972), Amihud and Mendelson create 7 equal portfolios sorted by spread, then by risk, creating a total of 49 portfolios. They report that beta and excess returns are increasing with spread, and that the correlation of excess returns and spread is twice as high as the correlation of excess return and beta. Though correlation does not imply causation, these
results certainly suggest that a more detailed look of the relations between these variables is warranted. So they proceed accordingly.

Amihud and Mendelson compare CAPM (with year dummy variables) to CAPM plus an independent spread variable. They find that spread is a significant predictor of excess returns, and that it takes away some of beta’s prediction power, suggesting that beta may be a partial proxy for spread. The find that a 1% increase in spread results in a 0.211% increase in monthly excess returns, significant both statistically and economically.

To test their hypothesis that expected returns are an increasing, concave function of spread, Amihud and Mendelson must control for two moving factors—portfolio and time differences. As such, they add 48 dummy variables to capture portfolio differences and 19 dummy variables to capture year to year differences. Also, up to now, the spread has been a single variable. To test for concavity, they create a relative spread dummy variable to signal which portfolio is in which spread category (there are 7 of these variables). Due to worries that OLS regressions do not adequately deal with heteroscedasticity, the authors also employ generalized least squares (GLS) regression method. The results do not differ too much due to different estimation methods.

Amihud and Mendelson report two major empirical findings. First, after adjusting for risk, excess returns increase with spread. The difference between the smallest and largest spread groups is estimated to be 0.857% by OLS and 0.681% by GLS in monthly excess returns. As far as their concavity prediction, the spread coefficients are positive, but generally decrease as with spread size, supporting their hypothesis.

However, these results may be driven by the small stock effect. High spread is correlated with size, so spread may just be a proxy for size. With this criticism in mind, the authors repeat
their analysis twice: once with a size independent variable and once with a log size independent variable. The log size variable makes the most sense, given the non-linearity first shown by Banz (1981). The result of this log-size test is profound.

The spread variable subsumes the size variable in predictive power. A simple OLS regression shows beta and spread variables have success explaining excess returns, while size does effects become insignificant. A more detailed GLS regression shows that size is only significant when all spread variables are excluded. That is, the most likely story is that size and spread are both correlated with the true underlying liquidity driver and spread is more closely linked than size. The implication is that the size effect is in fact not an anomaly, but rather a rational, measured response from investors to illiquidity. One area this paper fails to address is the January effect of the size effect, due to a lack of monthly data.

After showing that bid-ask spread does affect pricing, Amihud and Mendelson (1991) explicitly show a liquidity premium in the market and that investors do in fact trade higher liquidity for lower returns when trading U.S. Treasury securities. They compare yield to maturity for two types of US bonds: bills and notes. Notes are long-term bonds with semiannual coupon payments, while bills are short-term discount bonds. They are also different with respect to yield calculations, quote systems, and trading systems. Furthermore, traders in the note area tend not to focus on bills, and vice-versa. However, once the last coupon payment on the notes has been made, the securities are identical with respect to promised cash flow and risk, since the issuer is the same for both bonds (the government). Thus, under six months, the difference in yields should be zero if investors care only about risk and return. Surprisingly, Amihud and Mendelson show that notes have persistently higher yields than do bills. They hypothesize the difference is due to liquidity differences in the two securities.
Notes have much lower liquidity than bills. They suggest the reason for this is that note owners, who tend to own the note for a long period of time, tend to “lock away” these bonds, leaving them unavailable for trade, while bills by their very nature are common purchases for investors with short investment horizons. This liquidity difference is reflected in the quoted bid-ask spread for these two securities, which Amihud and Mendelson estimate to be different by a factor of four.

Amihud and Mendelson measure the difference in yield to maturity for notes over bills to average 0.428% annually, both economically and statistically significant different than 0. The security with lower liquidity has a higher yield. The authors also measure the persistence of this yield difference as time to maturity winds down. They find that the difference can be mapped by a decreasing, convex function of time to maturity. As time to maturity decreases, there is less time to depreciate the higher transaction costs of purchasing the note, so the premium will increase.

Amihud and Mendelson then document possible arbitrage opportunities, a natural extension of their paper given that otherwise identical assets are trading with different returns. They show that if an investor currently owns a bill, he can make an arbitrage profit by immediately selling at the bid price and buying a note at the ask price. Amihud and Mendelson also show, however, that pure arbitrage does not work. That is, the simultaneous buying of a note at the ask price and shorting a bill, factoring in broker fees, does not yield a consistent profit. They conclude their paper by arguing this evidence shows that any investor preference model should now include liquidity, along with the usual risk and return preferences.

Fama and French (1993) do not debate liquidity pricing factors; they instead seek out factors that best explain average stock and bond returns. They motivate their study by noting
that CAPM’s ability to predict average returns has been inconclusive at best. They find five common risk factors: three specific to stocks and two specific to bonds. Fama and French find all 5 factors contribute to accurate estimation of stock returns, but only the two bond factors accurately estimate bond returns, with the exception of low-grade corporate bonds, which are best explained with all five factors.

Fama and French use size, book-to-market, and the value weighted market itself as their stock specific factors. They refer to Banz (1981) for motivation in using size and Basu (1983) for motivation using book-to-market ratio. To create a size index, Fama and French take the median value of the NYSE stocks each year in June and then divide all the stocks in the NYSE/AMEX/NASDAQ into either the small or big portfolio based on this median. They then track the difference, or small minus big (SMB), as a proxy for the effects of size on market returns. To create the BE/ME index, they first divide all NYSE/AMEX/NASDAQ stocks into one of three categories: small (30%), medium (40%), or high (30%). Then, they make 6 portfolios in the intersections of the BE/ME and size categories, then take the simple average of the two high BE/ME portfolios and subtract the average of the two low BE/ME portfolios to create an index “High minus Low” or HML. Finally, the use of the value weighted market comes from the original CAPM innovators, Sharpe (1964) and Lintner (1965).

For factors in bond returns, Fama and French find two main sources of risk, term and default risk. Fama and French use the difference between long-term government bond returns and the one-month Treasury bill return (denoted TERM) and the difference between a portfolio of long term corporate bonds and long term government bonds (denoted DEF). TERM is a proxy for the expected return on bonds; shifts in term capture changes in current or expected interest rates. DEF is a proxy for business environment and the likelihood of corporate default.
With these five factors, Fama and French are able to explain a large fraction of the variation found in stock and bond returns.

After debating static liquidity’s role in asset pricing, researchers have moved a step further by suggesting that market-wide liquidity exists and an asset’s exposure to its movements is an undiversifiable risk that is priced by the markets. Chordia, Roll, and Subrahanyam (1999) break ground in liquidity research by arguing that empirical evidence supports the existence of common underlying determinants for individual stock liquidity, though they make no attempt to identify these factors. In determining the liquidity of an asset, dealers face two main risks: inventory and asymmetric information risk. Inventory risk probably changes with volume and volatility, suggesting that if common factors drive these events across securities, there will be co-movements in liquidity. With asymmetric information, our intuition suggests that this will have effects only on an individual stock level (the authors use the example of fraudulent bookkeeping). However, the authors suggest that there are other kinds of asymmetric information (e.g., a revolutionary technology) that will reshape the landscape of competition in a sector of the economy. In this case, co-movement would be confined to individual sectors.

Along with this a priori reasoning for co-movements in liquidity, there are some empirical backings as well. Obviously, asset prices change. When prices move, they move for many stocks at the same time. Thus, market activity is linked to times when there are large price shifts. Co-movement in prices leads to changes in dealer inventory, which leads to bid-ask spread, depth, and other liquidity measures changing. Chordia et al. then break down liquidity into two parts. First, there is day-to-day liquidity that seems to be priced. Second, there is dynamic liquidity that changes with market conditions.
Chordia et al. track 5 liquidity measures over time for 1169 securities: quoted and effective spread, proportional quoted and effective spread, and market depth. After applying a number of filters to the extensive data, each security’s values are averaged each day. This reduces the data from 2.7 billion transactions to roughly 14.8 million data points, or 0.5% of the original size. There is a lot of movement in costs over time: “The mean of the absolute value of the percentage change in the quoted spread is almost 24% a day.” In many of these measures, the standard deviations of the data are small, indicating that this large variability over time is shared by most of the other stocks.

Chordia et al. create a “market” liquidity measure by averaging the given variable for all the stocks in the sample. To test sensitivity to co-movements in liquidity, they create a “market” model for liquidity, like simple CAPM, and test for a positive value of “beta.” They do this twice; once with equal weight in measures and once with value weighting. They update this market model with leads and lags to capture the time it takes for the market to “update” as liquidity changes and market returns to take away any other misspecification. There is ample evidence of co-movement. All five liquidity measures have statistically significant betas using both market liquidity measures.

Their results suggest small firms are less sensitive than big firms to market-wide shocks. Liquidity betas go down when VW is used, which is the opposite of a market model with returns. To test the robustness of this assertion they split the market into size quintiles and compute portfolio liquidity betas. The results confirm their assertion. Betas are mostly increasing in size even though average spreads for large firms are smaller. This is in conflict with Pastor and Stambaugh (2002), who argue smaller firms have larger market liquidity betas. This first measure really only deals with the inventory risk. To try to differentiate asymmetric information
from inventory risk, they add a sector liquidity measure and recalculate their measure. Now, individual liquidity is affected by both liquidity measures, but sector liquidity is more powerful.

As another test of changes in liquidity, they estimate individual liquidity from average dollar size of transactions, number of trades, aggregate market volume and aggregate sector volume. Following Jones, Kaul, and Lipson (1994), Chordia et al. suspect that informed traders will split up their trades into smaller denominations to try and fly “under the radar.” They find that aggregate volume reduces spreads, as balancing risks for the dealer becomes easier. The number of trades increase spreads, in line with the asymmetric argument. Also, volume in industry increases spreads in most of the liquidity measures, suggesting informed traders again. Market-wide volume decreases spreads but sector liquidity increases them. Thus, we think that depth is created by only uninformed traders.

Finally, Chordia et al. acknowledge that a number of known individual liquidity drivers have been established and move to correct for their influences. After controlling for price and volatility, they test power of market-wide liquidity measure and both individual and market determinants. They find that market-wide liquidity is still statistically significant, indicating that commonality is a driver of individual liquidity. However, Chordia et al. fear there is non-systematic noise in individual liquidity measures, so they construct larger portfolios, sorted by size again, to see if explanatory power rises. Indeed, $R^2$ rises. For one liquidity measure, change in depth, $R^2$ equals 0.811. The other large results is that the market liquidity coefficient for the largest portfolio is the largest for 4 of 5 liquidity measures, again suggesting that market-wise liquidity shifts affect large firms more than small firms.

Pastor and Stambaugh (2002) try to take the liquidity effect further, arguing that expected returns are related to a stock’s fluctuations during aggregate liquidity shifts. They argue that
fluctuations in aggregate liquidity affect all stocks, just like a broad movement in the marketplace. The authors present evidence that liquidity shocks exhibit commonality across stocks. Thus, aggregate liquidity can be thought of as a “state” variable. Large liquidity shifts should therefore affect stocks with high sensitivities to these movements.6

For their market-wide liquidity measurement, the Pastor and Stambaugh focus on one part of liquidity: Temporary price fluctuations induced by order flow. That is, they try to capture the negative autocorrelation explained by Blume and Stambaugh (1983). We expect this sensitivity to be negative with lower liquidity stocks. Some investors are compensated for providing liquidity with higher expected returns by buying low or selling high to correct mispricing, and the authors hope to capture this event. The greater the expected reversal for a given dollar amount, the lower the liquidity of that stock. The authors then average individual stocks average liquidities over a month period. They then perform some econometric corrections and then look at the residuals of the resulting series as the innovations in liquidity.

Pastor and Stambaugh admit their metric of liquidity is somewhat lacking. Principally, volume measurements are prone to confused results. They cite evidence that volume can play a part in current versus lagged returns, asymmetric information can weaken reversals, and that momentum plays a role for some firms. This last concern is of some importance, given that low liquidity stocks tend to have positive autocorrelation in returns due to infrequent trading. As far as the basic empirical characteristics of this liquidity measure, most of the downward liquidity shocks occur during down markets. Also, this measure has a correlation of 0.36 with monthly return of the value-weighted NYSE/AMEX index.

The authors model the beta of the liquidity measure as a linear function of a constant and a vector of other predictors including average stock liquidity beta for that stock for 5 years prior,

6 Also, see Scholes (2000)
average value of own liquidity over previous 6 months, and a volatility measurement. They find historical liquidity beta is the most important determinant of predicted beta for the longest period, and that volatility is significant, but decreasingly so. They also find that own liquidity has a negative coefficient, indicating that stocks with low current liquidity are more prone to suffer during liquidity shocks.

The authors then sort the liquidity betas by size, finding results that may explain much of the size effect. The firms who are smallest in size tend to have the highest liquidity betas. Thus, if the evidence shows that the smallest firms have the highest expected returns, and that the smallest firms have the highest sensitivities to market-wide shifts in liquidity, one could speculate these sensitivities are indeed priced. That is, investors require compensation for holding assets sensitive to liquidity shocks. The authors then conclude that this market liquidity effect is sufficient to explain the size effect documented earlier. Constructing a portfolio based on high liquidity shift betas, the authors create an annual alpha of 4%.

A recent paper by Vayanos (2003) provides a theoretical foundation linking liquidity movements and expected returns. Vayanos develops a theoretical model that predicts a time sensitive link between volatility and investor risk premium, more negative volatility asset price correlation, higher inter-asset correlation, rising illiquid asset market betas, and rising illiquid asset expected returns. He also shows that an unconditional CAPM model with understate the true risks of illiquid assets, since their betas are time conditional and linked to market volatility levels.

Vayanos models a reasonable market setting. There are a number of assets, each with increasing trading costs. If an asset has high trading costs, Vayanos considers the asset to be illiquid. These trading costs are constant over time. Volatility is modeled as an exogenous
variable. Vayanos’ key assumption is that investors are fund managers who face implicit leverage. They derive utility from the size of their fund, in the sense they are given a percentage cut of assets under management every period. So, as a fund grows, the manager receives a higher fee. The fund is also subject to withdrawals as a random event or if performance in the previous period falls below a certain level. If the fund investors see a bad performance, they will pull all of their money, leaving the manager empty-handed.7 So, the managers must balance their desire for higher returns, which provide them higher payoffs, with increasing probability of withdrawals if volatility were to increase.

This assumption of implicit leverage provides a clear link between increasing volatility and increasing liquidity preference. As volatility increases, the likelihood of a bad outcome increases. The manager will cut down his risk and move to assets less exposed to volatility in a rational response to his implicit leverage constraint. While this paper assumes exogenous volatility, a more accurate model would have an endogenous volatility variable linked to implicit leverage constraints.

Since asset transaction costs are constant, the rising liquidity premium is not attributable to the costs themselves, but instead to investors’ willingness to hold illiquid assets. Of course, if illiquid assets increase in spread as volatility climbs, investor willingness to hold illiquid assets would decrease even faster. That is, we can expect an even higher liquidity premium if spreads are positively linked to rising volatility.

Vayanos also hypothesizes that the effect of volatility on the liquidity premium is first convex and then concave. He offers intuitive reasoning supporting this argument; when volatility is low, investors are very unlikely to order withdrawal. However, when volatility does increase, managers find the probability of withdrawal increases more than one to one with

7 For empirical evidence, see Chevalier and Ellison (1997) and Sirri and Tufano (1998)
volatility. If this effect of volatility on the investor is the direct effect, there is an indirect effect as well. As volatility increases, investors’ risk aversion increases as well and this risk aversion may be convex as well. The intuition is that as the likelihood of withdrawal increases, managers want to hold more secure assets, so the withdrawal component of the risk premium increases. Since withdrawal likelihood is convex, the risk premium increases convexly as well.

In our area of specific interest, illiquid assets, Vayanos offers three main points. First, illiquid assets have higher risks. Second, illiquid assets exhibit higher sensitivity to volatility changes. Third, unconditional CAPM can understate the risk to illiquid assets due to time linked liquidity and risk premium. That is, CAPM may overstate the soundness of a position based in illiquid assets.

According to Vayanos, convex risk and liquidity premium combine for two important results: time variation in both asset correlation and a rise in beta for illiquid assets. Both are driven by the same process. As volatility increases, the convexity of a manager’s allocation response makes volatility the driving factor in the asset’s pricing. Since all assets share a common volatility parameter, their correlations should be increasing in volatility. Also, since illiquid assets are more sensitive to volatility shifts, their market betas should increase as volatility rises.

The paper offers a litany of testable empirical patterns. First, changes in volatility should drive changes in liquidity premium, correlations, market betas, and expected returns. Second, when testing for links between liquidity and expected returns, Vayanos warns that the indirect effect of illiquidity leading to an increased risk premium can understate the pure illiquidity effect, since this indirect effect is hard to capture. Third, an asset pricing model should be based on sensitivities to the market, volatility, and transaction costs. That is, CAPM should now
include volatility and transaction cost independent variables. However, this paper does not explain a common underlying liquidity factor itself. Furthermore, it ignores diversification’s ability to control volatility’s impact on a portfolio through cancellation.

In contrast to Vayanos, Shleifer and Vishney (1997) create a model in which arbitrageurs are unable to correct fundamental mispricings in the market due to arbitrageur capital constraints. Their model also suggests why persistent pricing anomalies like the size effect persist.

In their model, there are a limited number of highly skilled arbitrageurs, who use other investors’ capital to invest in the market. The key assumption of this paper is so-called performance-based arbitrage (PBA). PBA requires some investors to pull funds from the arbitrageur if performance is poor in the previous period. This is very similar in spirit to implicit leverage, except it is the arbitrageur who is exposed to this constraint, not the pension or mutual fund manager.

Fundamental mispricings are created by noise traders who know little of the true value of assets in the market. In this setting, if the arbitrageur starts losing money on a sound position, he will be forced to partially liquidate to pay his investors. This series of events leads to the persistence of the fundamental mispricing. Furthermore, the arbitrageurs are the least aggressive when profit opportunities are greatest. The arbitrageurs are assumed to be unable to raise sufficient capital to correct the mispricing.

Shleifer and Vishney’s analysis also has interesting implications for the persistent market mispricing we have discussed; i.e. the size effect. They argue that professional arbitrageurs only enter into low risk markets they can model. The market for small stocks, in contrast, is inherently risky. The size of the idiosyncratic shocks from noise traders is larger in the equity markets than similar shocks in the fixed income markets. Since these shocks can force
liquidation by PBA dynamics, arbitrageurs stay away and the mispricing persists. However, we see the same effects in very liquid markets (e.g. bond markets), suggesting the PBA explanation is not completely satisfactory.\(^8\)

Longstaff (2002) empirically shows the existence of a flight to liquidity premium in U.S. Treasury bonds by tracking the difference in price between zero coupon strips of U.S. Treasury bonds and bonds issued by the Resolution Funding Corporation (Refcorp), a U.S. government agency, over 11 different maturities from April 1991 to March 2001. The government created Refcorp in the wake of the savings and loan crisis to aid in selling off insolvent institutions. Its bonds are guaranteed by the U.S. Treasury. Further, the tax treatment of both bonds is identical.

Therefore, Longstaff compares bonds with equal cash flow from the same source, but which differ only in market liquidity, which he terms “popularity.” In standard economic theory, these securities should have the same price. That is, bond popularity should not affect bond prices. Nevertheless, he finds a difference that averages 10 to 16 basis points which is statistically and economically different from 0, even after taking the serial correlation of the premium into account. He shows this premium results in prices differing by as much as 15%. Longstaff comes to the conclusion that the popularity of an asset directly affects its price.

Longstaff argues this flight to liquidity is a different event than the well documented flight to quality that is often discussed. In a flight to quality, investors may change their opinion of some debtor’s credit worthiness and buy U.S. Treasuries that are now relatively safer than previously thought. In a flight to liquidity, some investors suddenly want to hold highly-liquid securities, namely U.S. Treasury bonds. This point follows Scholes (2000), who argues investors wish nothing more than to “disengage” during these episodes.

\(^8\) See Kamara (1994) and Longstaff (2002)
Longstaff links changes in the premium to variables that signal possible flight to liquidity situations. He identifies variables that have “intuitive appeal” rather than those based on any theoretical foundation. He regresses the premium on a consumer confidence index, the change in Treasury debt held by foreign investors, flow into money market mutual funds (MMMF), flow into equity mutual funds, and the amount of Treasury securities available to the investor (the U.S. Treasury initiated a buyback program in 2000, reducing supply). Finally, Longstaff adds two more independent variables as controls: He adds a lagged yield difference to control for the serial correlation and the difference in yield between an index of AAA bonds and the Bloomberg BBB1 5 year industrial bond index to control for perceived credit risk. Longstaff concedes that another factor could be driving the premium; large investors lack the ability to liquidate a Refcorp position due to the smaller market size. In other words, the flight to liquidity could in this case result from investor aversion to holding assets than cannot be liquidated easily. Investors are unable to disengage.

Nevertheless, his regression results strongly suggest that these liquidity factors drive the premium. He concludes that the prices of Treasury bonds are directly affected by their popularity and liquidity.

III. Speculator Hesitation and Liquidity Shocks

We now introduce our model of the liquidity market and explain how liquidity shocks exist within a rational response framework. We then give an example to clarify.

III.i Outline

Unanticipated events lead to volatility spikes which in turn lead to an increase in hedging activity. This shift in demand leads to a rise in the price of liquidity and a possible profit opportunity for speculators. The speculators, not knowing whether this price increase is
temporary or permanent, may question their pricing models. Since they model the equilibrium price of liquidity, they intermediate liquidity shocks with widening spreads of the actual price over the model price of liquidity. As speculators pause to recheck their models and investigate the cause and implications of the shock, the price of liquidity might continue to rise. In this scenario, all actors behave rationally, but nevertheless the market experiences a liquidity shock.

III.ii Speculator Hesitation Model

In the liquidity market, hedgers demand liquidity while speculators provide liquidity. Hedgers view holding liquidity as an option to “disengage” from their investments as needs arise. That is, liquid assets have the built in option to convert assets to cash quickly and cheaply. The market price for liquidity—the liquidity premium—reflects the trade-off in returns hedgers are willing to part with in return for the option to disengage.

To link an increase in hedging demand to volatility, we follow Vayanos (2003) who argues many investors follow rules grounded in insurance or capital preservation. His key assumption is that investors are fund managers who face implicit leverage. Implicit leverage creates a trading constraint forcing investors with poor performances in one period to liquidate some positions in the next period due to institutional rules.

Institutional investors may face different constraints than normal investors due to competition in the field. As Vayanos argues, fund managers have a strong incentive to maintain fund size at a large and stable level. Institutions are frequently judged by its clients and risks fund withdrawals if performance lags behind other funds. Clients tend to move capital from under performing funds to over performing funds. These reallocations are rational. If a fund has poor returns, its manager may not be skilled or may be unlucky. However, the investor cannot

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9 See Longstaff (2002)
10 See Scholes (2000)
know the manager’s ability a priori. The investor will pull money after a poor return since it indicates a higher probability of low manager skill.

Fund manager incentives imply volatility linked liquidity preferences and a rising liquidity premium. These managers are paid a percentage of assets under management, a statistic directly linked to fund size while only indirectly linked to performance. A rise in volatility causes extreme asset pricing outcomes become more likely; this event threatens to shrink the size of their portfolio. Since managers want to maintain the size of their fund more than they want higher returns, they will trade out of illiquid, volatile assets into safe, liquid assets, even at high costs. Illiquid assets decrease in price while liquid assets increase in price. In other words, the liquidity premium starts to increase as expected volatility rises.

Some argue that most investors are long run investors who are not shaken by temporary swings in prices. A closer look at market participants forces us to acknowledge that many powerful investors who face implicit leverage may become hedgers in volatile periods: mutual fund managers, pension fund managers, investment bank traders, and hedge fund traders. The sheer size of the mutual and pension fund industries is a strong suggestion that these institutional constraints do indeed play out in the market. As for the traders, they can be fired if performance falls too far. Even individual investors might prefer to liquidate their holdings and move to more liquid and safe investments as a result of unanticipated shocks that increase volatility.

On the supply side, speculators create models to create fair price curves and actual price curves to identify mispricings. These models incorporate historical prices with factors that have shifted prices. The difference between the fair price and the actual price is called the “spread.” The speculator makes trades based on these spreads. If an asset’s fair price is below the actual price, he will buy. If the asset’s fair price is above the actual price, he will sell. These models
are at the heart of the speculation business. The speculators’ main concern is what causes the spreads to occur.

Speculators make money on spreads that revert. Price reversion occurs if the mispricing is caused by “flows” from hedgers and hedgers are willing to pay speculators for their services. For example, a mutual fund manager who faces an implicit leverage constraint starts to sell one of his positions heavily when volatility increases—this temporary increase in selling is a flow. After a flow, the actual price reverts to the true price over time.

Speculators lose money trying to correct permanent price changes caused by fundamental shifts in hedger expectations if the adjustment process is not instantaneous. Fundamental shifts alter the markets for a long time. For example, investors might conclude one day that the U.S. Treasury is more prone to default on its debts due to persistent budget deficits than bond prices reflect. In this case, Treasury yields will rise and never revert. In this case, the “mispricing” a concurrent shift in the actual price and the true price. Another case of non-reversion might be that investors become more pessimistic about the prospects for the economy and remain so for an extended period of time.

It is impossible for the speculators’ models to capture all relevant pricing factors in a given market. The speculator must judge which factors are first order and assume that the rest are second order. Obviously, those factors that might appear to be second order might indeed be first order.

When an apparent profit opportunity appears, the speculator must determine whether it arises from flows or from new factors changing the pricing equilibrium. If the speculator believes the spread comes from a flow, he will immediately act to supply liquidity and restore actual price to the true price. On the other hand, if the speculator is wary of the cause of the
spread, he can hesitate or more likely add to positions more slowly with the uncertainty to garner
time to evaluate the information set. He may employ more modeling and/or gather additional
information. The information this networking provides is clearly crucial to the success of the
speculator. In the end, the speculator must become more confident that the return to risk ratio is
sufficient to allocate capital. In the meantime he will withhold capital.

It might be the case that the larger the spread, the more time the speculator will hesitate.
If a flow causes a spread, however, the mispricing may grow as the implicit leverage continues to
drive the sale of assets by some fund managers and traders. In this situation, there might only be
liquidity buyers and no liquidity sellers. The price of liquidity will skyrocket. Therefore, the
combination of a flow induced spread because of external, unanticipated events and speculator
hesitation leads to a liquidity shock.

This occurs on a long-run time frame was well. Changes in the price of liquidity can be
linked to investor sentiment. As investors become more pessimistic, they will move towards
more liquid assets; conversely, as investors become optimistic, they will hold fewer liquid assets.
We can track investor confidence indices to link to changes in the price of liquidity.

IV. Data Analysis

IV.i Overview

To study the time-varying liquidity premium in the long term and liquidity shocks in the
short term, we concentrate in the equity market. The size effect has been debated for some time
by academics. One time series used in the debates has been equal minus the value weighted
Standard & Poor’s 500 index of returns (“S&P 500”). We examine whether a time-varying
liquidity premium explains the variation in returns on this time series.
The difference between the equal-weighted (EW) and value-weighted (VW) S&P 500 indices is long illiquidity and short liquidity—we call the position EW-VW. Value-weighting is an index where each stock affects the index in proportion to its market capitalization. Thus, large firms drive the returns of this index. In contrast, an equal-weighted index has each stock having equal affect on the index. Since the equal-weighting creates more weight proportionally on small firms, the comparison can be though of as small firms minus big firms. The motivation for this comparison is we expect that smaller firms have lower liquidity than larger firms. Thus, the EW-VW returns should include a liquidity premium, if it exists. We will also examine the presence of a liquidity factor in the Fama-French SMB asset pricing factor.

For liquidity shock research, we examine returns of the equal minus value weighted S&P around potential shocks seeking evidence of initial speculator hesitation and recovery over time. We do an event study style analysis to see if a common trend emerges after shocks. To proxy for liquidity shocks, which are hard to ascertain without extensive external information, we use shocks or large changes in expected volatility as a surrogate for external events.

**IV.ii S&P 500 Descriptive Statistics**

Data are from the Center for Research in Security Prices (CRSP) data files. We track the cumulative performance of EW-VW from January 1980 to December 2003 in Figure 1:
We notice that the cumulative return of EW-VW tends to be above 0 for most of the time frame, other than during the explosive growth of the economy during the so-called “dot.com bubble,” maybe a period of extreme optimism in the economy. This leads us to wonder if returns of EW-VW are different from 0. We expect this to be the case if there is a long-run liquidity premium and not enough speculators are willing to provide liquidity to the market. Also, this would be true if EW is a riskier position than VW, since higher risk should require higher returns over the long run. We test this hypothesis in Table 1.
Table 1: Testing EW_M_VW mean equals 0

<table>
<thead>
<tr>
<th>Hypothesis Testing for EW_M_VW</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample: 1980:01 2003:12</td>
<td></td>
</tr>
<tr>
<td>Included observations: 288</td>
<td></td>
</tr>
<tr>
<td>Test of Hypothesis: Mean = 0</td>
<td></td>
</tr>
<tr>
<td>Sample Mean = 0.0017</td>
<td></td>
</tr>
<tr>
<td>Sample Std. Dev. = 0.0164</td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>Value</td>
</tr>
<tr>
<td>t-statistic</td>
<td>1.79</td>
</tr>
</tbody>
</table>

EW will outperform the VW on average by 0.17% per month. We can say the true mean of EW-VW is greater than 0% with 92.5% certainty. So far, this just shows that the EW tends to have higher returns than the VW. We have not yet linked this to market sentiments about liquidity.

To test if a time-varying liquidity premium drives some of the differences in the EW-VW spread, we regress EW-VW on independent variables that may reflect changes in demand for liquidity using monthly time series. We chose many of these variables following Longstaff (2002).

**IV.ii EW-VW S&P 500 Long Term Analysis**

The first independent variable reflects consumer sentiment of the future state of the economy. We take data from the Conference Board’s monthly consumer surveys. We track the percentage change in “Consumer Expectations Index” (CON_EXP). A rise in CON_EXP signals that consumers have increased confidence in the future of the economy. This likely encourages investors to move from liquid to less liquid investments. If some variation in EW-VW reflects a time-varying liquidity premium, we expect a positive relationship between EW-VW and CON_EXP.

The second independent variable tracks changes in the level of implied volatility in the S&P 500 from the VIX index. This commonly cited measure gauges “investor fear,” i.e.
expectations of near term volatility.\textsuperscript{11} We obtain this data from the Chicago Board Options Exchange (CBOE). Recently, the CBOE changed the method of calculation for the VIX. The “old” VIX, now called the VXO, is a longer time series that the VIX. The new VIX combines more information and is considered a better measure of market sentiments by the CBOE. We wish to have as long a sample period as possible and use the best data. Since the series are highly correlated (above 0.98), we patch the time series together by using the VXO from 1986 to 1989 and the VIX from 1990 to 2003. We call percentage changes in this combined time series D\_IMP\_VOL. Illiquid positions should decline in value as investors sell them off as expected volatility rises. Therefore, we expect a negative relationship between EW-VW and D\_IMP\_VOL.

The third independent variable is the change in the price of gold. Gold is a solid, stable asset. The more uncertainty there is in the market, the higher the price of gold we can expect. When the price rises, we can expect a sell-off in illiquid assets. Therefore, we expect a negative relationship between EW-VW and gold.

Next, we track flows of money into and out of money market mutual funds (MMMF). These funds are safe investments that have low exposure to volatility swings. If investors increase investment in MMMF’s, we can interpret a rise in pessimism and fear of near term volatility. Again, we expect a sell-off in illiquid assets to occur and the EW-VW position to lose money. Therefore, we expect a negative relationship between MMMF flows and EW-VW. The Federal Reserve tracks MMMF flows.

The fifth independent variable is flows into and out of U.S. equity mutual funds, excluding international funds, measured in billions of dollars (EQUITY\_FLOW). We interpret this variable to track investor optimism in the market. As investors gain confidence, they will

\textsuperscript{11} See Whaley (2000)
invest in equity funds. When equity fund flow increases, we can expect a gain in the EW-VW position. Therefore, we expect a positive relationship between equity fund flow and EW-VW. We use data from Trimtabs.com to track equity fund flows.

The sixth independent variable is new offerings, defined as the combined dollar values of initial public offerings, secondary offerings, and conversions, measured in billions of dollars (NEW_OFFERINGS). An increase in new offerings is a signal of positive business sentiment. If companies rush to go public, as they did in the late 1990’s, they view market as receptive to risky ventures and willing to tolerate the risks associated with new ventures. However, NEW_OFFERINGS may be endogenous with market sentiment. That is, it may also be true that companies issue stock because the price is high, and the price might be high due to optimism. Also, NEW_OFFERINGS may be a signal of overpricing and investors may respond by selling. In summary, we think NEW_OFFERINGS will probably have a positive relation with EW_M_VW, but we are not fully convinced.

The seventh independent variable is announced stock buybacks (BUYBACKS). If companies would rather buy-in their stock, prices might be low enough to reacquire shares at a discount because of market pessimism. Therefore, if buybacks increase, we expect the price of liquidity to increase—there will be a sell-off in illiquid assets. We expect a negative relationship between BUYBACKS and EW-VW.

The eighth independent variable is completed cash takeovers (TAKEOVERS). This reasoning for the inclusion of this variable is similar to inflows into equity mutual funds. If investors feel they would trade cash for an asset in the market, we interpret increased optimism. As such, there may be a sell-off in safe, liquid investments. Therefore, we expect a positive relationship between TAKEOVERS and the EW-VW time series.
If the variables map to changes in optimism and pessimism as we suspect, they should also map to each other in a correlation matrix. For example, we suspect CON_EXP is positively linked to EW-VW while D_IMP_VOL is negatively linked. Together, we anticipate a negative correlation between CON_EXP and D_IMP_VOL. Table 2 is a correlation matrix of our independent variables.

Table 2: Correlation Matrix of Independent Variables

<table>
<thead>
<tr>
<th></th>
<th>CON_EXP</th>
<th>D_IMP_VOL</th>
<th>GOLD</th>
<th>EQUITY_FLOW</th>
<th>NEW_OFFERINGS</th>
<th>BUYBACKS</th>
<th>TAKEOVERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CON_EXP</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D_IMP_VOL</td>
<td>-0.17</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GOLD</td>
<td>-0.04</td>
<td>0.12</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MMMF</td>
<td>-0.11</td>
<td>0.01</td>
<td>-0.1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EQUITY_FLOW</td>
<td>0.13</td>
<td>-0.2</td>
<td>-0.04</td>
<td>0.08</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NEW_OFFERINGS</td>
<td>0.09</td>
<td>-0.02</td>
<td>0</td>
<td>0.15</td>
<td>0.45</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>BUYBACKS</td>
<td>-0.12</td>
<td>0.1</td>
<td>0.06</td>
<td>0.39</td>
<td>0.12</td>
<td>0.44</td>
<td>1</td>
</tr>
<tr>
<td>TAKEOVERS</td>
<td>-0.08</td>
<td>0.01</td>
<td>-0.07</td>
<td>0.33</td>
<td>0.21</td>
<td>0.27</td>
<td>0.35</td>
</tr>
</tbody>
</table>

As suspected, CON_EXP is negatively correlated with D_IMP_VOL. The only other large correlations are between the flow datasets, MMMF, EQUITY_FLOW, NEW_OFFERINGS, BUYBACKS, and TAKEOVERS. In fact, all the flow data are positively correlated, despite our expectations. For example, we would expect BUYBACKS and NEW_OFFERINGS to be negatively correlated if they both reflect sentiments about market conditions; we expect BUYBACKS to have a negative relationship with EW-VW and NEW_OFFERINGS to have a positive one. Instead, they have a correlation of 0.44. Therefore, we are not as confident that our choices for independent variables reflect market sentiment as much as we were before.

We also include basic descriptive statistics of the independent variables in Table 3 to give a sense of the typical magnitude and spread. After all, some are percentage changes while others are real changes. CON_EXP, D_IMP_VOL, and GOLD are all measured in percentage changes.
The other variables are monetary flows and measured in billions of dollars. Therefore, we must be careful when we interpret results. After all, a change in MMMF of $20 billion is not uncommon. When we look at regression coefficients, we must be careful to consider a typical change.

Table 3: Descriptive Statistics of Independent Variables

<table>
<thead>
<tr>
<th></th>
<th>CON_EXP</th>
<th>D_IMP_VOL</th>
<th>GOLD</th>
<th>MMMF_FLOW</th>
<th>EQUITY</th>
<th>NEW_OFFERINGS</th>
<th>BUY_BACKS</th>
<th>TAKEOVERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0049</td>
<td>0.0173</td>
<td>-0.0004</td>
<td>6.58</td>
<td>7.23</td>
<td>9.25</td>
<td>9.52</td>
<td>6.35</td>
</tr>
<tr>
<td>Median</td>
<td>0.0011</td>
<td>-0.0119</td>
<td>0.0000</td>
<td>4.00</td>
<td>6.82</td>
<td>6.68</td>
<td>6.86</td>
<td>4.29</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.5833</td>
<td>1.7440</td>
<td>0.2000</td>
<td>95.50</td>
<td>35.52</td>
<td>40.04</td>
<td>53.64</td>
<td>35.75</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.2908</td>
<td>-0.3267</td>
<td>-0.1700</td>
<td>-58.80</td>
<td>-49.03</td>
<td>0.23</td>
<td>0.37</td>
<td>0.00</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0881</td>
<td>0.2068</td>
<td>0.0443</td>
<td>17.33</td>
<td>9.81</td>
<td>7.99</td>
<td>8.14</td>
<td>6.88</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.1779</td>
<td>3.2246</td>
<td>0.3614</td>
<td>1.04</td>
<td>-0.99</td>
<td>1.45</td>
<td>1.67</td>
<td>2.05</td>
</tr>
<tr>
<td>Observations</td>
<td>286</td>
<td>215</td>
<td>276</td>
<td>287</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
</tr>
</tbody>
</table>

We notice a number of interesting individual statistics. First, of the percent changes variables, implied volatility is clearly the most volatile, with a standard deviation of 20%. This means that only 67% of daily movements in implied volatility are smaller than \[20\%\] if implied volatility is normally distributed. However, implied volatility is positively skewed. The tail on the positive end is much longer than the tail on of negative returns. \( D\_IMP\_VOL \) may be less volatile than we initially suspect. Of the flow variables, MMMF clearly shows the largest changes in investment month to month, with a standard deviation of $17.33 billion. The other flow variables are lower by a factor of 2. Therefore, when we interpret our results, we should be cognizant that some variables have much larger typical changes, which means they may have more influential than we initially deduce.

It is widely acknowledged in the financial economics literature, small cap securities tend to exhibit autocorrelation. In fact, we find that the monthly EW-VW portfolio has two
significant lags. Table 4 shows that positive serial correlation exists for two months in the EW-VW time series:

Table 4:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Statistic</th>
<th>Probability ≠ 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>EW_M_VW(-1)</td>
<td>0.201</td>
<td>0.060</td>
<td>3.370</td>
<td>99.91%</td>
</tr>
<tr>
<td>EW_M_VW(-2)</td>
<td>0.121</td>
<td>0.061</td>
<td>1.992</td>
<td>95.27%</td>
</tr>
</tbody>
</table>

This test shows we must be careful when using EW-VW as a dependent variable. If we use an independent variable that has the same time lag properties as EW-VW, we would find a spurious relationship that would bias our results, so we will be careful to first correct for the autocorrelation. To avoid finding a spurious driver of the EW-VW spread, we include two lagged EW-VW variables to correct for this problem.

Finally, we include a constant to capture any persistent trend.

So our regression is: 

\[
(EW - VW)_t = \beta_1 C + \\
\beta_2 CONspołeczn _EXP_t + \\
\beta_3 D_imp _VOL_t + \\
\beta_4 GOLD_t + \\
\beta_5 MMMF_t + \\
\beta_6 EQUITY _FLOW_t + \\
\beta_7 NEW _OFFERINGS_t + \\
\beta_8 BUYBACKS_t + \\
\beta_9 TAKEOVERS_t + \\
\beta_{10} (EW - VW)_{t-1} + \\
\beta_{11} (EW - VW)_{t-1} + \epsilon_t
\]
Table 5 presents the results:

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
<th>Coef. - 2 SE</th>
<th>Coef. + 2 SE</th>
<th>Prob. Coef. ≠ 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>CON_EXP</td>
<td>0.02558</td>
<td>0.01290</td>
<td>1.983</td>
<td>-0.00022</td>
<td>0.05137</td>
<td>95.12%</td>
</tr>
<tr>
<td>D_IMP_VOL</td>
<td>-0.01209</td>
<td>0.00570</td>
<td>-2.121</td>
<td>-0.02350</td>
<td>-0.00069</td>
<td>96.48%</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.02287</td>
<td>0.03259</td>
<td>0.702</td>
<td>-0.04232</td>
<td>0.08805</td>
<td>51.62%</td>
</tr>
<tr>
<td>MMMF</td>
<td>0.00010</td>
<td>0.00007</td>
<td>1.562</td>
<td>-0.00003</td>
<td>0.00023</td>
<td>88.01%</td>
</tr>
<tr>
<td>EQUITY_FLOW</td>
<td>0.00007</td>
<td>0.00014</td>
<td>0.480</td>
<td>-0.00021</td>
<td>0.00034</td>
<td>36.84%</td>
</tr>
<tr>
<td>NEW_OFFERINGS</td>
<td>0.00024</td>
<td>0.00019</td>
<td>1.281</td>
<td>-0.00013</td>
<td>0.00061</td>
<td>79.84%</td>
</tr>
<tr>
<td>BUYBACKS</td>
<td>-0.00032</td>
<td>0.00018</td>
<td>-1.795</td>
<td>-0.00068</td>
<td>0.00004</td>
<td>92.58%</td>
</tr>
<tr>
<td>TAKEOVERS</td>
<td>0.00026</td>
<td>0.00019</td>
<td>1.323</td>
<td>-0.00013</td>
<td>0.00064</td>
<td>81.25%</td>
</tr>
<tr>
<td>C</td>
<td>-0.00090</td>
<td>0.000205</td>
<td>-0.437</td>
<td>-0.00501</td>
<td>0.00321</td>
<td>33.76%</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.166546</td>
<td>Mean dependent var</td>
<td>0.001459</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.123136</td>
<td>S.D. dependent var</td>
<td>0.017401</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.016294</td>
<td>Akaike info criterion</td>
<td>-5.34337</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.050975</td>
<td>Schwarz criterion</td>
<td>-5.16383</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>553.3518</td>
<td>F-statistic</td>
<td>3.836653</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Durbin-Watson stat</td>
<td>1.946854</td>
<td>Prob(F-statistic)</td>
<td>0.000095</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results show that some of our intuition bore fruit as we expected. Many of the estimates are economically large, precisely estimated, and with the sign we anticipated. Consumer sentiment, implied volatility, and announced stock buybacks have the type of relationship we expected. Since each of the independent variables is different in distribution and size, we interpret results using a 1 standard deviation movement. To interpret one result, CON_EXP has a coefficient of 0.025 and a standard error of 0.0129. This means we are 95% confident that the true coefficient is between -0.0002 and 0.0514. This means for a change in CON_EXP of 20%, we can expect a 0.5% rise in EW-VW. To interpret another, BUYBACKS has a coefficient of negative 0.0003 with a standard error of 0.0002. This means we are 95% confident the true coefficient is between -0.0007 and 0.0000. For a BUYBACK flow of $10
billion, we can expect a -0.3% fall in EW-VW. Table 6 compares our intuition with the regression results.

Table 6:

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Expectation of Sign</th>
<th>Actual Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>CON_EXP</td>
<td>0.025579*</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>D_IMP_VOL</td>
<td>(0.012094)*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.0229</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>MMMF</td>
<td>0.0001</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>EQUITY_FLOW</td>
<td>0.0001</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>NEW_OFFERINGS</td>
<td>0.0002</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>BUYBACKS</td>
<td>(0.0003)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>TAKEOVERS</td>
<td>0.0003</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

* if significant at 90%
Parethesis denote negative number

This table shows our a priori reasoning was correct for the two statistically significant drivers of the difference in EW-VW: CON_EXP and D_IMP_VOL. GOLD and MMMF flows were incorrect guesses in sign, but since the estimate is not precise, we cannot say with any certainty that their coefficients are different from 0. Finally, all the mutual fund flows had the predicted sign, but again because of imprecision, we are not able to unequivocally say their coefficients are different from 0. Since these results are hard to interpret given that some are percent changes and some are flows, we present Table 7 which uses a one standard deviation move to show the impact of each variable in the movements of EW-VW:
Table 7:

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Standard Deviation</th>
<th>Move in EW-VW</th>
</tr>
</thead>
<tbody>
<tr>
<td>CON_EXP*</td>
<td>0.0256</td>
<td>0.0881</td>
<td>0.23%</td>
</tr>
<tr>
<td>D_IMP_VOL*</td>
<td>(0.0121)</td>
<td>0.2068</td>
<td>-0.25%</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.0229</td>
<td>0.0443</td>
<td>0.10%</td>
</tr>
<tr>
<td>MMMF</td>
<td>0.0001</td>
<td>17.33</td>
<td>0.18%</td>
</tr>
<tr>
<td>EQUITY_FLOW</td>
<td>0.0001</td>
<td>9.81</td>
<td>0.06%</td>
</tr>
<tr>
<td>NEW_OFFERINGS</td>
<td>0.0002</td>
<td>7.99</td>
<td>0.19%</td>
</tr>
<tr>
<td>BUYBACKS</td>
<td>(0.0003)</td>
<td>8.14</td>
<td>-0.26%</td>
</tr>
<tr>
<td>TAKEOVERS</td>
<td>0.0003</td>
<td>6.88</td>
<td>0.18%</td>
</tr>
</tbody>
</table>

* if significant at 95%
Paratheses denote negative number

Overall, our results are encouraging that a time-varying liquidity premium is driving some of the variation in the EW-VW position as we suspected. Also, this is only the first pass estimate because we assumed that the response is complete after one month. In reality, price adjustments may be cumulative, so our results may not be as powerful as they could be if we utilized other technologies.

**IV.iii Fama-French Analysis**

The Fama-French asset pricing factors have become commonplace in finance. Fama and French found 5 main factors that do a good job explaining average returns; three for equities and two for fixed income. Not all of the Fama-French factors, by themselves, are not intuitive drivers of returns. For example, there is not much theoretical backing for the persistence of SMB in predicting average returns. The more likely scenario is that they proxy for true, undiversifiable sources of risk. As we have documented above, liquidity is one such risk. Therefore, it is a natural extension of this paper to examine the existence of liquidity drivers in the Fama-French factors. Of all the factors, SMB is the prime candidate for a liquidity factor. After all, it is very close in spirit to EW-VW in its purpose of comparing small versus large firms.
IV.iv SMB Descriptive Statistics

Our argument thus far stresses the similar nature of SMB and EW-VW. We take time to highlight important differences in the series. First, SMB uses much smaller stock, on average, than EW-VW. Consequently, the time-varying liquidity premium should affect SMB more than EW-VW. Second, EW and VW S&P 500 indices today are tradable, either through traditional mutual funds or newly created exchange-traded funds (ETF’s). SMB, on the other hand, is a contrived portfolio that is not tradable on a mass scale. These differences add up. Despite the underlying similarity of the time series, their correlation is only 0.25. We want to stress that we are not analyzing the same series twice.

Nevertheless, due to the similar underpinnings, we believe we can find liquidity drivers of SMB just as we have with EW-VW. Therefore, we conduct the same analysis. Figure 2 presents cumulative returns on the SMB portfolio from January 1980 through December 2003:

Figure 2:
We notice that the cumulative return of SMB tends to be above 0. We test the hypothesis that the true mean of SMB is above 0 in Table 8. This may be true if there is a liquidity premium built in, or if this position is not balanced in risk.

Table 8: Testing SMB mean equals 0

<table>
<thead>
<tr>
<th>Hypothesis Testing for SMB</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample: 1980:01 2003:12</td>
<td></td>
</tr>
<tr>
<td>Included observations: 288</td>
<td></td>
</tr>
<tr>
<td>Test of Hypothesis: Mean = 0</td>
<td></td>
</tr>
<tr>
<td>Sample Mean = 0.001586</td>
<td></td>
</tr>
<tr>
<td>Sample Std. Dev. = 0.030868</td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>Value</td>
</tr>
<tr>
<td>t-statistic</td>
<td>0.872189</td>
</tr>
</tbody>
</table>

Over a month, the SMB will return 0.1% on average. However, there is little statistical support that the true mean of SMB is above 0. Nevertheless, we proceed. We have not yet linked SMB returns to market sentiments about liquidity. To test if the time-varying liquidity premium drives some of the differences in SMB, we regress SMB on independent variables that may reflect changes in demand for liquidity using monthly time series.

IV.v SMB Long Term Analysis

We expect our liquidity drivers to explain SMB in the same way they did for EW-VW. Specifically, we expect SMB to have positive relationships with CON_EXP, EQUITY_FLOW, NEW_OFFERINGS, and TAKEOVERS; we expect SMB to have negative relationships with D_IMP_VOL, GOLD, MMMF, and BUYBACKS.

Our regression is: \[ SMB_t = \beta_1 C + \]
\[ \beta_2 CON_{EXP_t} + \]
\[ \beta_3 D_{IMP_VOL_t} + \]
\[ \beta_4 GOLD_t + \]
\[ \beta_5 MMMF_t + \]
\[ \beta_{t,EQUITY\_FLOW_t} + \]
\[ \beta_{t,NEW\_OFFERINGS_t} + \]
\[ \beta_{t,BUYBACKS_t} + \]
\[ \beta_{t,TAKEOVERS_t} + \epsilon_t. \]

Table 8 presents the results:

Table 9:

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
<th>Coef. - 2 SE</th>
<th>Coef. + 2 SE</th>
<th>Prob. Coef. ≠ 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.00373</td>
<td>0.00390</td>
<td>-0.955</td>
<td>-0.0115</td>
<td>0.0041</td>
<td>65.92%</td>
</tr>
<tr>
<td>CON_EXP</td>
<td>0.04879</td>
<td>0.02452</td>
<td>1.990</td>
<td>-0.0002</td>
<td>0.0978</td>
<td>95.20%</td>
</tr>
<tr>
<td>D_IMP_VOL</td>
<td>-0.03386</td>
<td>0.01087</td>
<td>-3.115</td>
<td>-0.0556</td>
<td>-0.0121</td>
<td>99.79%</td>
</tr>
<tr>
<td>GOLD</td>
<td>0.14611</td>
<td>0.06210</td>
<td>2.353</td>
<td>0.0219</td>
<td>0.2703</td>
<td>98.04%</td>
</tr>
<tr>
<td>MMMF</td>
<td>0.00016</td>
<td>0.00012</td>
<td>1.266</td>
<td>-0.0001</td>
<td>0.0004</td>
<td>79.30%</td>
</tr>
<tr>
<td>EQUITY_FLOW</td>
<td>0.00022</td>
<td>0.00026</td>
<td>0.835</td>
<td>-0.0003</td>
<td>0.0007</td>
<td>59.50%</td>
</tr>
<tr>
<td>NEW_OFFERINGS</td>
<td>0.00093</td>
<td>0.00035</td>
<td>2.683</td>
<td>0.0002</td>
<td>0.0016</td>
<td>99.21%</td>
</tr>
<tr>
<td>BUYBACKS</td>
<td>-0.00080</td>
<td>0.00034</td>
<td>-2.372</td>
<td>-0.0015</td>
<td>-0.0001</td>
<td>98.13%</td>
</tr>
<tr>
<td>TAKEOVERS</td>
<td>0.00030</td>
<td>0.00036</td>
<td>0.854</td>
<td>-0.0004</td>
<td>0.0010</td>
<td>60.61%</td>
</tr>
</tbody>
</table>

These results indicate the existence of a liquidity driver is in the Fama-French SMB returns. CON_EXP, D_IMP_VOL, NEW_OFFERINGS, and BUYBACKS are all statistically different from 0 with the expected sign. Gold, however, also seems to be a significant driver, but in a direction we did not expect. Gold has a large positive coefficient with a t-statistic of 2.35; we expected a negative coefficient. Perhaps both equity returns and gold prices increase with the nominal rate of inflation; thus, an expected positive correlation. But VIX changes have no similar interactions and are a purer representation of the change in liquidity. Thus, it might be
that unanticipated changes in gold prices and unanticipated changes in SMB are correlated. To correct for this, once must take out the common component first. Further research could seek to explain this anomaly.

All of the SMB the independent variables that are statistically significant have larger coefficients than in the EW-VW regression. This evidence suggests the liquidity driver in SMB is larger than in EW-VW. SMB includes NYSE/AMEX/NASDAQ stocks that on average are smaller than S&P 500 stocks, which by definition are the largest stocks. This fact is consistent with our hypothesis of a prominent liquidity premium driver in returns.

**IV.iv Identification of Liquidity Shock**

Unanticipated events might lead to unanticipated changes in the expected volatility of stocks. These volatility shocks might be related to increases in the price of liquidity. The demand of hedgers increases while the supply of speculator capital is reduced or does not keep up with demand. Speculators need time to recalibrate or expand their models of valuation in light of the new information.

We propose that large unexpected fluctuations in expected volatility are the best signal for a liquidity shock without delving into time and computationally intensive microstructure data.\(^\text{12}\) We realize that an expected volatility spike does not necessarily imply a liquidity shock; however, we suspect the correlation is good enough to allow us to use expected volatility shocks as a proxy for liquidity shocks. If a volatility shock forces the implicitly levered to increase hedging activity, speculators may question their models, allowing for perceived mispricings to persist for some time. As the speculators pause, the price of liquidity will continue to rise. So, every volatility shock will force hedging activity. Whether or not the speculators question their

\(^{12}\) Kamara (1994) finds interest rate volatility correlates with increased yield differences between U.S. Treasury notes and bills.
models determines the extent of the price impact on liquidity—the speculators must pause for a liquidity shock to occur.

We use “z-scoring” to measure implied volatility shock events. For a given day, we take the previous 30 days of data and calculate the standard deviation of implied volatility returns; we then divide the current day’s return by this standard deviation to find its z-score. This z-score quantifies the given day’s implied volatility return in terms of standard deviations. We then collect all days where z-scores are above a given level (we use 2, 3, 4, and 5) and compare returns around these days.

Implied volatility shocks are a good view into investor sentiment. In theory, investor reaction to news should be distributed around 0. Put another way, if we tracked the percentage of positive versus negative shocks, again we should find a fifty-fifty split. However, a closer study of the changes in expected volatility reveals that investors have asymmetric responses to news. The skew of the D_IMP_VOL variable (3.22) suggests the distribution in changes is not evenly distributed around 0. Large upwards movements are more common than large downward changes. In other words, when investors “calm down,” they do so gradually. On the other hand, when investors “freak out,” they do so strongly. This suggests that large implied volatility changes are predominately positive. That is, liquidity dries up quickly much more often than liquidity rushes into the market. Figure 3 tracks the percentage of positive daily changes in implied volatility over an 18 year period:
The graph shows an asymmetric response that is increasing, initially convex, and then concave as the number of “qualifying shocks” grows smaller. This graph suggests that when a pessimistic shock occurs, it is likely to be much stronger than an optimistic shock. The breakeven shock size is 0.91; the percentage of shocks that are positive and larger than 0.91 are all greater than 50%. This evidence, in turn, leads us to wonder about changes in investor sentiment generally.

**IV.v Testing the Shape of the Response Function**

To test the shape of market reaction to implied volatility shocks, we use data before and after implied volatility shocks to see if there is a common response following upswings in pessimism. We use both the EW-VW and SMB series for analysis. While we do not have a good answer to how big a movement in implied volatility is enough to signal a shock, we test a number of levels since larger the implied volatility shock, the more likely a liquidity shock is to occur. We use standard deviation movements of 2, 3, 4, and 5 based on the previous 30 days.
Though we suspect major liquidity shocks are rare, as in a 5 or above SD movement, small movements may also trigger speculator reaction.

We track returns 10 days before the event, on the event day, and 50 days after the event and call the results our “response function.” We then average each day (days -10 to 50) to see if there is a common reaction to these shocks. Since z-scores indicate either an increase or decrease in implied volatility, we assume that investor reactions are opposite for positive and negative events. That is, we will take the opposite position (VW-EW or “big minus small”) on negative implied volatility shocks.

We expect more pronounced effects in SMB than in EW-VW because of the difference relative liquidities of the portfolios. EW-VW includes only stocks in the S&P 500, which by definition are the largest companies in the United States. Therefore, the liquidity of all members will be high compared to a vast majority of other stocks in the market. SMB includes stocks from 3 different exchanges—NYSE, AMEX, and NASDAQ—implying lower overall liquidity.

If investors had no liquidity preference, we could expect that there would be no change in portfolio allocation when implied volatility changes dramatically. In the context of our test, the EW-VW portfolio should have no reaction to these shocks. As we demonstrated above, the time-varying liquidity premium is a likely driver of returns. Results below confirm the presence of a liquidity driver in short run returns as well. Figures 4-7 document the results:
Examining these graphs, we find a number of interesting results that support our theory of speculator hesitation. To interpret these graphs, we keep in mind the worse an illiquid versus liquid position does, the higher the price of liquidity must be. Investors now value liquid assets relatively more than illiquid assets. The difference in price between the liquid and illiquid position is the liquidity premium. Therefore, the statement the SMB portfolio lost money maps closely, though not exactly, to the statement the liquidity premium rose. After all, there are other drivers of SMB and EW-VW besides the liquidity premium.

The first general observation is that the size of the shock has a large impact on the returns of the portfolios. For example, the figure 4 shows a small price reaction on the day of the shock, but nothing very pronounced. Afterwards, returns do not seem to be much different from 0. When we get to the large shocks, the price impact is pronounced. For example, in figure 7, there is an average price movement by SMB of -1.91% in the 8 days following the shock.

The second general observation is that SMB and EW-VW reaction functions are correlated, but SMB reactions are indeed must larger than EW-VW. These facts fit into our time-varying liquidity premium model. Since both SMB and EW-VW are sensitive to changes in the time-varying liquidity premium, they should exhibit co-movement when there are changes in the premium. For example, the correlation between series in figure 7 is 0.736. However, since SMB has more exposure to the time-varying liquidity premium, its reaction to changes in the premium will be larger.

On the day of the implied volatility shock itself, reaction for both EW-VW and SMB are small. This is certainly a surprising result. Perhaps first exercise their liquidity options in their liquid shares before selling off their illiquid assets. Data from the crash of October, 1987 support this hypothesis. On the day of the crash 10/19 (the S&P 500 VW fell over 19%), EW-VW and
SMB actually have positive returns. However, on 10/20, EW-VW and SMB have large negative returns. It may take a day for hedging activity to increase and the liquidity market process to start. On the day after the shock, EW-VW immediately reacts downward. Hedgers move out of the illiquid assets (EW) towards liquid assets (VW) as we expected. In other words, the price of liquidity rises. The initial response seems proportional to the size of the shock. The SMB falls as well, but faster. In every shock level, SMB falls more than EW-VW. Again, since SMB has lower relative liquidity, the reaction should be larger if in fact a time-varying liquidity premium is driving some of the variation.

After the initial shock, the price of liquidity continues to sharply rise, especially for large shocks. This observation fits with our model of speculator hesitation. For speculators, the sharp fall in EW-VW and SMB present profit opportunities since this price fall might be a flow as a result of implicit leverage. That is, hedgers might be selling illiquid assets not because of better information, but rather out of a liquidity preference. However, the sudden and sharp nature of the shock may present reasons to hesitate. In this situation, there is a risk to the speculator of a shift, not a flow. This is a spread that may not correct revert. This result could also imply that hedgers become more and more worried. If this is true, speculators might back away as hedging builds because they know the hedging wave is not instantaneous. Our tests cannot differentiate between these two explanations.

Finally, our results suggest the return is not mean-reverting. Speculators seem to step away for a longer period of time or demand for hedging is matched by supply after a week, so the price effect becomes somewhat permanent. That is, a regime shift might have occurred such that pessimism reigns for a considerable period.
In summary, our short term analysis supports the theory that speculators hesitate and check their models after a liquidity shock. While hedgers reallocate towards liquidity on the day of the shock and maybe for days after the shock, the speculators take longer to reassure themselves of their models, leading to the continued rise in the price of liquidity and a loss for the EW-VW and SMB positions that are relatively illiquid. We must also consider that this process may have changed over time as hedgers and speculators learn from each other. The hedgers may decrease demand if their previous calls for liquidity were not answered by speculators.

V. Conclusion

In this paper we have looked at the time-varying liquidity premium in equities from both a short and long run framework. In the long run setting, we find that changes in consumer expectations and implied volatility drive some of the variation between equal and value weightings of the S&P 500 index and the Fama-French “Small minus Big” pricing factor. We also find BUYBACKS has a significant negative effect on SMB. The combination of the theoretical link between these factors and liquidity and their empirical strength makes us conclude that a time-varying liquidity factor does drive some of the variation in returns. Additionally, we find these drivers to be more prominent in the Fama-French SMB pricing factor. Since the SMB portfolio is more heavily weighted towards illiquid stocks, this prominence is consistent with a time-varying liquidity premium driving returns.

In a short run framework, we find evidence of both increased hedging activity directly after an implied volatility shock and speculator hesitation in response to the increased demand for liquidity. The price of liquidity rises sharply initially. Speculators are absent, despite the fact investors with implicit leverage may be liquidating their accounts—exactly the situation where a
speculator makes money. In other words, the speculators may be missing a flow. This absence cause the implicitly levered to continue lowering their price for illiquid assets, so a potential fundamental mispricing persists—the liquidity premium experiences a shock. The larger the implied volatility shock, the more the hedgers demand liquidity while the longer it takes the speculators to check their models.

For future research, researchers could conduct this analysis with better measures of liquidity shocks. Certainly using microstructure data would aid in this pursuit. Also, this analysis should be conducted using fixed income data, especially since models used by liquidity providers can be built. Approaching the situation from the speculator’s perspective can add value by determining whether their hesitation is a rational reaction to a liquidity crisis empirically. Also, researchers could look into whether shocks have occurred in January more than other months to explain Keim’s “January effect.” Finally, researchers should try co-integration to find the underlying liquidity premium moving beneath all returns at least partially driven by time-varying liquidity preferences.
References


