Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility*

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Abstract

We examine the cross-sectional relation between idiosyncratic volatility (IV) and stock returns and propose that the joint effect of the percentage of zero returns, that affects the loading on the systematic risk factors, and the bid-ask spread, that inflates the variance of the returns, can bias the estimate of IV and the resulting pricing ability of IV. We model the microstructure influence on returns and derive a closed-form solution for the bias in the estimated IV. Motivated by this theory, our empirical results show that controlling for the liquidity costs on the estimation of IV diminishes to insignificance the ability of value-weighted IV estimates to predict future returns. We confirm our findings by examining external shocks to liquidity, due to reductions in the stated quotes after 1997 and the decimalization of quotes in 2001, and find a significant reduction in the pricing ability of IV. Finally, minimizing liquidity's influence on the estimated IV, by orthogonalizing the percentage of zero return and spread effects on the estimated IV, demonstrates that the resulting IV estimate has no pricing ability.

Keywords: Cross-Sectional Return, Idiosyncratic Volatility, Zero Returns, Bid-Ask Spread

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1 Introduction

The question of whether cross-sectional idiosyncratic volatility predicts returns strikes at the heart of empirical asset pricing. In a well regarded paper, Ang, Hodrick, Xing, and Zhang (2006) present evidence that idiosyncratic volatility is priced in expected returns. Ang et al. (2006) demonstrate that the spread between the extreme value-weighted quintile portfolios, ranked by idiosyncratic volatility estimated from the three-factor Fama-French model, earn 1.0% per month in abnormal returns, and even large NYSE listed firms earn approximately 0.66% per month. The market appears to price unsystematic risk in addition to the commonly defined systematic risk factors. Understanding the source of the mispricing is fundamental to a better implementation of empirical asset pricing models and the predictions that arise from these models.

We attempt to elucidate why idiosyncratic volatility (hereafter, IV) predicts one-month-ahead returns given the underlying return structure. We argue that liquidity costs are important in understanding the causes of the "mispricing" of IV, in terms of both zero returns (Lesmond, Ogden, and Trzcinka, 1999) that affect the estimation of systematic risk elements and the bid-ask bounce that biases the daily security returns (Blume and Stambaugh, 1983). We show that IV, as commonly measured, is positively and non-linearly related to the percentage of zero returns, a commonly used liquidity cost proxy. That is, an increased level of zero returns (liquidity costs) indicates an increased level of IV, a result that in turn produces a negative and significant relation between IV and future returns. Consistent with the fundamental tenets of asset pricing, which posit only the pricing of systematic risk factors, we find that specifically reflecting the combined influence of the bid-ask spread and the incidence of zero returns demonstrates that IV is not priced in expected returns.

It is generally acknowledged that liquidity is important in asset pricing (Amihud and Mendelson, 1986; Acharya and Pedersen, 2005), yet conventional courses of testing of liquidity effects on IV fail to acknowledge the influence of liquidity on the estimation of IV itself. For example, Spiegel and Wang (2005) find that while liquidity proxies are positively associated with future returns, the relation between IV and returns is much stronger than is liquidity's relation to returns. Similarly, Ang et al. (2006) show that the significance in the relation between IV and value-weighted returns persists even after controlling for the bid-ask spread liquidity measure. However, while the results of both analyses appear valid within the context of their testing methodologies, neither study addresses the inextricable role of liquidity costs on the estimation of IV - an omission that we propose engenders a bias in the IV estimate.

We conjecture that liquidity costs affect the measurement of IV in two ways. The first effect is due to the bid-ask bounce that increases the variance of the returns leading to an inflated IV estimate. Blume and Stambaugh (1983) show that the bid-ask bounce (microstructure noise) induces an upward bias in expected stock returns, due to Jensen's inequality, that is proportional to the variance of the bid-ask spread. Modeling the microstructure noise using the Blume and Stambaugh framework, we show that microstructure noise leads to a 35% increase in the estimated IV for even the largest firms. The second influence is through the incidence of zero returns. These zero returns affect the loading on the systematic risk factors by distorting the covariance between returns and the systematic risk factors leading to a biased estimate of IV. More importantly, zero returns also capture more expansive liquidity cost elements (such as price impact costs and opportunity costs) than the spread (Lesmond, Ogden, and Trzcinka, 1999) leading to a more general examination of liquidity cost effects.[1]

By using the underlying return structure that reflects liquidity costs as a central theme, our results indicate that the results of Spiegel and Wang (2005) and Ang et al. (2006) may hinge on the inflation of the IV measurement, thereby suggesting significance for IV's pricing power that may be spurious.[2] However, our results demonstrate that the prior literature's findings are not incorrect per se, but that the focus of the tests is misplaced. That is, it is not that IV has more power than liquidity in explaining future returns, but that IV has an embedded liquidity cost effect.

[1]Liquidity effects also extend to the measurement of the future return. Common tests of IV's pricing ability utilize future *monthly* returns. However, Amihud and Mendelson (1986) show that, in expectation, investors amortize higher liquidity costs by lengthening the holding period and hence reducing expected returns. Blume and Stambaugh (1983) show that microstructure noise is mitigated using a buy-and-hold strategy that is captured by longer holding periods. By using monthly returns in the prediction phase of testing, we are minimizing the liquidity cost effect on the returns. Thus, the twin effects of an inflated (biased) IV estimate and a liquidity cost minimized future monthly return lead to the reported negative relation between IV and future returns.

[2]Generally, these results would also explain the findings of Bali and Cakici (2008) who find that different trading horizons, different breakpoints used to sort IV into quintiles, and different screens for price, size, and liquidity costs determine whether IV is priced. Their cross-sectional tests merely proxy for the estimation effects that liquidity costs impose on IV and the liquidity cost effect on future returns.

Quintile sorting tests utilized by Ang et al. (2006) or regression tests employed by Spiegel and Wang (2005) that incorporate both IV and liquidity costs are affected by multicollinearity. Attempting to test whether IV is priced in a transaction costs environment, without specifically reflecting on the influence of liquidity on returns, negates the primary effect of these costs on the pricing ability of IV.

Using a three-factor Fama-French model over a one-month time interval to estimate the IV from 1983 to 2006, the difference between the two extreme value-weighted quintile Fama-French IV portfolios (hereafter, High-Low) reports a significant three-factor Fama-French alpha (Fama and French, 1996) of -1.429% per month and a significant four-factor Carhart alpha (Carhart, 1997) of -0.939% per month. These results are consistent with Ang, Hodrick, Xing, and Zhang (2006).

However, controlling for the percentage of zero returns in the sort procedure reduces the difference in abnormal returns between the highest and lowest IV quintiles to insignificance for the majority of portfolios. These results are brought into sharper focus when we estimate IV using quote midpoint based returns that specifically minimizes the microstructure noise. Using the quote midpoint return estimated IV reduces the abnormal performance between the High-Low portfolios to *insignificance* when using the four-factor Carhart alpha.

We exploit exogenous liquidity shocks to the market by focusing on those periods that have experienced a significant regulatory reduction in the quoted spread. These periods are outlined by Bekaert, Harvey, and Lundblad (2007) who argue that when the NYSE/Amex/NASDAQ exchanges reduced the tick size to 1/16 in 1997 and the exchanges reverted to the decimalization of quotes in 2001, liquidity costs embodied in both the bid ask spread and the percentage of zero returns also fell significantly. We find that the ability of IV to predict future returns becomes insignificant from 1997 to 2006 using the Carhart alpha and insignificant from 2001 to 2006 using either the Fama-French alpha or the Carhart alpha.

We extend this analysis to examine the period from 1983 to 1997 that exhibits the largest percentage of zero returns (liquidity costs) and, not incidentally, the highest association between IV and future returns. We find that if we restrict the sample during this time period to include only those firms that experience at most one zero return per month then the resulting relation between IV and future returns is insignificant. The Fama-French alpha for the High-Low IV portfolio is a paltry -0.084% per month in contrast to -1.560% per month for all firms regardless of the percentage of zero returns. The disparate results from sorts that control for liquidity costs and those that do not are striking and point to the importance of liquidity costs embodied in both zero returns and the bid-ask spread when assessing IV's ability to predict future returns.

Concluding our tests, we attempt to disentangle the liquidity influence from the IV effect in predicting future returns. In a departure from the prior literature, we run a regression residual approach to remove the influence of both the zero returns and the spread effects on IV by first regressing the IV estimates on both the percentage of zero returns and the spread. This procedure orthogonalizes the IV estimate from the liquidity cost effect thereby reducing the multicollinearity bias in the regression tests. We then use the residual from this regression (termed the IV-residual) in quintile sorts and in Fama-MacBeth regression tests. These tests specifically address the assertions of Spiegel and Wang (2005) who argue that IV is more powerful than is liquidity in predicting future returns.

We find that using quintile sorts of the IV-residual do not produce significant Fama-French alphas or Carhart alphas. The Fama-French alpha for the High-Low IV portfolio falls to -0.619% per month (from -1.429% per month in the baseline sort results), and the Carhart alpha falls to -0.388% per month (from -0.939% per month in the baseline sort results). Neither of the alphas is significant. These results are consistent with the intuition that IV is affected by measurement issues in estimation due to the occurrence of zero returns and by the bid-ask spread that inflates the IV measurement. More importantly, the IV-residual results indicate that the IV's predictive power may reflect liquidity effects after all.

Extending the cross-sectional analysis to a value-weighted Fama and MacBeth (1973) framework allows for controlling multiple influences on future returns that encompass one-month lagged returns (Jegadeesh, 1990), book-to-market (Daniel and Titman, 1997), coskewness (Harvey and Siddique, 2000), number of analyst estimates (Diether, Malloy, and Scherbina, 2002), institutional holdings (Chen, Hong, and Stein, 2002), and firm size. The baseline result is that IV and returns are significantly associated even after these controls are instituted in the regression and this would be construed as consistent with the results of Ang, Hodrick, Xing, and Zhang (2006, 2008). However, as is found in the quintile sorts, the IV-residual is not significantly associated with future returns in the regressions. Robustness checks made by extending the regression analysis to IV estimates based on quote midpoint returns reveal a similar result.

These results are important for the following reasons. The asset pricing literature's focus on liquidity and returns may be neglecting the importance of the liquidity effect on the systematic risk factors that is dependent on both the occurrence of zero returns and the more direct bid-ask bounce effect on returns. Liquidity's importance in asset pricing tests may lie more in the estimation phase than in the execution costs of trading. Relatedly, the level of idiosyncratic volatility is an important input in the study of diversification benefits. The diversification effects noted by Merton (1987) and extended to IV measurement by Malkiel and Xu (2004) should consider the effect of zero returns on asset pricing specifications and on the tests of these asset pricing predictions. The percentage of zero returns may be the demonstrable signal of incomplete diversification effects that are amplified by the bid-ask spread and may point to a more complete asset pricing model that prices liquidity risk as well as other systematic risk factors.

The paper is organized as follows. Section 2 models the microstructure effect on idiosyncratic volatility estimation. Section 3 outlines the estimation of the idiosyncratic volatility and the various control variables. Section 4 presents summary statistics. Section 5 presents the basic value-weighted sorting results outlining the importance of zero returns and quote midpoint returns in explaining the pricing of IV. Section 6 examines the effect that exogenous liquidity shocks exert on IV's ability in predicting future returns. Section 7 presents the results of using a regression residual approach to disaggregating idiosyncratic volatility from liquidity effects and the resultant effects on IV's ability to predict future returns. Section 8 concludes.

2 Microstructure Noise on Idiosyncratic Volatility Estimation

We present a model based on microstructure noise to illustrate the effect on idiosyncratic volatility estimation and present calculations for the magnitude of the microstructure bias on the estimated idiosyncratic volatility. This section will motivate our focus on zero returns, the proportional spread, and the quote midpoint returns in the empirical tests.

2.1 The model

Blume and Stambaugh (1983) model a microstructure effect that generates a difference between the observed return, $\tilde{R}_t$, and the true return, R_t. Consequently, observed returns are measured with error with the relation between the gross observed return (price ratio) and the gross true return given as:

$$\tilde{R}_t = R_t\left(\frac{1+\delta_t}{1+\delta_{t-1}}\right). \tag{1}$$

The microstructure noise induced by the bid-ask spread is represented by δ_t. We assume, as does Blume and Stambaugh (1983), that δ_t is a normally distributed random variable, i.e. $\delta_t \sim N(0, \sigma_\delta^2)$ and is independently distributed across time, t. Expanding the denominator via Taylor-series expansion, as performed in Blume and Stambaugh (1983), we find:

$$\tilde{R}_t \approx R_t(1+\delta_t)(1-\delta_{t-1}+\delta_{t-1}^2). \tag{2}$$

This yields the following relation for the rate of return:

$$\tilde{r}_t = (1+\delta_t)(1-\delta_{t-1}+\delta_{t-1}^2)(r_t+1)-1. \tag{3}$$

Simplifying the expression by eliminating the higher order term, $\delta_t\delta_{t-1}^2$, results in:

$$\tilde{r}_t = r_t[1+(1-\delta_{t-1})(\delta_t-\delta_{t-1})]+[(1-\delta_{t-1})(\delta_t-\delta_{t-1})]. \tag{4}$$

Setting $\epsilon_t = (1 - \delta_{t-1})(\delta_t - \delta_{t-1})$ allows for a compact representation of the microstructure effect on returns that is both multiplicative and additive. This is represented as:

$$\tilde{r}_t = r_t(1 + \epsilon_t) + \epsilon_t \tag{5}$$

To derive the microstructure effect on idiosyncratic volatility, we first take the first two moments of the ϵ_t term. The resulting expression drops the cross-products and sets the expectation of δ_t^4 equal to the fourth moment which is given by $3\sigma_\delta^4$. In addition, the expectation of $\delta_t^2 \delta_{t-1}^2$ is equal to σ_δ^4. The first two moments are then given as:

$$E(\epsilon_t) = E(\delta_t - \delta_{t-1} - \delta_t \delta_{t-1} + \delta_{t-1}^2) = \sigma_\delta^2. \tag{6}$$

$$\begin{aligned} Var(\epsilon_t) &= E(\epsilon^2) - [E(\epsilon)]^2 \\ &= E[(\delta_t - \delta_{t-1} - \delta_t \delta_{t-1} + \delta_{t-1}^2)^2] - \sigma_\delta^4 \\ &= 2\sigma_\delta^2 + 3\sigma_\delta^4 \end{aligned} \tag{7}$$

As is shown, the mean of the distribution for ϵ_t is non-zero. To ensure a zero-mean residual term for the regression we rewrite $\epsilon_t = e_t + \sigma_\delta^2$, that ensures e_t is mean zero, and we have:

$$\tilde{r}_t = r_t(1 + \sigma_\delta^2 + e_t) + (\sigma_\delta^2 + e_t). \tag{8}$$

For simplicity, assuming that the true return is generated by a single factor model, $r_t = \alpha + \beta X_t + \nu_t$, and substituting into Equation (8) results in:

$$\tilde{r}_t = \alpha^* + \beta^* X_t + \nu_t^* \tag{9}$$

where $\alpha^* = \alpha(1 + \sigma_\delta^2) + \sigma_\delta^2$ and $\beta^* = \beta(1 + \sigma_\delta^2)$.[3]

[3] We specifically assume no endogeneity between the explanatory variable, X_t and ϵ_t. This is a departure from the work of Asparouhova, Bessembinder, and Kalcheva (2009) who specifically assume an endogenous relation between the market factor and the microstructure effect.

Consequently, the error term is given as:

$$\nu_t^* = (1 + r_t)e_t + \nu_t(1 + \sigma_\delta^2) + \nu_t e_t \tag{10}$$

Assuming that independence between the regression model residual, ν_t, and the random shock, e_t, both of which are zero mean allows the following representation for the variance of ν_t^* which is then generally stated as:

$$Var(\nu_t^*) = (1 + r_t)^2 Var(e_t) + (1 + \sigma_\delta^2)^2 Var(\nu_t) + Var(\nu_t e_t) \tag{11}$$

The last term of Equation (11) can be decomposed as follows (Note that the mean value is assumed to be zero for both ν_t and e_t).

$$\begin{aligned} Var(\nu_t e_t) &= E(\nu_t^2 e_t^2) - [E(\nu_t e_t)]^2 \\ &= E(\nu_t^2)E(e_t^2) - [E(\nu_t)E(e_t)]^2 \\ &= Var(\nu_t)Var(e_t) \end{aligned} \tag{12}$$

Substituting Equation (12) for the last term of Equation (11) yields:

$$\begin{aligned} Var(\nu_t^*) &= (1 + r_t)^2 Var(e_t) + (1 + \sigma_\delta^2)^2 Var(\nu_t) + Var(\nu_t)Var(e_t) \\ &= [(1 + r_t)^2 + \sigma_\nu^2](2\sigma_\delta^2 + 3\sigma_\delta^4) + (1 + \sigma_\delta^2)^2 \sigma_\nu^2. \end{aligned} \tag{13}$$

Expanding the last term in Equation (13) and noting that the variance of ν_t equals σ_ν^2 results in the bias described as follows:

$$\begin{aligned} Var(\nu_t^*) - Var(\nu_t) &= [(1 + r_t)^2 + \sigma_\nu^2](2\sigma_\delta^2 + 3\sigma_\delta^4) + (2 + \sigma_\delta^2)\sigma_\delta^2\sigma_\nu^2 \\ &= [(1 + 2r_t + r_t^2) + \sigma_\nu^2](2\sigma_\delta^2 + 3\sigma_\delta^4) + (2 + \sigma_\delta^2)\sigma_\delta^2\sigma_\nu^2 \\ &= 2(1 + 2r_t + r_t^2 + \sigma_\nu^2)\sigma_\delta^2 + 3(1 + 2r_t + r_t^2 + \sigma_\nu^2)\sigma_\delta^4 + (2 + \sigma_\delta^2)\sigma_\delta^2\sigma_\nu^2 \end{aligned} \tag{14}$$

For comparative analysis, all the terms in Equation (14) are positive indicating that the bid-ask microstructure effect on the asset return *increases* the resulting residual variance. This illustrates that a microstructure effect embedded in the return structure can yield an inflated IV estimate. The dominant effect on the residual variance bias contained in Equation (14) is the microstructure induced variance effect, $2\sigma_\delta^2$, with the remaining terms an order of magnitude lower.

2.2 The magnitude of the microstructure bias on idiosyncratic volatility

This microstructure effect is noted to increase in importance when the residual variance is converted to an idiosyncratic volatility (i.e. by taking the square root). Given that Blume and Stambaugh (1983) postulate that the true price is the quote midpoint and the variance of the microstructure noise, σ_δ^2 is equal to the square of the proportional bid-ask spread, we begin this exercise by noting that the bias in the idiosyncratic volatility is 1.414 times the proportional spread (or $\sqrt{2\sigma_\delta^2}$). Based on averages from 1983 to 2006, large firms (i.e. those in the largest two size deciles) that are the principal focus of value-weighted idiosyncratic volatility studies, experience an average idiosyncratic volatility of 2.07% with a corresponding average bias effect of 0.91% (i.e. proportional bid-ask spread of 0.65% times 1.414). The microstructure noise effect on the bias is sizeable relative to the level of the estimated idiosyncratic volatility and can potentially account for more than 40% of the estimated idiosyncratic volatility. The microstructure effect is corroborated when comparing the idiosyncratic volatility estimated using the observed returns (with the bid-ask bounce) and the true returns using the quote midpoint. Again, the idiosyncratic volatility computed from the observed (bid-ask bounce influenced) returns is 2.07%, while the idiosyncratic volatility computed from the quote midpoint return is 1.35%. The induced bias is 35%, roughly comparable to our prior analysis.

2.3 Zero return bias on risk estimation

An ancillary effect of microstructure noise on observed returns is the generation of zero returns (Lesmond, Ogden, and Trzcinka, 1999). These zero returns, in turn, bias the systematic risk estimates, as well as the resulting intercept term. We present this in general form using the "partialling out" coefficient interpretation, based on the Frisch-Waugh Theorem (Greene, 2003), of multiple regression. Generally, the systematic risk estimate for any factor can be stated as:

$$\beta_i = \frac{\sum_{t=1}^{n} \hat{\omega}_{ti} \tilde{r}_t}{\sum_{t=1}^{n} \hat{\omega}_{ti}^2} \tag{15}$$

where $\hat{\omega}$ is the residual of the regression of the i^{th} systematic risk factor on the remaining factors. The effect on the systematic risk factor can be clearly seen in Equation (15) and arises because the numerator is affected by the incidence of zero returns, or the number of days where the observed return, $\tilde{r}_t$, is zero, while the denominator is unaffected. If the covariance between the true return (without liquidity costs) and the systematic risk factor is positive, but a zero return is observed, then a negative bias would be induced. Conversely, if the covariance between the true return and the systematic risk factor is negative, but a zero return is observed, then the induced bias is positive. Hence, we cannot unambiguously determine the direction of this effect on each firm's systematic risk estimate, only that the systematic risk estimate will be biased. Regardless, if the systematic risk estimates are biased then the estimate of idiosyncratic volatility will also be biased and consequently the idiosyncratic volatility estimate will be biased.

3 Idiosyncratic Volatility Estimation, Liquidity Estimation, and Firm Attribute Controls

We present an outline for the measurement of idiosyncratic volatility, a specification of our microstructure measures, and a detailed outline of our firm and market controls that will be used in our empirical tests.

3.1 Estimating Fama-French Based Idiosyncratic Volatility

Following Ang, Hodrick, Xing, and Zhang (2006) and Malkiel and Xu (2004), we focus our main tests on the idiosyncratic volatility estimated from the Fama-French three-factor model. Specifically, we estimate monthly idiosyncratic volatility as the standard deviation of the residuals (RMSE) from the Fama-French three-factor model where each month we regress the daily stock excess returns r_{it} on the market excess returns, $r_{mkt,t}$, returns on the SMB factor, $r_{smb,t}$, and returns on the HML factor, $r_{hml,t}$,

$$r_{it} = \alpha_i + \beta_{mkt,i} r_{mkt,t} + \beta_{smb,i} r_{smb,t} + \beta_{hml,i} r_{hml,t} + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_i^2). \tag{16}$$

Firm-level idiosyncratic volatility is then given as: $IV_i = \hat{\sigma}_i$. We then construct the time-series of monthly IV estimates on a firm-level basis. We specifically exclude ADR's, REIT's, closed-end funds, and primes and scores (or those stocks that do not have a CRSP share code of 10 or 11). It should be noted that focusing on daily returns mitigates the need for GARCH corrections for time-varying properties in the estimation of IV.

To conform to the findings of Ang, Hodrick, Xing, and Zhang (2006), our trading strategy focuses exclusively on a one month estimation period that is immediately followed by a one month return holding period (this is equivalent to their 1/0/1 nomenclature). Following Ang, Hodrick, Xing, and Zhang (2006), we analyze value-weighted portfolio returns based on these idiosyncratic volatility estimates. The value-weighted results are weighted by firm size to reduce the influence of small stocks on the IV and return relation. Our sample runs from 1983:07 (July of 1983) to 2006:06 (June of 2006) for a total of 276 months.

3.2 Liquidity Measures

The Trades and Quotes (TAQ), the Institute for the Study of Security Markets (ISSM), and CRSP databases are used to estimate both the proportional and effective spread costs. The ISSM database covers NASDAQ firms from 1987 to 2006, and NYSE/AMEX firms from 1983 to 2006. We utilize the CRSP database for NASDAQ firms from 1983 to 1987 to complete our sample period from 1983 to 2006.

For each stock, we obtain the daily end-of-day closing quotes and prices using the ISSM, TAQ, and CRSP databases for all NYSE/AMEX/NASDAQ stocks for the same month as we estimate the idiosyncratic volatility.[4] The proportional spread is the ask minus the bid quote divided by

[4]This procedure is problematic for the 2001 to 2006 trading period because of the proliferation of alternative

the mid-quote average. The effective spread is defined as two times the absolute value of the price minus the quote mid-point divided by the price. The daily proportional and effective spreads are averaged over the month providing monthly spread estimates.

3.3 Firm Attribute Controls

We also estimate the variables that have been shown to be related to future returns or idiosyncratic volatility (IV). These include past returns, coskewness risk, value versus growth, firm size, institutional holdings, and analyst coverage. Reversals in returns has been widely documented (see, e.g., Jegadeesh, 1990). Furthermore, Huang, Qianqiu, Rhee, and Zhang (2006) provide evidence that the cross-sectional pricing power of IV may be subsumed by one-month past returns. Negative coskewness risk is shown to be associated with higher returns (Harvey and Siddique, 2000), and idiosyncratic volatility may in part capture that element (Boyer, Mitton, and Vorkink, 2007). Firm size is known to be associated with returns with smaller firms experiencing higher expected returns than larger firms. Book-to-market proxies for the value and growth phenomena (Lakonishok, Schleifer, and Vishny, 1994). Book-to-market relies on the Compustat, where we extract the book value of assets, and the CRSP, where we calculate the market value of equity as the year-end price multiplied by the number of shares outstanding, following Fama and French (1993). We delete any observations from the analysis that have either non-positive book-to-market ratios or missing information on the book value of the assets.

Roughly classified, institutional holdings and analyst following proxy for an information environment explanation for returns. The percentage of institutional holdings is taken from the Thompson Financial database using the 13-f filings. We measure the percentage of shares held by all institutions at the end of each quarter and then use that percentage for the next three months. The percentage of holdings is adjusted for the newest 13-f filing each quarter and the procedure is repeated. If there is no institutional holding for a firm, we substitute a zero for that quarter. This

market maker and after-hours trading. During these years the TAQ database is "painted" with single-side quotes whereby only one quote, either the ask or bid, is relevant. We control for this by taking the last available quote with complete bid and ask prices that corresponds to the last price that is set by CRSP. This allows for a direct comparison of across all of our liquidity cost measures.

is consistent with Gompers and Metrick (2001).

The data on analyst coverage derives from the I/B/E/S Historical Summary File and is available on a monthly basis for our entire sample period. Stocks covered by a larger number of analysts have lower expected returns (see, e.g., Diether, Malloy, and Scherbina, 2002). We use analyst following rather than the standard deviation of forecasts to ensure both small and large firms are included in our sample. Similar to the procedure employed for institutional holdings, if a stock has no analyst following, we substitute a zero for the number of analyst estimates for that month. Mechanically, if the CRSP cusip does not match any cusip on I/B/E/S than the analyst coverage is assumed to be non-existent or zero. This procedure is similar to that of Ang, Hodrick, Xing, and Zhang (2008) and Hong, Lim, and Stein (2000). We find that many firms are not covered by analysts and that the earlier time periods are more prone to the lack of coverage as does Hong, Lim, and Stein (2000).

4 Preliminary Results and Summary Statistics

To illustrate the relation between zero returns (or liquidity costs) and IV, we present a representative plot for April, 1988. The 1980's experiences a large number of zero returns as noted by Lesmond, Ogden, and Trzcinka (1999) so the effect of the zero returns on IV measurement can be more easily visualized for this time period. Figure 1 reports the firm-level IV estimates as well as a trend line versus the percentage of zero returns in the return structure. As is shown, the trend in the Fama-French based IV is increasing with the percentage of zero returns, reaching a peak at about 60% zero returns. The estimated IV begins to decrease afterwards and falls to zero when all of the returns (during the month) are zero. The overall trend between IV and the zero returns is also noted to be non-linear. The individual IV estimates display considerable dispersion, but the overall observation is that IV is increasing with the percentage of zero returns, and consequently liquidity costs do affect the IV estimates.

We initially sort the stocks into quintiles by the percentage of zero returns to provide a relative comparison of IV with other explanatory variables that have been used to explain the IV effect. These sort statistics are equal-weighted and are shown in Table 1. As is shown, sorting by the percentage of zero returns demonstrates a relative correspondence between the percentage of zero returns and IV. The percentage of zero returns increases from 5.588% for the lowest quintile to 53.571% for the highest quintile. To put this into perspective, of the approximately 21 daily returns each month, the lowest zero return quintile contains those firms that experience one zero return per month while the highest zero return quintile contains those firms that experience 11 zero returns per month. Consequently, the IV estimates rise from 2.772% to 3.840% across the zero return quintiles, but reaching the maximum at the fourth zero return quintile instead. The lack of a monotonic relation between IV and the percentage of zero stems from the non-linearity between IV and zero returns as illustrated in Figure 1. The sort examines only the linear component of the relation whereas the non-linear component is just as important. Also, the results demonstrate that the zero returns bias the systematic risk estimates leading to biased IV estimates.

The increase in the zero returns is matched by an increase in the bid-ask spread costs that rise from 1.778% (1.136% effective spread) to 10.836% (3.088% effective spread) across the zero return quintiles. Because NASDAQ firms are typically smaller than NYSE/Amex firms, the inclusion of NASDAQ firms, especially prior to 1991, greatly increases the liquidity costs evident in our sample. The zero return and the bid-ask (and effective) spread's relation with IV illustrates the importance of *both* liquidity aspects in potentially explaining IV's pricing ability. However, we argue that the spread costs unambiguously upward biases the estimated IV, while the occurrence of zero returns simply biases the estimated IV.

The liquidity costs are also related to many of the potential explanatory variables used in Ang, Hodrick, Xing, and Zhang (2006). Lagged return displays a very interesting trend with a positive lagged return of 2.244% for the lowest zero return quintile and then reverts to a negative return of 0.428% for the highest zero return quintile. The lowest zero return quintile also contains more value stocks than does the high zero return quintile as evidenced by the decline in the book-to-market across the zero return portfolios. Size and price display the same monotonic decline across the quintiles. Downside risk, or coskewness, displays little trend with either the percentage of zero returns or with IV. The relatively low percentage of analyst following and institutional holdings reflects a sparse information environment for high IV firms that also have a large percentage of days that experience no price movement.

5 Value-Weighted IV Sort Results With Liquidity Controls

In this section, we present the various sort results of IV quintiles that illustrate the influence of zero returns and the bid-ask spread on IV's ability to predict future returns.

5.1 Sort results with the percentage of zero returns and the bid-ask spread

We examine the effect of holding constant either the percentage of zero returns or bid-ask spread and allowing IV to vary within each liquidity category. The zero returns will allow for an examination of both the estimation issues surrounding the zero returns as well as providing controls for the microstructure influence on IV measurement. The more focused bid-ask spread liquidity measure will allow for an examination of the relative importance of the spread itself in controlling for IV's ability to predict future returns. This is important because both Spiegel and Wang (2005) and Ang, Hodrick, Xing, and Zhang (2006) have dismissed liquidity costs, as measured by the bid-ask spread or other liquidity cost proxies, as an explanation for the pricing of IV. The structure of this test relies on Ang et al. who utilize a double sort in their examination of size effects on the abnormal pricing of IV.

For these set of tests, we first sort the stocks into three groups either according to the percentage of zero returns or the bid-ask spread. [5] Then within each liquidity group we further sort stocks into five quintiles according to their IV estimates. We then form value-weighted portfolios within each of the IV quintiles. Hence, we hold liquidity effects relatively constant while allowing IV to vary within each liquidity category. We then regress the quintile portfolio returns against four-factor (Carhart, momentum) model to estimate the Carhart alpha. We focus on the Carhart alpha to control for momentum effects on the abnormal return measurement. Table 2 reports the abnormal performance of the IV quintile portfolios and the High-Low arbitrage portfolio within each liquidity

[5] We use three groups because of the non-continuous and limited distribution caused by the integer counts of the zero returns.

category.

As reported in Table 2, controlling for the zero returns significantly reduces IV's ability to predict future returns. IV is not significantly associated with future returns in two of the three zero return categories. The Carhart alpha of the High-Low IV portfolios is relatively U-shaped across the categories of the percentage of zero returns. It is evident that the percentage of zero returns dominates IV in its relation to future returns.

The bid-ask spread is not as effective in controlling for IV's ability to predict future returns, consistent with the prior findings of both Spiegel and Wang (2005) and Ang, Hodrick, Xing, and Zhang (2006). The abnormal return of the High-Low IV portfolio is monotonically increasing with increasing spread costs, and is significant for all but the lowest spread category, reaching a peak of -1.842% per month for the highest spread category. However, the results do indicate that for low spread cost firms IV cannot predict future returns highlighting a liquidity cost influence on the inferences for IV.

These results are indicative of the measurement issue, engendered by zero returns as well as the direct microstructure effect typified by the bid-ask bounce, that affects the ability of the standard methodology to properly estimate IV. Using daily returns exacerbates the effect that both zero returns and microstructure noise exerts on the measurement of IV. In particular, the bid-ask spread effects are potentially more in evidence during the estimation phase, rather than ex-post testing phase.

5.2 Using quote-midpoint returns to estimate IV for value-weighted quintile portfolios

To operationalize our microstructure model we employ the quote mid-points to address the microstructure noise that may be evident in the estimate of IV. This procedure specifically minimizes the bid-ask bounce effect on the measured returns and reflects the model implication offered by Blume and Stambaugh (1983) that the true price is the quote midpoint. We calculate the quote mid-point returns in a manner consistent with that performed by CRSP using end-of-day prices and correcting for stock splits and dividends in the calculation of quote-midpoint returns. In order to assess the magnitude of the microstructure noise bias in IV measurement, we also present the IV measured using the closing returns provided by CRSP. [6]

For all the sort results, we concentrate on NYSE/Amex/NASDAQ firms to conform to the sample used by the prior literature. We sort stocks into quintiles based on their monthly estimates of IV, form quintile-sorted portfolios, and then difference the highest and lowest IV quintiles. Specifically, at the beginning of each month, stocks are sorted into five quintiles based on the IV estimated using the daily returns of the last month. A value-weighted portfolio is formed from the stocks within each quintile. The portfolios are held for one month and then re-balanced. We then regress the quintile portfolio returns against either the three-factor (Fama-French) model or the four-factor (Carhart, momentum) model to estimate the Fama-French or Carhart alpha, respectively. We finally compare the performance between the portfolio with the highest IV (High) and the portfolio with the lowest IV (Low). The difference is the abnormal return one would earn on a zero-cost (arbitrage) portfolio formed by taking a long position in the highest ranked quintile portfolio and taking a short position in the lowest ranked quintile portfolio (High-Low).

The results are presented in Table 3 with Panel A focusing on the baseline results using CRSP based closing returns and Panel B focusing on the quote midpoint returns.

As shown in Panel A of Table 3, the FF-IV estimates based on CRSP closing returns increases monotonically from the Low IV quintile portfolio, recorded to be 1.042%, to the High IV quintile portfolio, recorded to be 6.482%. The High-Low estimated FF-IV is 5.440% per month and significant at the 1% level.

The Fama-French alpha of the arbitrage portfolio is -1.429% per month with a robust t-statistic of 4.82, a result comparable to that of Ang, Hodrick, Xing, and Zhang (2006). This result shows that even with an alternative time span, the FF-IV is still significantly related to future returns. The Carhart alpha is -0.939% per month and highly significant, which suggests that including

[6] Also, because our sample period, from 1983 to 2006, is significantly different than that of Ang, Hodrick, Xing, and Zhang (2006), who examine the period from 1963 to 2000, this presentation will confirm the basic sorting results to illustrate the robustness of the IV effect for this alternative time period.

a systematic momentum factor does not sufficiently control for the IV's ability to predict one-month ahead returns although it does reduce the abnormal performance. However, the abnormal performance appears to be most evident in the extreme quintiles, with the bulk of the abnormal performance concentrated in the highest IV quintile.

Notable in these results is the monotonically increasing trend in the value-weighted percentage of zero returns and the spread from the lowest ranked IV quintile to the highest ranked IV quintile. The percentage of zero returns rises from 8% for the Low IV quintile, to 14.5% for the High IV quintile. This trend is also matched by the spread that rises from 0.7% to 3.8%. This trend is important because it highlights the effect that the return structure has on the estimated IV.

We now turn to quote mid-points to minimize the bid-ask bounce effect on measured returns. As shown in Table 3, the estimated FF-IV is demonstrably less than that measured using CRSP closing returns. The benchmark High-Low FF-IV from the CRSP based returns is 5.440% while the High-Low quote midpoint based FF-IV is significantly reduced to 4.044, or a 25% reduction in the estimated IV. As would be expected for a microstructure influence, most of the reduction is garnered in the High IV quintile that witnesses a decline to 5.020% (from the benchmark 6.482%). This clearly illustrates the inflation in IV due to microstructure noise and consistent with our microstructure theory.

The effect on abnormal performance due to microstructure noise is more striking. Controlling for the microstructure noise in the computed return shows that while the FF-alpha of -0.894% remains significant, it is greatly reduced from the CRSP based results of -1.429%. The reduction is almost 50%, consistent with our model predictions. However, the Carhart alpha, that specifically controls for a momentum effect on the abnormal performance also reports a greatly reduced abnormal performance of only -0.521% (baseline result of -0.939%), but is *insignificantly* different from zero.[7] The bid-ask bounce plays a considerable role in estimation of IV and in the subsequent performance of IV in predicting future returns.

[7] Arena, Haggard, and Yan (2008) argue for a momentum effect on IV performance and find that higher returns for high IV stocks are associated with quicker and larger return reversals. These results show the importance of the microstructure effect on IV measurement and subsequent performance, but also notes the importance of the momentum effect on the pricing ability of IV.

6 Exogenous Shock to Liquidity: Value-Weighted IV Sort Results

To simultaneously control for measurement issues engendered by zero returns and microstructure noise, we propose a natural experiment using those time periods that experience a sudden and severe external liquidity shock. Conveniently, these periods have been outlined in Bekaert, Harvey, and Lundblad (2007) who show that when NYSE/Amex/NASDAQ stocks reduced the quotes to sixteenth pricing in 1997 and when NYSE/Amex/NASDAQ stocks altered the quotes to decimal pricing in 2001 the percentage of zero returns also fell significantly reflecting reduced liquidity costs. In tandem, the bid-ask spread liquidity costs fell during decimalization, even for the largest stocks. However, spread costs did not specifically fall during the conversion to sixteenth pricing. This departure will allow for a separate examination of the zero return effect on returns and the direct microstructure effect on returns. We also conduct robustness tests by restricting the sample to firms with low incidence of zero returns in the periods when IV displays the strongest ability to predict future returns.

6.1 Exogenous liquidity shock periods

Figure 2 shows a standardized plot of the average percentage of zero returns, the average bid-ask spread, and the average Fama-French IV from 1983 to 2006. As is clearly shown, 1997 marks a significant and precipitous decline in the percentage of zero returns that progresses through the decimalization of all of stock quotes in 2001. The percentage of zero returns clearly shows a marked decline around these two periods. Interestingly, the spread costs experience similar changes, but only subsequent to the 2001 decimalization. The spread costs also exhibit more volatility during the NASDAQ growth and decline from 1999 to 2002. The idiosyncratic volatility thus also shows a marked increase in it's own volatility during the period from 1999 to 2002, but IV does trend downward from 2001 to 2006. The "volatility" in the IV during the 1999 to 2002 period will work against the liquidity cost hypothesis.[8]

[8] The 1980's shows a marked upward trend in idiosyncratic volatility, consistent with the findings of Campbell, Lettau, Malkiel, and Xu (2001). In much of the 1990's and continuing after 2000, IV is trending downward, consistent with the findings of Brandt, Brav, Graham, and Kumar (2008). Indeed, from 1991 to 2006 both the percentage of zero returns and IV can be seen to more gradually decline. The downward trend in IV is somewhat contrary to Cao,

We focus on the period from 1997 to 2006 to encapsulate the change to sixteenth pricing in Panel A of Table 4, and the period from 2001 to 2006 to encapsulate the change to decimal pricing in Panel B of Table 4. Unlike using monthly returns commonly utilized in GARCH model applications, using daily returns in estimating IV will allow for an exact identification of these periods. Again, we focus on NYSE/Amex/NASDAQ stocks. For these sort results we only sort on IV allowing the percentage of zero returns and the spread to vary independently with the IV quintile.

As shown in Panel A of Table 4, the sort results report a marked decline in the percentage of zero returns across all the IV quintiles, ranging from 2.2% to 3.7%, when compared to the whole sample period from 1983 to 2006 where the percentage of zero returns are ranging form 8% to 14.5% across the IV quintiles (shown in Table 3). The spread costs are also shown to decrease, but the decrease is most evident in the largest high IV quintile, where it demonstrates a decrease to 1.3% from the baseline case of 3.8% (shown in Table 3). The increased underlying "volatility" in the Fama-French idiosyncratic volatility exhibited during the NASDAQ bubble from 1999 to 2002 is evident. The FF-IV shows a marked increase from 1.152% for the low IV quintile to 6.466% for the high IV quintile. The resulting High-Low FF-IV of 5.314% is somewhat reduced from the baseline result of 5.440%. However the bias exerted by the zero returns and the bid-ask spread alters the composition of firms in the highest FF-IV quintile causing a very different effect on the abnormal performance.

The resulting High-Low Carhart alpha does *not* display significance in any of the IV quintiles nor does it register significance in the High-Low abnormal performance. The reported High-Low Carhart alpha is reduced to -0.517% per month down from -0.939% per month obtained in the period from 1983 to 2006. The abnormal performance is not even marginally significant displaying a t-statistic of only 1.17. The Fama-French alpha is -1.063% per month and significant at the 5% level. However, this result is likely due to price run-up and momentum before the Internet bubble burst in 2000. Thus the period from 1997 to 2006 experiences a degradation in IV performance of more than 35%. We would argue that this decrease in the IV's ability to predict returns is likely

Simin, and Zhao (2008) who argue that growth options can explain the increasing trend in IV over time because growth options were increasing from 1991 to 2000, yet IV is seen to decrease over that time period. These results would indicate that liquidity costs have more to do with IV than do growth options.

due to the decreased level of zero returns, as well as reduced spread costs subsequent to 2001.

Turning to period from 2001 to 2006 in Panel B shows an even more marked decline in the estimate of the FF-IV and in the pricing ability of IV. For this time period, the High-Low FF-IV estimate is reduced to 4.660% demonstrating the microstructure influence of a reduced bid-ask spread. The microstructure noise controlled abnormal performance exhibits an even more dramatic effect.

The Fama-French alpha is now *positive* at 0.074% per month and insignificant. The Carhart alpha is also positive at 0.107% per month and also insignificant. We conjecture that the insignificance in the pricing ability of IV during the decimalization period is due to the sustained and persistent reduction in the zero return frequency and the reduction in the bid-ask spread. The spread falls to less than 1%, and is matched by a comparable reduction in the percentage of zero returns, regardless of IV quintile. The reduction in the spread minimizes the microstructure influence on the estimation of IV and the falloff in the percentage of zero returns allows for a more adequately mapping of the systematic risk factors to the underlying returns greatly reducing IV's pricing ability.

6.2 Robustness check on the liquidity effect on IV measurement

For robustness, we now address the time period from 1983 to 1997 that has been shown to experience an upward trend in IV from 1983 to 1990 and then a relatively steady level in IV from 1991 to 1997. We examine the effect of both the zero returns and the spread effects by focusing on those firms that experience no more than one zero return each month (out of the approximately 21 trading days each month). We use the zero returns because it is a convenient integer number. This filter allows for a direct examination of liquidity's influence on IV's ability to predict future returns during a period where IV's pricing ability is particularly high. The results are shown in Table 5. Panel A delineates the unrestricted sample results and Panel B focuses only on those firms that experience at most one zero returns. As previously noted, the sort results are only sorted by IV allowing both the percentage of zero returns and the spread to vary within each IV quintile.

Panel A shows that the period from 1983 to 1997 is evidenced by a greatly increased level in IV, percentage of zero returns, and bid-ask spread liquidity costs. The estimated High-Low FF-IV is 5.521%. The resulting Fama-French alpha for the High-Low IV portfolio is -1.560% per month and is highly significant. The Carhart alpha is somewhat less at -1.413% per month, but still highly significant.

However, turning to Panel B of Table 5 that focuses only on those firms that experience relatively few zero returns (or low liquidity costs) allows for a better mapping of the systematic factors onto returns and lower microstructure noise, shows that the High-Low FF-IV estimate is greatly reduced and is now only 3.419%, compared to the prior estimated FF-IV of 5.521% for all firms during the same period. This plays a direct role in the abnormal performance.

The Fama-French alpha is now only -0.084% per month. Although still negative, it could be construed as zero. The Carhart alpha is a paltry -0.018% and also insignificant. The zero return (liquidity cost) effect is noticeable across all of the IV quintiles where all of the alphas are insignificant. Indeed, for the highest IV quintile, where the majority of the abnormal performance resides, the Fama-French alpha is now -0.029% per month, which is now insignificant. In contrast, the unrestricted case shows a highly significant Fama-French alpha of -1.427% per month.

An interesting feature of these results can be seen for the lowest quintile of IV from Panels A and B. The unrestricted zero return case of Panel A, shows the percentage of zero returns to be 11.7% and the spread costs to be 0.8%, while the restricted zero return case of Panel B shows a percentage of zero returns of 2.5%, but a very similar spread cost of 0.6%. Controlling for the percentage of zero returns does add to the explanatory power of liquidity over and above the spread costs.

These results demonstrate that liquidity costs materially affect the pricing ability of IV even for time periods where IV is more prone to produce significant pricing power with future returns. Increased liquidity costs embodied in both the bid-ask spread and in the occurrence of zero returns upward biases the IV estimate leading to a negative relation with future returns. Focusing on low liquidity cost firms allows for a more proper mapping of the systematic risk factors onto returns and reduced microstructure noise removing the ability of IV to predict future returns, consistent with the most basic tenets of asset pricing.

7 Regression Residual Approach and Quote Mid-Point Returns

Spiegel and Wang (2005) argue that IV is more powerful than is liquidity in explaining future returns. The problem in testing the relative strength of liquidity over IV is simply that IV already contains a liquidity cost component embedded by both the zero returns and the direct microstructure influence. In this section we further examine the relation of IV with the percentage of zero returns and the spread and attempt to disentangle the liquidity effects from the IV effects in predicting future returns by examining the residual of a regression of IV on the liquidity cost measures.

7.1 The relation between IV, zero returns, and the bid-ask spread

In Table 6, we attempt to provide some statistical merit to our graphical depiction of the zero return influence on the IV estimates shown in Figure 1. Given the uncertainty in modeling the zero return effects, we present two sets of results. First, we model the zero return effect using linear and non-linear zero return influences, evident in Figure 1, along with the bid-ask spread. Second, we include an interaction term for the joint zero return and bid-ask spread effect on the IV estimation. The regression is estimated each month over the full sample period from 1983 to 2006 using the Fama-MacBeth framework and is generally stated as

$$\text{FF-IV} = \alpha_0 + \alpha_1\%\text{Zeros} + \alpha_2(\%\text{Zeros})^2 + \alpha_3\text{Spread} + \alpha_4\%\text{Zeros} \times \text{Spread} + \epsilon. \tag{17}$$

The results of Table 6 indicate that IV is concave with respect to the zero returns. The linear term of the percentage of zero returns is positively related to IV and the non-linear (squared) term of the percentage of zero returns is negatively related to IV.[9] The proportional spread is also incrementally

[9] Pantzalis and Park (2007) find that the relation between mispricing and idiosyncratic risk (measured by $1 - R^2$) is U-shaped, which seems to be consistent with our finding because high percentage of zero return stocks tend to

associated with the Fama-French IV. In fact much of the goodness-of-fit results from the inclusion of the direct liquidity measure.[10]

We term the regression residual, ϵ, from Equation 17 the residual-IV. This method provides a basis for decomposing the FF-IV into an orthogonal idiosyncratic volatility estimate, the residual-IV, that is devoid of both the zero return effect and the direct microstructure effect on the estimated IV. Using the residual-IV provides an assessment on the relative strength of IV to predict future returns after specifically controlling for liquidity costs embedded in the estimate of IV.

7.2 Value-weighted IV-residual sort results

Each month, we sort stocks into quintiles by the estimated IV-residual, form value-weighted quintile portfolios, and compare the abnormal performance of the quintile portfolios and the High-Low arbitrage portfolio. This test is performed over the period 1983 to 2006. The results are reported in Panel A of Table 7 without the interaction term and in Panel B of Table 7 with all the terms.

As is shown in Panel A, the first three IV quintiles are remarkably now negative, while the last two are positive. The High-Low estimated IV is reduced (from the baseline case of 5.440% shown in Panel A of Table 3) to 3.710%. This is a 32% reduction in the High-Low IV. Also evident is the lack of monotonicity with the percentage of zero returns and spread demonstrating the effectiveness of the residual approach. In fact, the lowest quintile has the highest percentage of zero returns and highest spread costs of any IV quintile.

The Carhart alpha of the High-Low IV-residual portfolio is only -0.396% per month and insignificant, suggesting no pricing ability in IV, over and above liquidity cost influences. This is indicative of the "problem" of testing for a liquidity cost effect *after* the estimation of IV and illustrates the liquidity cost component embedded in the estimate of IV. The Fama-French alpha of the High-Low IV-residual portfolio is -0.619% per month, which is significant at the 5% level, but it is much reduced from the baseline result. For comparison purposes, the baseline value-weighted

have large mispricing.

[10] Although not reported, the effective spread produces similar results.

results of Panel A of Table 3) shows a Fama-French alpha of -1.429% per month. Obviously, the power of IV to predict future returns is greatly reduced after we control for the liquidity costs.

For robustness, we allow for an interaction between the percentage of zero returns and the spread in the estimation of the IV-residual. Panel B of Table 7 reports the sorting results for this more general specification. This interaction will control for the marginal effects exerted on IV by the direct and indirect liquidity cost effects. As is shown, allowing for the interaction between the percentage of zero returns and the spread now completely removes the ability of the IV-residual in predicting future returns. The Fama-French alpha of High-Low IV-residual portfolio is -0.304% per month and the Carhart alpha is -0.190% per month. Neither of these abnormal performance measures is significant.

The results are telling for a number of reasons. First the full sample period is noted to exhibit very strong results for IV's ability to predict future returns, yet over the same period orthogonalizing the effect of the percentage of zero returns and bid-ask spread on the IV estimate reduces to insignificance IV's ability to predict future returns. These results point to the influence of zero returns and bid-ask spread costs on the IV estimation and allow for a control that is both consistent and tractable.

7.3 Fama-MacBeth regression tests

The prior sorting results provide one picture of the relation between IV and returns, but they focus primarily on the extreme portfolios. In order to gain some insight on the overall behavior of the IV and return relation, but simultaneously controlling for additional risk factors or anomalies shown to affect future returns, we employ the Fama and MacBeth (1973) methodology with six lags for the Newey and West (1987) correction.

We first partition the results in terms of the control variables used by Ang, Hodrick, Xing, and Zhang (2008) that isolate information effects, reversal effects, firm controls, and market effects. The information variables are the percentage of institutional holdings and the number of analysts estimates. Reversal effects are controlled for by one-month lagged returns. Firm controls are log scaled book-to-market ratio and log scaled firm size. Market effects are measured by coskewness risk. The institutional holdings measure is measured quarterly, and the book-to-market ratio is measure annually, but we use the information determined prior to the measured return. We designate the lagged quarterly value with a subscript $q-1$ and the lagged annual value with a subscript $a-1$. Other control variables are measured coincident with the IV, i.e. lagging the returns by one month (subscript $m-1$). IV is measured using the Fama-French three factor model. These controls are by no means exhaustive, but they represent the principal variables used to model the aspects commonly known to affect expected returns.

We generalize these results by including the proportional spread or the effective spread to corroborate the collinearity issues evident in the Spiegel and Wang (2005) results. We also use the estimated FF-IV as well as the residual-IV. This procedure has a two-fold appeal. Statistically, it corrects for any multicollinearity issues that may arise from the observed high correlation between liquidity and IV. Second, it expressly examines the incremental ability of IV in predicting returns after controlling for liquidity influences on the estimation of IV itself. In addition, we also estimate the FF-IV using the quote midpoint return as a robustness check of our residual regression IV estimate. Our microstructure theory posits that the estimated IV is upward biased due to microstructure noise and this regression test will highlight that hypothesis.

To be consistent with Ang, Hodrick, Xing, and Zhang (2006), we employ a value-weighted Fama-MacBeth regression using firm size at the beginning of the month as the weight. Ang, Hodrick, Xing, and Zhang (2008) perform a similar regression test for emerging markets. The general specification is given as:

$$\begin{aligned}\text{Return}_{i,m} = {} & \beta_0 + \beta_1 \text{IV}_{i,m-1} + \beta_2 \text{Lagged Return}_{i,m-1} + \beta_3 \text{Book-to-Market}_{i,a-1} + \beta_4 \text{Firm Size}_{i,m-1} \\ & + \beta_5 \text{Coskewness}_{i,m} + \beta_6 \#\ \text{Estimates}_{i,m-1} + \beta_7 \text{Inst. Holdings}_{i,q-1} + \beta_8 \text{Liquidity}_{i,m-1} + \epsilon,\end{aligned} \tag{18}$$

where liquidity refers to either the bid-ask or effective spread estimates. IV refers to either the FF-IV computed from closing CRSP based returns, the IV-residual or the IV estimated using the quote midpoint. The regression results are presented in Table 8 for NYSE/Amex/NASDAQ exchange listed firms.

The first prominent result in Table 8 is that the FF-IV remains significantly related to future returns regardless of the controls included. The estimated marginal effect of FF-IV on future returns is approximately 22 basis points regardless of the specification used for the regression. Contrary to Fu (2008), the reversal effect does not control for the pricing ability of IV. However, consistent with the results of Spiegel and Wang (2005), IV appears to dominate liquidity in its relation to future returns. In fact, the spread variables even have the wrong sign, although value-weighting could possibly affect these inferences.

However, using the residual of the regression specified in Equation (17), results in a far different outcome. These results are shown in columns five and six of Table 8. Now the residual of IV (labeled "Residual w/ Zero Sq") is insignificantly, although negatively, related to future returns. This result implies that the prior regression results controlling for liquidity as an added variable to the regression is affected by multicollinearity concerns. Orthogonalizing IV and liquidity allows for a specification that specifically tests whether IV alone (without the liquidity influence) is associated with future returns. The residual coefficient would indicate that the pure IV marginal effect (without the liquidity influence) is now only 15 basis points and insignificant. The conclusion reached by Spiegel and Wang (2005) is not incorrect, but it does not properly control for the liquidity influence. IV does dominate liquidity as can be seen by the still robust 15 basis point effect on future returns whereas liquidity accounts for only a 7 basis point effect. But removing liquidity's influence on IV also removes the significance of IV in predicting future returns. Using an alternative specification for the liquidity cost effect on the estimated IV that includes the interaction between the spread and the %zero return (labeled "Residual w/ Zeros X Spread"), shows a similar result. Separating the influence of liquidity costs from the estimate of IV results in no pricing ability of IV.

Finally, for robustness, we focus on the quote midpoint as a basis of estimating the FF-IV. For this specification we use the quote midpoint based return to estimate the IV. This result is shown in the last column of Table 8. As is shown, the marginal effect of IV on future returns is remarkably similar to that produced by the residual regression and is shown to be 16 basis points. Moreover, the significance level of the resultant association is below 5% and we would argue that this insignificant result, in conjunction with the residual IV results, demonstrates that the pricing power of IV is subject to the underlying liquidity costs embedded in returns.

8 Conclusions

We analyze the empirical relation between cross-sectional idiosyncratic volatility (IV) and expected stock returns. The literature has presented a very vexing set of results with Ang, Hodrick, Xing, and Zhang (2006) finding that Fama-French based IV is negatively related to value-weighted returns, even for the largest market capitalization firms. Numerous explanations have been offered to explain this findings such as return reversal (lagged returns), information asymmetry (analyst coverage and institutional holdings), momentum, market friction (short-sale constraint), and liquidity, while others question the robustness of the findings.

We show that microstructure influences are fundamental to the estimation of IV and in the value-weighted IV's ability to predict future returns. Microstructure influences are noted both by an increasing percentage of zero returns that biases the systematic risk estimates and in a daily bid-ask bounce bias that inflates the IV leading to the observed negative relation with future returns. In effect, the IV estimated from the standard methodology has an embedded liquidity component. We find that controlling for the liquidity cost effect on IV estimation, either by examining the returns derived from quote midpoints or by filtering by the zero returns, can significantly reduce IV's ability to predict future returns. Regulatory changes that reduced liquidity costs, such as occurred during the 1997 and 2001 periods (Bekaert, Harvey, and Lundblad, 2007) provide a natural experiment to test our microstructure hypothesis. We show that the reductions in the tick size or decimalization of quotes led to a rapid and lasting reduction in the percentage of zero returns and the spread that, not surprisingly, led to a vast reduction in the the statistical and economic importance of IV in predicting future returns.

The importance of the findings lies in the link to existing microstructure influences noted clearly in Blume and Stambaugh (1983) and Amihud and Mendelson (1986). However, the arguments for liquidity are often predicated on liquidity issues after the estimation of IV is complete. We raise the issue whether the estimation of IV in a three-factor Fama-French model should reflect the underlying microstructure influences. We conclude that microstructure influences are much broader than have been previously thought and extending microstructure influences to include zero returns and the return bias engendered by the bid-ask bounce on the measurement of IV itself appears to be a first order influence on asset pricing consistent with Acharya and Pedersen (2005). It appears that the rejection of liquidity as an explanation for IV's ability to predict future returns is premature.

More telling is the recent work by Ang, Hodrick, Xing, and Zhang (2008) who present strong international evidence, which, similar to the evidence in the US, shows that high idiosyncratic volatility stocks yield low returns. However, they fail to find any evidence supporting the notion of exposure to zero returns for this phenomenon. Because liquidity costs in other countries are much higher than in the US, we suspect that the strong relation between IV and returns is again due to liquidity. We would postulate that the incidence of zero returns indicates a liquidity costs effect on the returns. The estimation of IV should account for the bid-ask bounce in returns before concluding that IV is priced, rather than testing for a liquidity cost effect after the estimation of IV. Future work should incorporate this issue.

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Table 1: Summary Statistics

This table presents the summary statistics for a quintile sort using the percentage of zero returns as the basis. The percentage of zero returns (%Zeros) is the fraction of trading days in a month that experiences no price movement from the prior end-of-day price estimated using CRSP daily stock returns. We estimate the idiosyncratic volatility using the Fama-French three factor model specification for all firms listed on the NYSE/Amex/NASDAQ exchanges. Book-to-market is taken from Compustat and is measured annually. Firm size multiplies the month end price by the shares outstanding. Coskewness is calculated using the relation: $\frac{E[\epsilon_{i,t}\epsilon^2_{M,t}]}{\sqrt{E[\epsilon^2_{i,t}]E[\epsilon^2_{M,t}]}}$ as recommended by Campbell and Siddique (2000). Both the analyst coverage and institutional holdings commence in 1981. Analyst coverage is provided by I/B/E/S and is a monthly count of the number of one-year ahead earnings forecasts. Institutional holdings is taken from Thompson Financial's recording of the 13-f filings. We measure the total percentage of shares held by institutions estimated quarterly. We project the quarterly holdings for the next three months to complete the monthly statistics. The (proportional) spread is defined as the ask minus the bid divided by the quote midpoint and the effective spread is defined as two times the absolute value of the difference between the price and the quote midpoint divided by the price. Our sample period runs from 1983:7 to 2006:6 for a total of 276 months and this period encapsulates the bid-ask spread observations.

Rank	%Zeros	FF-IV(%)	Spread(%)	Effective Spread(%)	Lagged Return(%)	B/M	Size	Price	CoSkew	Analyst	Institutional Holdings
Low	5.588**	2.772**	1.778**	1.136**	2.244**	5.227**	2894.016**	36.292**	-0.011**	8.082**	0.412**
	(8.58)	(27.90)	(16.06)	(17.82)	(6.32)	(10.97)	(12.05)	(26.91)	(-4.71)	(33.35)	(40.32)
2	14.600**	3.627**	3.323**	2.266**	3.300**	4.292**	948.803**	20.983**	-0.011**	4.269**	0.293**
	(12.58)	(30.44)	(25.51)	(24.99)	(5.73)	(12.83)	(10.33)	(17.79)	(-2.68)	(46.37)	(40.20)
3	21.328**	3.608**	4.110**	2.754**	1.257**	4.254**	618.657**	19.485**	-0.019**	2.920**	0.248**
	(12.47)	(29.97)	(15.34)	(15.34)	(3.62)	(8.65)	(5.95)	(10.08)	(-6.81)	(42.44)	(19.75)
4	31.021**	3.993**	5.704**	3.339**	0.612	3.714**	281.447**	15.800**	-0.018**	1.640**	0.177**
	(13.48)	(29.65)	(16.32)	(15.57)	(1.80)	(10.35)	(4.97)	(6.31)	(-7.64)	(25.50)	(19.06)
High	53.571**	3.840**	10.836**	3.088**	-0.428	3.862**	92.908**	10.491**	-0.014**	0.561**	0.098**
	(14.32)	(23.26)	(11.59)	(8.77)	(-1.48)	(9.15)	(4.98)	(6.13)	(-7.26)	(9.50)	(10.56)
High - Low	47.983**	1.068**	9.058**	1.952**	-2.672**	-1.365*	-2801.108**	-25.802**	-0.002	-7.521**	-0.314**
	(15.26)	(8.91)	(10.21)	(5.99)	(-10.75)	(-2.37)	(-11.99)	(-11.82)	(-1.27)	(-26.40)	(-52.51)

Table 2: Double Sort Performance of Liquidity Measures and Idiosyncratic Volatility

Carhart (1997) four-factor alphas, with Newey and West (1987) robust t-statistics in parentheses, are reported for idiosyncratic volatility (IV) sorted portfolios that are first sorted by different liquidity measures. For each liquidity measure we perform double sorts by first sorting on the liquidity measure and then, within these partitions, further sorting on IV. Panel A reports the sort results using the percentage of zero returns and Panel B reports the sort results using the proportional bid-ask spread. "%Zeros Low" partition contains those firms with the fewest number of zero returns recorded each month while the "%Zero High" partition contains those firms with the largest number of zero returns recorded each month. The bid-ask spread results are similarly arranged with "Spread Low" representing those firms experiencing the lowest liquidity costs and "Spread High" representing those firms with the highest liquidity costs. "High - Low" is the difference in Carhart alpha between the highest IV ("High") quintile and the lowest IV ("Low") quintile. Significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank of IV	Low	2	3	4	High	High - Low
Panel A: Double Sort with %Zeros						
%Zeros Low	0.028	-0.058	0.029	-0.126	-0.529*	-0.558
	(0.39)	(-1.12)	(0.30)	(-0.82)	(-2.25)	(-1.95)
%Zeros 2	0.117	0.040	0.213	-0.501*	-0.674*	-0.791*
	(1.24)	(0.36)	(1.15)	(-2.13)	(-2.02)	(-2.16)
%Zeros High	0.086	0.133	-0.120	-0.410	-0.538	-0.624
	(0.65)	(0.66)	(-0.68)	(-1.53)	(-1.39)	(-1.59)
Panel B: Double Sort with Proportional Spread						
Spread Low	0.131	0.012	0.019	0.149	-0.031	-0.162
	(1.73)	(0.16)	(0.21)	(1.16)	(-0.13)	(-0.60)
Spread 2	-0.083	-0.063	-0.195	-0.316*	-0.978**	-0.895**
	(-0.59)	(-0.52)	(-1.22)	(-2.24)	(-4.00)	(-2.62)
Spread High	0.249	0.039	-0.382	-0.447	-1.594**	-1.842**
	(1.33)	(0.21)	(-1.44)	(-1.28)	(-3.95)	(-4.53)

Table 3: Idiosyncratic Volatility Estimated from CRSP Returns and Mid-Quote Prices

We estimate idiosyncratic volatility using both the CRSP provided closing returns in Panel A and by computing daily returns using the mid-quote prices in Panel B. We then employ these two return definitions to estimate the idiosyncratic volatility using the Fama-French three-factor model over one month and finally sort stocks using the estimated IV measures. The sample period runs from 1983 to 2006. The row labeled High-Low refers to the difference between the portfolio with the highest IV (High) and the portfolio with the lowest IV (Low). The columns are defined as follows: FF-IV is the Fama-French based IV estimated from either CRSP based closing returns or from daily returns computed from the mid-quote prices; %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios; Fama-French Alpha is the alpha estimated from Fama-French three factor model; Carhart Alpha is the alpha estimated from Carhart (1997) four-factor model. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank	FF-IV(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: CRSP Closing Return Estimated IV						
Low	1.042**	7.956**	0.693**	0.757**	0.137*	0.079
	(28.12)	(10.17)	(14.49)	(3.78)	(2.04)	(1.12)
2	1.711**	7.524**	0.934**	0.623*	-0.087	-0.051
	(32.26)	(9.91)	(14.18)	(2.38)	(-1.24)	(-0.80)
3	2.509**	8.826**	1.242**	0.604	-0.084	0.050
	(30.96)	(9.60)	(13.26)	(1.79)	(-0.77)	(0.56)
4	3.670**	10.922**	1.895**	0.142	-0.489**	-0.262
	(29.91)	(9.43)	(10.72)	(0.32)	(-2.88)	(-1.66)
High	6.482**	14.470**	3.799**	-0.600	-1.292**	-0.860**
	(30.32)	(9.65)	(9.79)	(-1.16)	(-5.16)	(-3.48)
High - Low	5.440**	6.514**	3.106**	-1.358**	-1.429**	-0.939**
	(29.11)	(7.68)	(8.41)	(-3.05)	(-4.82)	(-3.24)
Panel B: Quote Mid-Point Estimated IV						
Low	0.976**	9.176**	0.684**	0.679**	0.084	0.047
	(25.63)	(10.33)	(14.87)	(3.28)	(1.27)	(0.69)
2	1.457**	7.352**	0.762**	0.712**	0.048	0.075
	(27.51)	(10.15)	(15.98)	(2.93)	(1.13)	(1.56)
3	2.102**	7.726**	0.981**	0.609	-0.061	0.098
	(27.52)	(10.18)	(17.01)	(1.86)	(-0.55)	(1.01)
4	3.053**	8.965**	1.364**	0.436	-0.207	-0.012
	(29.01)	(9.79)	(15.55)	(1.03)	(-1.36)	(-0.08)
High	5.020**	11.503**	3.714**	-0.252	-0.810**	-0.474
	(34.00)	(9.65)	(5.83)	(-0.48)	(-3.32)	(-1.89)
High - Low	4.044**	2.327**	3.030**	-0.931*	-0.894**	-0.521
	(34.72)	(4.05)	(4.79)	(-2.10)	(-3.15)	(-1.82)

Table 4: Sort Performance of Idiosyncratic Volatility after Exogenous Liquidity Shocks
We exploit exogenous liquidity shocks by examining the periods from 1997 to 2006 and from 2001 to 2006 that have been shown to experience significant reductions to liquidity costs. These periods coincide with the NYSE/Amex/NASDAQ move to sixteenth pricing and the decimalization in quotes, respectively. We sort on the Fama-French based idiosyncratic volatility (FF-IV). The row labeled High-Low refers to the difference between the portfolio with the highest IV (High) and the portfolio with the lowest IV (Low). The columns are defined as follows: FF-IV is the Fama-French based IV; %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios; Fama-French Alpha is the alpha estimated from Fama-French three factor model; Carhart Alpha is the alpha estimated from Carhart (1997) four-factor model. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank	FF-IV(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: From 1997:06 to 2006:06						
Low	1.152**	2.217**	0.572**	0.570	0.136	0.075
	(14.54)	(7.43)	(5.17)	(1.84)	(1.05)	(0.55)
2	1.827**	1.891**	0.728**	0.411	-0.095	-0.048
	(16.36)	(7.13)	(5.17)	(0.89)	(-0.69)	(-0.37)
3	2.634**	2.093**	0.729**	0.499	-0.021	0.109
	(15.55)	(6.10)	(5.92)	(0.76)	(-0.12)	(0.68)
4	3.800**	2.549**	0.789**	0.191	-0.340	-0.128
	(15.15)	(5.85)	(6.34)	(0.20)	(-1.26)	(-0.49)
High	6.466**	3.728**	1.307**	-0.166	-0.927*	-0.442
	(15.96)	(6.09)	(6.60)	(-0.15)	(-2.08)	(-1.21)
High - Low	5.314**	1.511**	0.735**	-0.736	-1.063*	-0.517
	(16.06)	(3.90)	(4.63)	(-0.76)	(-2.03)	(-1.17)
Panel B: From 2001:04 to 2006:06						
Low	0.954**	1.243**	0.281**	0.336	0.053	0.052
	(13.90)	(22.82)	(3.15)	(0.85)	(0.48)	(0.45)
2	1.549**	1.094**	0.356**	0.297	-0.253*	-0.256*
	(15.40)	(20.84)	(3.24)	(0.47)	(-2.07)	(-2.11)
3	2.229**	1.151**	0.384**	0.550	-0.102	-0.107
	(13.32)	(28.54)	(3.79)	(0.68)	(-0.46)	(-0.49)
4	3.226**	1.442**	0.444**	0.444	-0.116	-0.100
	(12.24)	(22.71)	(4.76)	(0.40)	(-0.39)	(-0.31)
High	5.614**	2.131**	0.827**	0.807	0.127	0.159
	(11.74)	(18.82)	(4.76)	(0.58)	(0.30)	(0.34)
High - Low	4.660**	0.889**	0.546**	0.472	0.074	0.107
	(11.34)	(5.79)	(4.50)	(0.43)	(0.15)	(0.20)

Table 5: Sort Performance of Idiosyncratic Volatility for Restrictions on the Zero Returns
We control for the effect of the zero returns by restricting the sample to include only those firms that experience at most one zero return each month. We compare these results with those of including all the firms without the restriction on the zero returns. The sample period runs from 1983 to 1996. We sort on the Fama-French based idiosyncratic volatility (FF-IV). The row labeled High-Low refers to the difference between the portfolio with the highest IV (High) and the portfolio with the lowest IV (Low). The columns are defined as follows: FF-IV is the Fama-French based IV; %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios; Fama-French Alpha is the alpha estimated from Fama-French three factor model; Carhart Alpha is the alpha estimated from Carhart (1997) four-factor model. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank	FF-IV(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: From 1983:07 to 1997:05						
Low	0.969**	11.723**	0.772**	0.857**	0.132**	0.114*
	(42.26)	(29.77)	(36.88)	(3.35)	(3.17)	(2.55)
2	1.635**	11.228**	1.070**	0.728*	0.004	0.017
	(38.52)	(34.70)	(26.77)	(2.39)	(0.07)	(0.26)
3	2.425**	13.263**	1.578**	0.615	0.030	0.080
	(34.07)	(30.20)	(20.84)	(1.71)	(0.30)	(0.80)
4	3.584**	16.447**	2.624**	0.033	-0.457**	-0.335*
	(30.50)	(26.68)	(17.19)	(0.08)	(-3.45)	(-2.44)
High	6.490**	21.552**	5.439**	-0.990*	-1.427**	-1.299**
	(27.38)	(25.59)	(16.27)	(-2.12)	(-7.08)	(-5.60)
High - Low	5.521**	9.830**	4.667**	-1.847**	-1.560**	-1.413**
	(24.92)	(11.44)	(14.37)	(-4.95)	(-7.31)	(-5.73)
Panel B: From 1983:07 to 1997:05, Zeros <= 1						
Low	0.942**	2.478**	0.595**	0.779**	0.055	0.036
	(42.49)	(30.90)	(28.16)	(2.72)	(0.71)	(0.45)
2	1.422**	2.511**	0.760**	0.806*	0.027	0.032
	(39.75)	(34.86)	(34.48)	(2.52)	(0.26)	(0.28)
3	1.884**	2.494**	0.936**	0.625*	0.022	0.052
	(29.74)	(36.02)	(17.00)	(2.05)	(0.17)	(0.39)
4	2.539**	2.589**	1.053**	0.356	-0.236	-0.228
	(25.63)	(38.14)	(12.57)	(0.94)	(-1.38)	(-1.31)
High	4.091**	2.625**	1.374**	0.249	-0.029	0.018
	(27.32)	(35.67)	(17.31)	(0.57)	(-0.13)	(0.07)
High - Low	3.149**	0.146*	0.779**	-0.529	-0.084	-0.018
	(23.19)	(2.05)	(10.68)	(-1.53)	(-0.32)	(-0.06)

Table 6: Regressions of IV on the Zero Returns and the Bid-Ask Spread

We present regression results of the Fama-French idiosyncratic volatility (termed FF-IV) on the influences of liquidity presented by the percentage of zero returns and the proportional bid-ask spread. We run a sequential regression test by including each variable to assess the relative association of each variable on IV. We include the percentage of zero returns and the square of the percentage of zero returns. These two terms control for the non-linearity evident in the association between the zero returns and the estimated IV. We also include the proportional bid-ask spread as well as an interaction effect of both the %zero returns and the bid-ask spread. The sample period runs from 1983 to 2006. Each of these microstructure controls are estimated contemporaneously with the IV measurement. Columns four and five will constitute the bulk of our subsequent tests. T-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

	FF-IV	FF-IV	FF-IV	FF-IV	FF-IV
Intercept	2.938**	2.382**	2.053**	1.823**	1.756**
	(27.01)	(16.83)	(20.19)	(14.22)	(15.43)
%Zeros	3.090**	8.480**		2.209*	-1.666**
	(9.34)	(16.80)		(2.47)	(-4.53)
Squared %Zeros		-10.32**		-9.507**	-0.0400
		(-12.24)		(-10.17)	(-0.09)
Spread			37.99**	44.75**	69.23**
			(11.95)	(15.60)	(43.61)
%Zeros×Spread					-58.08**
					(-14.85)
N	1229194	1229194	1229194	1229194	1229194
adj. R^2	0.020	0.037	0.341	0.419	0.495

Table 7: Sort Performance of Idiosyncratic Volatility Residuals

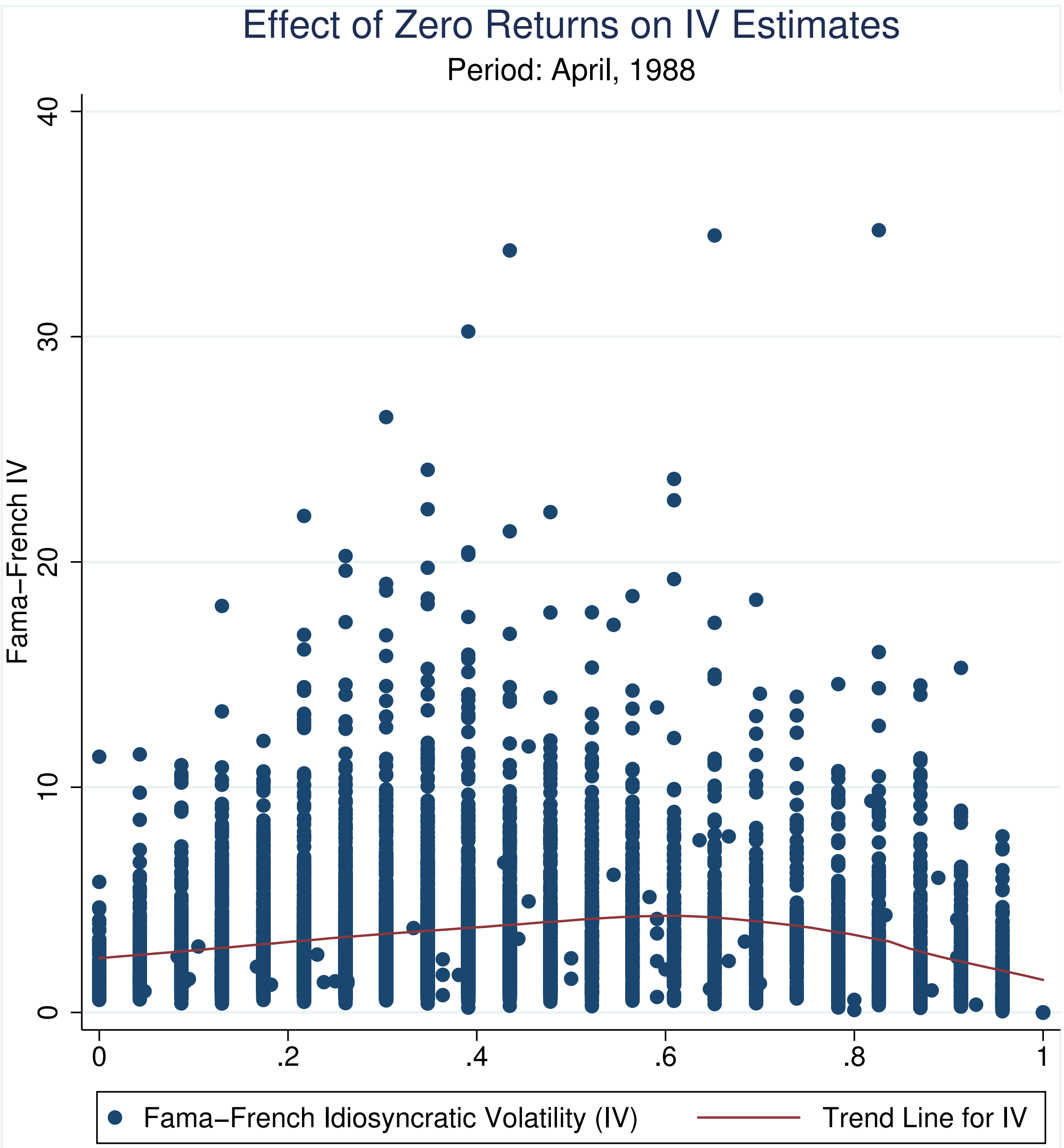
We use the residual of a monthly regression of IV on various specifications for the liquidity effects in quintile sorts. The IV is estimated using the Fama-French three-factor model over one month using daily returns. The first specification, shown in Panel A, is a residual of IV on the percentage of zero returns, the squared percentage of zero returns, and the bid-ask spread in sort tests. Panel B includes an additional interaction term, the % Zeros × Spread. The sample period runs from 1983 to 2006. The row labeled High-Low refers to the difference between the portfolio with the highest IV (High) and the portfolio with the lowest IV (Low). The columns are defined as follows: IV-Resid is the residual of the Fama-French based IV; %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios; Fama-French Alpha is the alpha estimated from Fama-French three factor model; Carhart Alpha is the alpha estimated from Carhart (1997) four-factor model. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank	IV-Resid(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: IV residual (%Zeros, Sq. %Zeros, Spread)						
Low	-1.589**	11.633**	0.968**	0.706**	0.058	0.042
	(-22.88)	(8.11)	(14.09)	(3.46)	(0.79)	(0.54)
2	-0.992**	7.999**	0.734**	0.545*	-0.048	-0.055
	(-20.39)	(9.65)	(15.32)	(2.18)	(-0.63)	(-0.81)
3	-0.393**	6.405**	0.751**	0.585	0.043	0.105
	(-16.95)	(9.63)	(15.10)	(1.85)	(0.42)	(1.02)
4	0.378**	5.941**	0.873**	0.522	0.052	0.107
	(22.06)	(8.78)	(14.07)	(1.27)	(0.37)	(0.82)
High	2.121**	8.200**	1.438**	-0.025	-0.561*	-0.346
	(26.23)	(10.67)	(13.47)	(-0.05)	(-2.36)	(-1.55)
High - Low	3.710**	-3.433**	0.470**	-0.731	-0.619*	-0.388
	(24.99)	(-3.54)	(5.53)	(-1.73)	(-2.24)	(-1.46)
Panel B: IV residual (%Zeros, Sq. %Zeros, Spread, %Zeros×Spread)						
Low	-1.373**	10.757**	1.558**	0.657**	-0.025	-0.006
	(-16.80)	(9.39)	(12.01)	(3.06)	(-0.31)	(-0.06)
2	-0.818**	8.040**	0.752**	0.622**	0.028	-0.000
	(-14.21)	(9.64)	(14.71)	(2.74)	(0.41)	(-0.00)
3	-0.334**	7.103**	0.678**	0.542	-0.027	-0.014
	(-12.33)	(9.63)	(15.36)	(1.83)	(-0.34)	(-0.16)
4	0.341**	7.094**	0.777**	0.544	0.093	0.142
	(16.59)	(9.71)	(14.82)	(1.35)	(0.63)	(1.03)
High	1.887**	8.143**	1.128**	0.167	-0.329	-0.195
	(20.18)	(9.70)	(13.86)	(0.33)	(-1.46)	(-0.91)
High - Low	3.261**	-2.613**	-0.429**	-0.490	-0.304	-0.190
	(18.72)	(-4.80)	(-4.50)	(-1.15)	(-1.18)	(-0.74)

Table 8: Fama-MacBeth Regressions

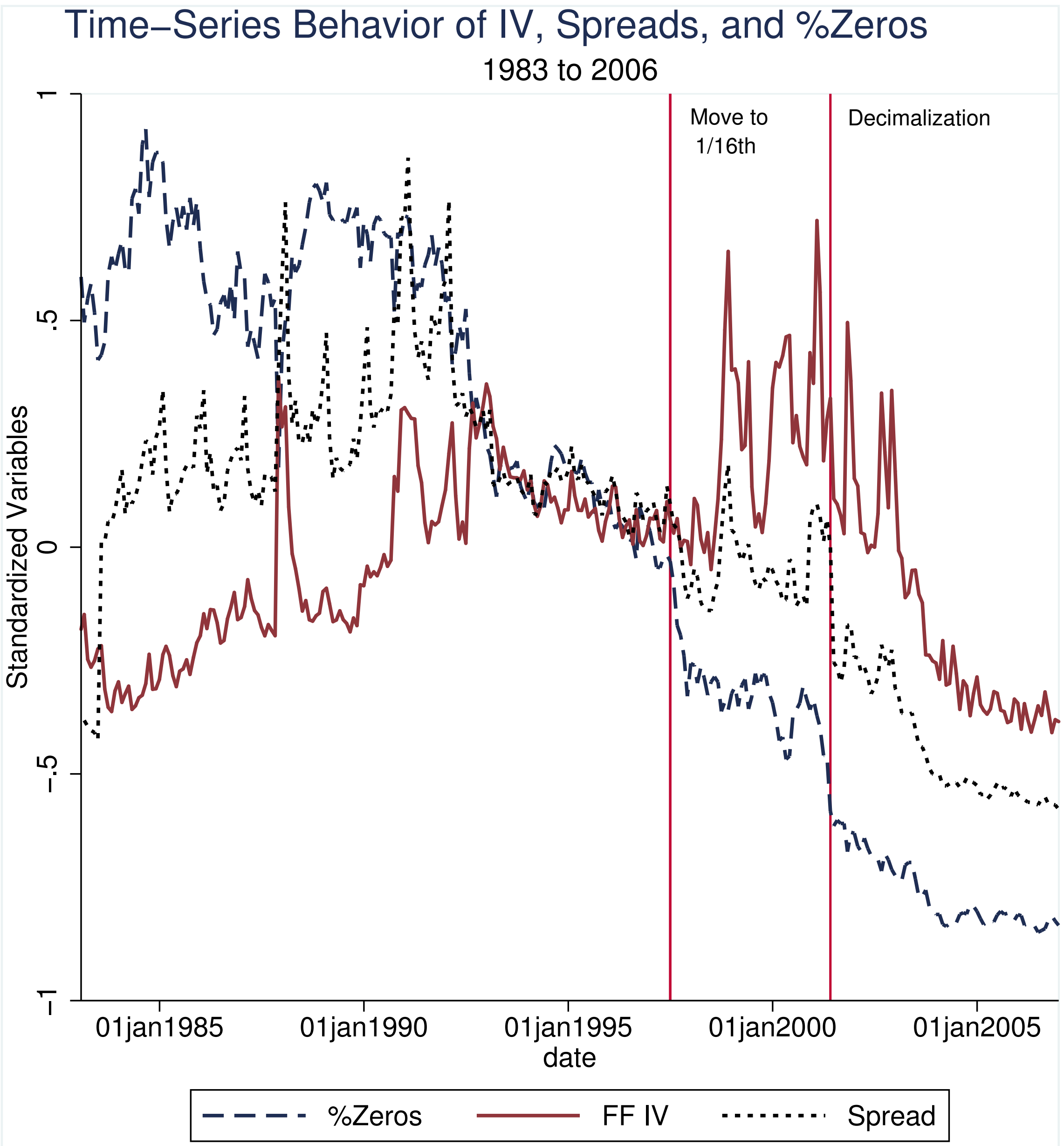
We regress the return against lagged control variables that comprise risk, return reversal, and information environment variables. Each of the regressions is value-weighted using lagged firm size as the weight. We have 276 months in our sample that span from 1983:7 to 2006:6. We measure the idiosyncratic volatility using the Fama-French three factor model for all firms listed on the NYSE/Amex/NASDAQ exchanges. Lagged returns measure the return reversal effect on returns. Book-to-market and firm size measure risk effects, while Coskewness measures downside risk. Analyst coverage and institutional holdings measure the general information environment. With the exceptions of institutional holdings and book-to-market, each of these control variables is measured in the month prior to the return measurement. Annual book-to-market is log scaled and is estimated from Compustat. Firm size is log scaled and multiplies the month end price by the shares outstanding. Coskewness is calculated using the relation: $\frac{E[\epsilon_{i,t}\epsilon_{M,t}^2]}{\sqrt{E[\epsilon_{i,t}^2]}E[\epsilon_{M,t}^2]}$ as recommended by Campbell and Siddique (2000). Analyst coverage is provided by I/B/E/S and is a monthly count of the number of one-year ahead earnings forecasts. Institutional holdings is taken from Thompson Financial's recording of the 13-f filings and is the total percentage of shares held by institutions estimated quarterly. We project the quarterly holdings for the next three months to complete the monthly statistics. Our liquidity variables are the proportional spread and the effective spread. We use the FF-IV estimated from the closing CRSP returns, the residuals of a regression of the Fama-French based IV on the % zero returns, the squared % of zero returns, and the spread (and including the interaction of the % zero returns and the spread), and the FF-IV estimated using the quote mid-points. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

	Return	Return	Return	Return	Return	Return	Return
Intercept	2.42**	2.31**	2.53**	2.38**	1.26	1.28	1.87**
	(3.13)	(3.66)	(3.75)	(3.79)	(1.79)	(1.82)	(2.79)
CRSP IV	-0.215*	-0.22*	-0.211*	-0.218*			
	(-2.34)	(-2.39)	(-2.25)	(-2.30)			
Residual w/ Zeros Sq.					-0.151		
					(-1.71)		
Residual w/ Zeros×Spread						-0.167	
						(-1.82)	
MidPoint IV							-0.159
							(-1.91)
Lagged Return	-1.95**	-1.91**	-2.02**	-1.97**	-2.02**	-2.04**	-1.71**
	(-2.99)	(-3.03)	(-3.16)	(-3.06)	(-3.19)	(-3.19)	(-2.68)
Ln(Firm Size)	0.0787	0.0947	0.0696	0.066	0.0749	0.0822	0.109
	(0.83)	(1.00)	(0.63)	(0.58)	(0.68)	(0.74)	(1.13)
Ln(Book-to-Market)	-0.0563	-0.0658	-0.0781	-0.0708	-0.0273	-0.0253	-0.0407
	(-1.32)	(-1.69)	(-1.68)	(-1.63)	(-0.62)	(-0.57)	(-0.99)
CoSkewness	-0.136	-0.125	-0.113	-0.114	-0.105	-0.0987	-0.105
	(-1.32)	(-1.22)	(-0.88)	(-0.87)	(-0.81)	(-0.77)	(-0.60)
# Estimates(×100)		0.177	0.212	0.244	0.0904	0.0647	0.328
		(0.34)	(0.27)	(0.31)	(0.12)	(0.08)	(0.57)
Inst. Holdings		0.51	0.501	0.504	0.598*	0.594*	0.528
		(1.92)	(1.76)	(1.75)	(2.22)	(2.21)	(1.97)
Prop. Spread			-7.7				
			(-1.24)				
Eff. Spread				-7.32			
				(-0.81)			
N	1530260	1514869	1228477	1213384	1228477	1228477	1352803
adj. R^2	0.071	0.083	0.094	0.094	0.091	0.090	0.086



IV versus the Percentage of Zero Returns are shown for one representative month

Figure 1



All Variables are standardized with respect to their individual global mean and standard deviation.

Figure 2