Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility

Yufeng Han and David Lesmond *

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Abstract

We examine the cross-sectional relation between idiosyncratic volatility 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, biases the estimate of idiosyncratic volatility and the resulting pricing ability of idiosyncratic volatility. We model the microstructure influence on returns and derive a closed-form solution for the bias in the estimated idiosyncratic volatility. Motivated by this theory, our empirical results show that controlling for the liquidity costs on the estimation of idiosyncratic volatility diminishes to insignificance the ability of idiosyncratic volatility 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 idiosyncratic volatility. Finally, minimizing liquidity's influence on the estimated idiosyncratic volatility, by orthogonalizing the percentage of zero return and spread effects on the estimated idiosyncratic volatility, demonstrates that the resulting idiosyncratic volatility estimate has little pricing ability.

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

*Yufeng Han is in residence at the University of Colorado at Denver and David Lesmond is in residence at the Freeman School of Business, Tulane University.

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 quintiles of stocks sorted by idiosyncratic volatility earns an abnormal return of 1% 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 predicts one-month-ahead returns given the underlying return structure. We argue that liquidity costs, in terms of both the bid-ask bounce that biases the daily security returns (Blume and Stambaugh, 1983) and zero returns (Lesmond, Ogden, and Trzcinka, 1999) that affect the estimation of systematic risk elements, are important in understanding the causes of the mispricing of idiosyncratic volatility. We show, both theoretically and empirically, that the bid-ask bounce upward biases the idiosyncratic volatility estimate and the preponderance of zero returns affects idiosyncratic volatility due to biased systematic risk estimates. Controlling for the tandem effects of the bid-ask bounce and zero returns sufficiently reduces the bias in idiosyncratic volatility eliminating the pricing ability of idiosyncratic volatility. These results are consistent with the central paradigm of asset pricing and generally acknowledged importance of liquidity in asset pricing (Amihud and Mendelson, 1986; Acharya and Pedersen, 2005).

Huang, Qianqiu, Rhee, and Zhang (2009) and Fu (2009) offer a reversal effect as an alternative explanation for the pricing ability of idiosyncratic volatility. Huang, Qianqiu, Rhee, and Zhang (2009) argue that neglecting the return reversal effect (Jegadeesh, 1990) results in an omitted variable bias. Focusing only on the extreme value-weighted idiosyncratic volatility portfolios, they show that a specially constructed reversal "factor" reduces the pricing ability of idiosyncratic volatility to insignificance.[1] In contrast, our value-weighted regressions across all stocks,[2] performed in a manner identical to Ang, Hodrick, Xing, and Zhang (2009), show that the reversal effect, while negatively and significantly associated with future returns, does *not* eliminate the pricing ability of idiosyncratic volatility,[3] while the liquidity bias corrected idiosyncratic volatility estimate does eliminate the abnormal performance.

It should be noted that prior period returns are also used as a control for liquidity effects. For instance, Jegadeesh and Titman (1993), among many others, exclude the prior month's return to control for a liquidity cost effect on future returns. However, our model and findings focus on the mechanism that liquidity exerts on returns and precisely describe how liquidity affects the estimation of idiosyncratic volatility. Our treatment of the liquidity bias in returns due to microstructure noise is fundamentally different than using prior returns as a control for liquidity effects. The focus of attention is on the estimation of idiosyncratic volatility, not on the ex-poste testing of omitted variables.

Liquidity explanations (notwithstanding the use of the prior month's return as a liquidity cost proxy), have been extensively examined and refuted as an explanation for the pricing ability of idiosyncratic volatility. For example, Spiegel and Wang (2005) find that while liquidity proxies are positively associated with future returns, the relation between idiosyncratic volatility 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 idiosyncratic volatility and value-weighted returns persists even after controlling for the bid-ask spread liquidity measure. However, neither study addresses the inextricable impact of liquidity costs on the *estimation* of idiosyncratic volatility - an omission that engenders a liquidity bias in the estimated volatility and a multicollinearity bias in the reported

[1] Although not reported, we show that these results are not robust to the reversal "factor" construction. Using the reversal factor provided on Ken French's website, with an identical empirical specification for the time-series regression as employed by Huang et al. (2009), our time-series regression tests show the reversal effect cannot remove the pricing ability of idiosyncratic volatility.

[2] Ang, Liu, and Schwartz (2009) provide an analysis of the relative benefits of individual-security versus portfolio level analysis in empirical asset pricing applications. Fama and French (2008) also note that firms in the extreme quintiles have unusual distributional qualities stemming from differences in firm size.

[3] This also marks a departure from Fu (2009) who argues that the pricing ability of lagged idiosyncratic volatility noted in Ang, Hodrick, Xing, and Zhang (2006) is driven by a small subset of firms with high idiosyncratic volatility which he shows is somewhat associated with prior period returns. He construes this evidence as consistent with a return reversal effect. Our evidence shows the return reversal cannot explain the pricing of idiosyncratic volatility across all stocks.

results.

We conjecture that liquidity costs affect the measurement of idiosyncratic volatility in two ways. The first effect is due to the bid-ask bounce that increases the variance of the returns leading to an inflated idiosyncratic volatility 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[4] using the Blume and Stambaugh framework, we show that the bias in the idiosyncratic volatility estimate is proportional to $\sqrt{2}$ times the bid-ask spread. The size of the bias is substantial with even large firm portfolios recording an 18% increase in the estimated idiosyncratic volatility. 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 idiosyncratic volatility. 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.[5]

By using the underlying return structure that reflects liquidity costs as a central theme, our results indicate that Ang et al. (2006) findings hinge on the bias in the idiosyncratic volatility measurement, thereby suggesting significance for idiosyncratic volatility's pricing power that is, in fact, insignificant. Generally, these results also explain the findings of Bali and Cakici (2008) who find that different trading horizons, different breakpoints used to sort idiosyncratic volatility into quintiles, and different screens for price, size, and liquidity costs determine whether idiosyncratic volatility is priced. Their cross-sectional tests merely proxy for the liquidity effect on the estimate

[4] The advent of microstructure noise models in the literature is growing. Recently, Asparouhova, Bessembinder, and Kalcheva (2009) model microstructure noise in a similar framework to our model, but more generally, in equally weighted asset pricing tests and find significant effects on returns due to microstructure noise.

[5] Liquidity effects also extend to the measurement of the future return. Common tests of idiosyncratic volatility'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) idiosyncratic volatility estimate and a liquidity cost minimized future monthly return lead to the reported negative relation between idiosyncratic volatility and future returns.

of idiosyncratic volatility. The evidence suggests that testing liquidity's effect on the pricing of idiosyncratic volatility cannot be accomplished without first reflecting on liquidity's effect on the returns themselves. Thus, it cannot be argued that idiosyncratic volatility has more power than liquidity in explaining future returns (Spiegel and Wang, 2005), but rather that liquidity and the estimation of idiosyncratic volatility are intertwined. The resulting multicollinearity between idiosyncratic volatility and liquidity, evident in the quintile sorting tests utilized by Ang et al. (2006) or regression tests employed by Spiegel and Wang (2005), illustrates the importance of liquidity induced estimation bias in the statistical tests showing the pricing ability of idiosyncratic volatility.

We estimate the idiosyncratic volatility over a one month period from 1984 to 2008 in a manner consistent with Ang et al. (2006), and test for the pricing of idiosyncratic volatility using either quintile sorts or value-weighted Fama-MacBeth regressions.

We initially demonstrate the importance of our hypothesized zero return liquidity variable in double sorts of idiosyncratic volatility and the percentage of zero returns. The results show no significance in the idiosyncratic volatility pricing ability. To more directly control for the bias produced by the bid-ask bounce, we then estimate idiosyncratic volatility based on quote midpoint returns. Consistent with our theory, using quote midpoint returns reduces the magnitude of the idiosyncratic volatility estimate dramatically and changes the composition of firms in the largest idiosyncratic volatility portfolio greatly altering the reported pricing ability in the sort tests. Statistical tests of the extreme quintile portfolios that result using the quote midpoint idiosyncratic volatility estimate report no significant abnormal performance when using the four-factor Carhart alpha.[6] As a benchmark, the CRSP-based return (closing price) produces a highly significant difference between the extreme quintile portfolios regardless of using either the Fama-French or Carhart alpha.

We examine the effect of sudden and lasting (regulatory) changes in liquidity on idiosyncratic volatility estimates and pricing ability by exploiting exogenous liquidity shocks to the market. These periods are outlined by Bekaert, Harvey, and Lundblad (2007) who argue that when the

[6]The Fama-French alpha shows a much reduced level of the abnormal return and a much weaker significance level.

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 precipitously. We find that the ability of idiosyncratic volatility to predict future returns becomes insignificant from 1997 to 2008 using the Carhart alpha and insignificant from 2001 to 2008 using either the Fama-French alpha or the Carhart alpha.[7]

We control for the tandem liquidity effects by first regressing the idiosyncratic volatility estimates on both the percentage of zero returns and the spread. This procedure orthogonalizes the influence of both the zero returns and the spread effect on the volatility estimate. We then use the residual from this regression (termed the residual idiosyncratic volatility) in quintile sorts and in Fama-MacBeth regression tests. These tests specifically address the assertions of Spiegel and Wang (2005) who argue that idiosyncratic volatility is more powerful than is liquidity in predicting future returns.

We find that using quintile sorts of the residual idiosyncratic volatility do not produce a significant Fama-French or Carhart alpha. The Fama-French alpha for the spread between the extreme idiosyncratic volatility portfolios falls to -0.411% per month (from -1.338% per month in the baseline sort results), and the Carhart alpha falls to -0.272% per month (from -0.834% per month in the baseline sort results). These results clearly illustrate a liquidity induced estimation bias embedded in the idiosyncratic volatility estimate. Thus, idiosyncratic volatility results reported in the literature may reflect liquidity effects after all.

Extending the cross-sectional analysis to a value-weighted Fama and MacBeth (1973) framework[8] allows for controlling multiple influences on future returns that encompass one-month lagged returns (Huang, Qianqiu, Rhee, and Zhang, 2009) and six-month momentum returns (Jegadeesh and Titman, 1993), book-to-market (Daniel and Titman, 1997), coskewness (Harvey and Siddique, 2000), dispersion in analyst forecasts (Diether, Malloy, and Scherbina, 2002), institutional holdings

[7]We also find a general decline in the pricing ability of idiosyncratic volatility from 1992 to 2008 that corresponds to a secular reduction in both the percentage of zero returns and the bid-ask spread subsequent to 1992.

[8]Asparouhova, Bessembinder, and Kalcheva (2009) note that if return regressions are conducted using value-weighting, thereby mitigating microstructure noise bias in returns, then the cross-sectional regression will yield consistent parameter estimates, in the absence of other specification problems. This feature draws a distinction between our work and that of Asparouhova et al. in that our model shows microstructure noise still induces a bias in the idiosyncratic volatility estimate and the consequent pricing ability.

(Chen, Hong, and Stein, 2002), leverage (Johnson, 2004), and firm size. The baseline result is that idiosyncratic volatility 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, 2009). However, as is found in the quintile sorts, the residual idiosyncratic volatility is not significantly associated with future returns in the regressions, nor is the idiosyncratic volatility estimate based solely on quote midpoint returns.

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 idiosyncratic volatility measurement by Malkiel and Xu (2004) should consider the liquidity effect 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 value-weighted sorting results. Section 6 examines the effect that exogenous liquidity shocks exert on idiosyncratic volatility'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 idiosyncratic volatility'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 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 at time t 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[9] 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 $\beta^* = \beta(1 + \sigma_\delta^2)$. Setting $\hat{r}_t = \alpha + \beta X_t$ allows for a compact

[9]Note that in Asparouhova, Bessembinder, and Kalcheva (2009), if the regressors and the microstructure noise are not related, then their proposition 1 reduces down to Equation (9). The parameter that Asparouhova et al. calls λ becomes zero in this case, and the matrix that they call Γ becomes a diagonal $N \times N$ matrix (where N is the number of securities) with one plus the variances of the noise variables for the different securities on the diagonal.

representation of the error term[10] stated as:

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

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:

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

The last term of Equation (11) can be decomposed as follows:

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

Substituting Equation (12) for the last term of Equation (11), noting that the variance of ν_t equals σ_ν^2, and reflecting that the variance of ϵ_t is given in Equation (7) yield:

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

Expanding the last term in Equation (13) results in the bias described as follows:

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

[10] Asparouhova, Bessembinder, and Kalcheva (2009) are more focused on cross-sectional correlation than on endogeneity bias, while the endogeneity bias in our derivation is structurally embedded due to microstructure noise. Our endogeneity bias stems from the inclusion of $\hat{r}_t$ (representing $\alpha + \beta X_t$) into the error term ν_t^*. However, we would not anticipate any correlation between the market factor and the pricing noise so any endogeneity bias in our results would be minimal.

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[11] embedded in the return structure can yield an inflated idiosyncratic volatility 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 root mean square). 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 $\sqrt{2\sigma_\delta^2}$). This is then divided by $\sqrt{21}$ to convert the monthly bias to a daily bias to get the comparable values for the idiosyncratic volatility reported in the tables.

Based on averages from 1984 to 2008, large firms (i.e. those in the largest two size deciles) experience a closing price based idiosyncratic volatility of 1.048% with a corresponding average spread of 0.592%. The model would predict a bias of 0.183% (i.e. proportional bid-ask spread of 0.596% times 1.414 divided by $\sqrt{21}$). Thus the midquote idiosyncratic volatility would be predicted to have an idiosyncratic volatility estimate of 0.865% (or an 18% error in estimated idiosyncratic volatility). The actual estimate of idiosyncratic volatility using quote midpoints is 0.886%. This is both a sizeable percentage error and a very good estimate of the bias.

The smallest firms, and those with the highest idiosyncratic volatilities, would be expected to experience a larger bias, in absolute terms, due to higher spread costs. The spread costs are 3.564% and the estimated bias is 1.099%. Given a closing price estimated idiosyncratic volatility of 6.416%,

[11] Also of note, as shown in Asparouhova, Bessembinder, and Kalcheva (2009), with the restriction on λ and Γ, the difference between the true volatility and the estimated one is a function of the variance they call D_{nt}. Lemma 3 of Asparouhova et al. computes $Cov(D_{nt}, D_{nt-1})$. The computation of $Cov(D_{nt}, D_{nt})$ is analogous and after dropping the higher order terms, one gets to the same leading term as we derive, namely σ_δ^2.

we would predict a "true" idiosyncratic volatility of 5.316%. The actual estimate of idiosyncratic volatility using quote midpoints is 5.367%.

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 the 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.

The effect on idiosyncratic volatility due to an increasing percentage of zero returns is intuitively downward biased. In the limit, if we observe 100% zero returns, the total volatility is zero and, of course, the idiosyncratic volatility is zero. If the percentage of zero returns is lessened, then the bias on idiosyncratic volatility will be reduced.

However, we argue that the bid-ask spread directly affects the estimated idiosyncratic volatility through an inflation in the daily return, while the occurrence of zero returns indirectly biases idiosyncratic volatility through biased systematic risk elements. We would conjecture that as a result the bid-ask spread effect, by increasing the variance of the returns, on the idiosyncratic volatility would be a larger effect than would be the zero return effect.

The inflation (or bias) in the idiosyncratic volatility estimate differentially affects stocks because all stocks are not subject to identical bid-ask spreads. In the sort tests, the quote midpoint return based idiosyncratic volatility effectively alters the composition of firms in the extreme portfolios, relative to the sort using CRSP based closing return idiosyncratic volatility estimate. In the Fama-MacBeth tests, using the midquote based idiosyncratic volatility affects the mean in each cross-section. The sampling distribution then reflects both the mean in each cross-section and the variance of the mean across the time-series. Given that the correction for the inflation in the idiosyncratic volatility estimate, we would expect the mean in each cross-section to be reduced (relative to the closing return based idiosyncratic volatility), and the resulting sampling variance to be affected.

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 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 each month is then given as: $\hat{\sigma}_{it}$. We also delete any firm-month with less than five observations. 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 idiosyncratic volatility.

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 quintile 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 idiosyncratic volatility and return relation. Our sample runs from 1984:01 (January of 1984) to 2008:06 (June of 2008) for a total of 282 months. We specifically exclude the "crash" experienced at the end of 2008 to preclude an exogenous shock to the market induced by the sub-prime crisis and the failures of Lehman Brothers and Bear Stearns.

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 the proportional spread. The ISSM database covers NASDAQ firms from 1987 to 2008, and NYSE/AMEX firms from 1984 to 2008. We utilize the CRSP database for NASDAQ firms from 1984 to 1987 to complete our sample period from 1984 to 2008.

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.[12] The proportional spread is the ask minus the bid quote divided by

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

the midquote average. We also include the percentage of zero returns observed each month and we compute Amihud's measure each day and then average this estimate over the month.

3.3 Firm Attribute Controls

We also estimate the variables that have been shown to be related to future returns or idiosyncratic volatility. These include past returns, co-skewness risk, value versus growth, firm size, institutional holdings, analyst coverage, and leverage. Reversals in returns has been widely documented (see, e.g., Jegadeesh, 1990). Furthermore, Huang, Qianqiu, Rhee, and Zhang (2009) provide evidence that the cross-sectional pricing power of idiosyncratic volatility may be subsumed by one-month past returns. We extend the prior return controls by including the widely used six-month momentum return (see, e.g., Jegadeesh and Titman, 1993). Negative co-skewness risk is thought to be associated with higher returns (Harvey and Siddique, 2000), and idiosyncratic volatility may in part capture that element (Boyer, Mitton, and Vorkink, 2007). Johnson (2004) shows that raising information uncertainty about asset values leads to lower expected returns and consequently adding to idiosyncratic volatility. 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 quarterly Compustat[13] where we extract the book value of equity, and CRSP where we calculate the market value of equity as the month-end price multiplied by the number of shares outstanding, following Fama and French (1993). Using the monthly market value, we are able to compute a monthly book-to-market ratio. We delete any observations from the analysis that have either negative book-to-market ratios or missing information on the book value of the equity.

Roughly classified, institutional holdings and analyst following proxy for an information environment explanation for returns. The percentage of institutional holdings is taken from the

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.

[13]Quarterly book equity is calculated using Total Assets (item #6) - [Total Liabilities (item #181) + Preferred Stock (item #10)] + Deferred Taxes (item #35) + Convertible Debt (item #79).

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 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). To be consistent with Deither et al. and Johnson (2004) we use the standard deviation of forecasts.

4 Summary Statistics

We initially sort the stocks into quintiles by the percentage of zero returns to provide a relative comparison of idiosyncratic volatility with other explanatory variables that have been used to explain the idiosyncratic volatility 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 idiosyncratic volatility. The percentage of zero returns increases from 5.062% for the lowest quintile to 49.839% 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 idiosyncratic volatility estimates rise from 2.778% to 3.801% across the zero return quintiles, but reaching the maximum of 3.965% at the fourth quintile instead. The lack of a monotonic relation between idiosyncratic volatility and the percentage of zero potentially stems from non-linearity between idiosyncratic volatility and zero returns.

The increase in the zero returns is matched by an increase in the bid-ask spread costs that rise from 1.704% to 10.232% 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 spread's relation with idiosyncratic volatility illustrates the importance of *both* liquidity aspects in explaining idiosyncratic volatility's pricing ability.

The liquidity costs are also related to many of the potential explanatory variables used in Ang, Hodrick, Xing, and Zhang (2006) and Huang, Qianqiu, Rhee, and Zhang (2009). Lagged return displays a very interesting trend with a positive lagged return of 2.151% for the lowest zero return quintile that reverts to a negative return of 0.442% for the highest zero return quintile. This trend is matched by the six-month momentum return. The highest zero return quintile also contains more value stocks than does the low zero return quintile as evidenced by the increase in the book-to-market across the zero return portfolios. The highest zero return portfolio is dominated by smaller firms and small firms are known to experience higher liquidity costs. The highest zero return category is also matched by the highest dispersion in analyst forecasts and the lowest level of institutional holdings. Finally, leverage does appear somewhat related to idiosyncratic volatility, but more to the level of the percentage of zero returns (liquidity costs). Downside risk, or co-skewness, displays little trend with either the percentage of zero returns or with idiosyncratic volatility.

5 Value-Weighted Idiosyncratic Volatility Sort Results With Liquidity Controls

In this section, we present the various sort results of idiosyncratic volatility quintiles that illustrate the influence of zero returns and the bid-ask spread on idiosyncratic volatility'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 idiosyncratic volatility 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 idiosyncratic volatility 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 idiosyncratic volatility'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 idiosyncratic volatility. The structure of this test relies on Ang et al. (2006) who utilize a double sort in their examination of alternative variables, including the bid-ask spread, on the abnormal pricing of idiosyncratic volatility.

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.[14] Then within each liquidity group we further sort stocks into five quintiles according to their idiosyncratic volatility estimates. We then form value-weighted portfolios within each of the idiosyncratic volatility quintiles. Hence, we hold liquidity effects relatively constant while allowing idiosyncratic volatility 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[15] on the abnormal return measurement. Table 2 reports the abnormal performance of the idiosyncratic volatility quintile portfolios and the High-Low arbitrage portfolio within each liquidity category.

As reported in Panel A of Table 2, the bid-ask spread is not effective in controlling for idiosyncratic volatility'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 idiosyncratic volatility portfolio is monotonically increasing with increasing spread costs, and is significant for all but the lowest spread category, reaching a peak of -1.694% per month for the highest spread category. However, the results do indicate that for low spread cost firms idiosyncratic volatility cannot predict future returns highlighting a liquidity cost influence on the

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

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

inferences for idiosyncratic volatility. This would be confirmatory that the spread and idiosyncratic volatility are highly correlated, but that controlling for liquidity's effect *after* the estimation of idiosyncratic volatility only reflects a multicollinearity bias.

Far different results are obtained by controlling for the zero returns. Panel B of Table 2 reports a significantly reduced ability of idiosyncratic volatility's ability to predict future returns regardless of the zero return categories, although the pricing ability of idiosyncratic volatility for the lowest percentage of zero returns is very close to significance. Increasing the percentage of zero returns, does significantly reduce the pricing ability of idiosyncratic volatility. However, the lack of sufficient variability in the percentage of zero returns precludes a finer delineation in the sort tests.

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 idiosyncratic volatility. Using daily returns exacerbates the effect that both zero returns and microstructure noise exerts on the measurement of idiosyncratic volatility. In particular, the bid-ask spread affect on the pricing of idiosyncratic volatility are more in evidence during the estimation phase than in the ex-post testing phase.

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

To operationalize our microstructure model we employ the quote midpoints to address the microstructure noise that may be evident in the estimate of idiosyncratic volatility. 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 midpoint 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 idiosyncratic volatility measurement, we also present the idiosyncratic volatility measured using the closing returns provided by CRSP.[16]

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 idiosyncratic volatility, form quintile-sorted portfolios, and then difference the highest and lowest idiosyncratic volatility quintiles. Specifically, at the beginning of each month, stocks are sorted into five quintiles based on the idiosyncratic volatility 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 idiosyncratic volatility (High) and the portfolio with the lowest idiosyncratic volatility (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 Fama-French alpha of the arbitrage portfolio is -1.338% per month with a robust t-statistic of 4.75, a result comparable to that of Ang, Hodrick, Xing, and Zhang (2006). This result shows that even with an alternative time span, the idiosyncratic volatility is still significantly related to future returns. The Carhart alpha is -0.83% per month and highly significant, which suggests that including a systematic momentum factor does not sufficiently control for the idiosyncratic volatility's ability to predict one-month ahead returns although it does reduce the level of abnormal performance. As found by a host of prior research, the abnormal performance appears to be most evident in the highest idiosyncratic volatility 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 idiosyncratic volatility quintile to the highest

[16] Also, because our sample period, from 1984 to 2008, 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 idiosyncratic volatility effect for this alternative time period.

ranked idiosyncratic volatility quintile. The percentage of zero returns rises from 7.02% for the Low idiosyncratic volatility quintile, to 13.24% for the High idiosyncratic volatility quintile. This trend is also matched by the spread that rises from 0.59% to 3.56%. This trend is important because it highlights the effect that the return structure has on the estimated idiosyncratic volatility.

We now turn to quote midpoints to better focus on the "true" return before estimating idiosyncratic volatility. As shown in Table 3, the quote midpoint estimated idiosyncratic volatility's are demonstrably less than is measured using CRSP closing returns. The benchmark High-Low idiosyncratic volatility from the CRSP based returns is 5.368% while the High-Low quote midpoint based idiosyncratic volatility is significantly reduced to 4.481%, or a 16% reduction in the estimated idiosyncratic volatility. As would be expected for a microstructure influence, most of the reduction is garnered in the High idiosyncratic volatility quintile that witnesses a decline to 5.367% (from the benchmark 6.416%). This clearly illustrates the inflation in idiosyncratic volatility due to microstructure noise and is entirely consistent with our microstructure theory.

The effect on abnormal performance using quote midpoint based idiosyncratic volatility is striking. Controlling for the microstructure noise in the computed return shows that while the Fama-French alpha of -0.943% remains significant, it is greatly reduced from the CRSP based results of -1.338%. The reduction is almost 30%. However, the Carhart alpha, that specifically controls for a momentum effect on the abnormal performance also reports a greatly reduced abnormal performance of only -0.510% (baseline result of -0.834%), but is *insignificantly* different from zero. The bid-ask bounce plays a considerable role in estimation of idiosyncratic volatility and in the subsequent performance of idiosyncratic volatility in predicting future returns.

6 Exogenous Shock to Liquidity: Value-Weighted Idiosyncratic Volatility 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.

6.1 Exogenous liquidity shock periods

Figure 1 shows a standardized plot of the average percentage of zero returns, the average bid-ask spread, and the average idiosyncratic volatility from 1984 to 2008. As is clearly shown, 1997 marks a significant and precipitous decline in the percentage of zero returns that progresses through the decimalization of all 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 idiosyncratic volatility does trend downward from 2001 to 2008. The "volatility" in the idiosyncratic volatility during the 1999 to 2002 period will work against the liquidity cost hypothesis.[17]

We focus on the period from 1997 to 2008 to encapsulate the change to sixteenth pricing in Panel A of Table 4, and the period from 2001 to 2008 to encapsulate the change to decimal pricing in Panel B of Table 4. Unlike using monthly returns commonly utilized in GARCH model applications,

[17]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 2001, idiosyncratic volatility is trending downward, consistent with the findings of Brandt, Brav, Graham, and Kumar (2008). Indeed, from 1992 to 2008 both the percentage of zero returns and idiosyncratic volatility can be seen to more gradually decline. The downward trend in idiosyncratic volatility is somewhat contrary to Cao, Simin, and Zhao (2008) who argue that growth options can explain the increasing trend in idiosyncratic volatility over time because growth options were increasing from 1992 to 2000, yet idiosyncratic volatility is seen to decrease over that time period. These results would indicate that liquidity costs have more to do with idiosyncratic volatility than do growth options.

using daily returns in estimating idiosyncratic volatility will allow for an exact identification of these periods. Again, we focus on NYSE/Amex/NASDAQ stocks.

As shown in Panel A of Table 4, the sort results report a marked decline in the percentage of zero returns across all the idiosyncratic volatility quintiles, ranging from 1.886% to 3.337%, when compared to the whole sample period from 1984 to 2008 where the percentage of zero returns are ranging form 7.018% to 13.242% across the idiosyncratic volatility quintiles (shown in Table 3). The spread costs are also shown to decrease, but the decrease is most evident in the highest idiosyncratic volatility quintile, where it demonstrates a decrease to 1.157% from the baseline case of 3.573% (shown in Table 3). The increased underlying dispersion in idiosyncratic volatility exhibited during the NASDAQ bubble from 1999 to 2002 is evident. The idiosyncratic volatility shows a marked increase from 1.119% for the low idiosyncratic volatility quintile to 6.199% for the high idiosyncratic volatility quintile. The resulting High-Low idiosyncratic volatility of 5.080% is somewhat reduced from the baseline result of 5.373%. However the reduced bias exerted by the zero returns and the bid-ask spread alters the composition of firms in the highest idiosyncratic volatility quintile causing a very different effect on the abnormal performance.

The resulting High-Low Carhart alpha does *not* display significance in any of the idiosyncratic volatility quintiles nor does it register significance in the High-Low abnormal performance. The reported High-Low Carhart alpha is reduced to -0.445% per month down from -0.830% per month obtained in the period from 1984 to 2008. The abnormal performance is not even marginally significant displaying a t-statistic of only 1.21. The Fama-French alpha is -0.991% 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 2008 experiences a degradation in idiosyncratic volatility performance of more than 35%. We would argue that this decrease in the idiosyncratic volatility's ability to predict returns is likely due to the decreased level of zero returns, as well as reduced spread costs subsequent to 2001.

Turning to the 2001 to 2008 period in Panel B shows an even more marked decline in the estimate of the idiosyncratic volatility and in the pricing ability of idiosyncratic volatility. For this time period, the High-Low idiosyncratic volatility estimate is reduced to 4.437% demonstrating the microstructure influence of a reduced bid-ask spread.

The Fama-French alpha is greatly reduced to only -0.284% per month and insignificant. The Carhart alpha is now *positive* at 0.028% per month and also insignificant. We conjecture that the insignificance in the pricing ability of idiosyncratic volatility 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 idiosyncratic volatility quintile. The reduction in the spread minimizes the microstructure influence on the estimation of idiosyncratic volatility 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 idiosyncratic volatility's pricing ability.

We provide the following caveat in this experiment. While our results show little ability of idiosyncratic volatility in explaining future returns, the results are subject to a statistical power concern. The relative brevity of the sample period from 2001:04 to 2008:06 may not allow for sufficient power in the statistical tests.

7 Regression Residual Approach and Quote MidPoint Returns

Spiegel and Wang (2005) argue that idiosyncratic volatility is more powerful than is liquidity in explaining future returns. The problem in testing the relative strength of liquidity over idiosyncratic volatility is that idiosyncratic volatility 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 idiosyncratic volatility with the percentage of zero returns and the spread and attempt to disentangle the liquidity effects from the idiosyncratic volatility effects in predicting future returns by examining the residual of a regression of idiosyncratic volatility on the liquidity cost measures. The use of the regression residual to orthogonalize collinear effects in a Fama-MacBeth setting has been utilized by Johnson (2004).

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

In Table 5, we attempt to provide some statistical merit to our graphical depiction of the relation between the zero returns and spread with the idiosyncratic volatility estimate shown in Figure 1. For robustness in modeling the zero return and the spread effect, we present a number of separate regression specifications. First, we model the spread effect using linear and non-linear spread influences, evident in the sort results of Table 3, along with the percentage of zero returns. The inclusion of the squared spread is consistent with our theory because it is a higher order term in the derivation of the bias. Although its influence is small compared to the linear effect it does have incremental value. Second, we include an interaction term for the joint zero return and bid-ask spread effect on the idiosyncratic volatility estimation because Lesmond, Ogden, and Trzcinka (1999) note that the percentage of zero returns is a proxy for the spread. The regression is estimated each month over the period from 1984 to 2008 and is generally stated as

$$\text{Idiosyncratic Volatility} = \alpha_0 + \alpha_1\%\text{Zeros} + \alpha_2\text{Spread} + \alpha_3\text{Spread}^2 + \alpha_4\%\text{Zeros} \times \text{Spread} + \epsilon. \quad (17)$$

The results of Table 5 indicate that the spread alone explains 33% of the cross-sectional variation in the idiosyncratic volatility. In addition, the linear term of the spread is positively related to idiosyncratic volatility and the non-linear (squared) term of the spread is negatively related to idiosyncratic volatility[18] indicating that idiosyncratic volatility is concave with respect to the spread.

The zero returns are negatively related to the idiosyncratic volatility which is intuitively expected. As the zero returns increase, in the limit, the resulting idiosyncratic volatility would be driven to zero. Including the interactive term does not reduce the significance of either the zero returns, the spread, or the square of the spread. This is important because the correlation between the zero returns and the spread (Lesmond, Ogden, and Trzcinka, 1999) may have affected the direct

[18] 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 findings because high spread firms tend to have large mispricing as shown in Table 3.

liquidity influences.

Finally, we include a measure of trade difficulty that is conveniently estimated by Amihud's measure (Amihud, 2002). Table 5 does show that Amihud's price impact measure is positively and significantly related to idiosyncratic volatility. Thus, idiosyncratic volatility appears to be dependent on liquidity, regardless of how liquidity is measured.

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

7.2 Value-weighted residual idiosyncratic volatility sort results: Spread and zero returns

Each month, we sort stocks into quintiles by the estimated residual idiosyncratic volatility, form value-weighted quintile portfolios, and compare the abnormal performance of the quintile portfolios and the High-Low arbitrage portfolio. As a point of reference, Fama and French (2008) also use regression residuals in quintile sort tests. This test is performed over the period 1984 to 2008. The results are reported in Panel A of Table 6. In Panel B of Table 6 we replace the CRSP closing price idiosyncratic volatility with the quote midpoint idiosyncratic volatility. We perform this later test to control for the zero returns, that occur using the quote midpoint prices, on the estimated idiosyncratic volatility.

As is shown in Panel A, none of the idiosyncratic volatility quintile alphas are significant and many are now positive. This is found regardless of using either the Fama-French or the Carhart basis of determining abnormal performance. The lack of significance in abnormal performance extends to the High-Low extreme quintile difference. The Fama-French High-Low alpha is reduced (from the baseline case of -1.338% shown in Panel A of Table 3) to -0.411%. This is a 70% reduction in the High-Low abnormal pricing ability of idiosyncratic volatility. 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 idiosyncratic volatility quintile.

The Carhart alpha of the High-Low residual idiosyncratic volatility portfolio is only -0.272% per month and also insignificant, suggesting no pricing ability in idiosyncratic volatility over and above liquidity cost influences. These results are indicative of the "problem" of testing for a liquidity cost effect *after* the estimation of idiosyncratic volatility and illustrate the liquidity cost component embedded in the estimate of idiosyncratic volatility.

For robustness, we show the added influence of the zero returns on the quote midpoint based idiosyncratic volatility in Panel B of Table 6. As is shown, the zero returns do affect the pricing ability of idiosyncratic volatility over and above the spread effect. For this set of tests, we note that the Carhart alpha's is reduced to -0.349% (from the baseline result in Table 3 of -0.510%) and insignificant.

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

7.3 Value-weighted residual idiosyncratic volatility sort results: Amihud's measure

Our theory is predicated on a liquidity effect on returns that affects the estimate of idiosyncratic volatility. However, it could be argued that firms with both higher spreads and zero returns are more illiquid and hence harder to arbitrage. In effect, trade difficulty and liquidity are so intertwined that controlling for the spread and zero returns in the orthogonalization approach does nothing more than control for arbitrage difficulty in the estimate of idiosyncratic volatility. Amihud's measure has been used in tests of asset pricing (Acharya and Pedersen, 2005) to determine if trade difficulty is important. We will use the residual of idiosyncratic volatility on Amihud's measure to determine if controlling for arbitrage difficulty in the estimate of idiosyncratic volatility can explain the pricing of idiosyncratic volatility.

The quintile sort results are shown in Table 7. As is shown in Panel A of Table 7, the Amihud based residual does *not* remove the pricing ability of idiosyncratic volatility. Both the Fama-French and Carhart alphas are negative and highly significant.

A natural question may arise that using Amihud's measure alone may not be the proper basis of comparison with the prior spread and zero return residual idiosyncratic volatility regressions. To address this concern, we include the zero returns to estimate the residual idiosyncratic volatility. The results are shown in Panel B of Table 7. The results of Panel B clearly show that trade difficulty cannot explain the pricing ability of idiosyncratic volatility regardless of the specification for the regression residual.

These results are instructive for two reasons. First, the significance of the residual idiosyncratic volatility using Amihud's measure clarifies the importance of the spread and to a lesser extent the zero returns in explaining the pricing ability of idiosyncratic volatility. Second, only the spread and zero returns, that affect the return structure and consequently the estimate of idiosyncratic volatility, lead to significant improvements in the performance of the asset pricing models.

7.4 Fama-MacBeth regression tests

The prior sorting results provide one picture of the relation between idiosyncratic volatility and returns, but they focus primarily on the extreme portfolios. In order to gain some insight on the overall behavior of the idiosyncratic volatility 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 nine 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 (2009) that isolate information effects, momentum returns, reversal effects, firm controls, and market effects. These controls encompass one month lagged returns (Huang, Qianqiu, Rhee, and Zhang, 2009), and six-month momentum returns (Jegadeesh and Titman, 1993), book-to-market (Daniel and Titman, 1997), coskewness (Harvey and Siddique, 2000), dispersion in analyst forecasts (Diether, Malloy, and Scherbina, 2002), institutional holdings (Chen, Hong, and Stein, 2002), leverage (Johnson, 2004), and firm size. Also, we include the contemporaneous Fama-French risk measures as modeled in Ang, Hodrick, Xing, and Zhang (2009). 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, in addition to Amihud's measure, the percentage of zero returns and interactive liquidity terms, to corroborate the collinearity issues evident in the Spiegel and Wang (2005) results. We also use the CRSP based (closing price) idiosyncratic volatility as well as the residual idiosyncratic volatility, the quote midpoint based idiosyncratic volatility, and the midquote residual idiosyncratic volatility. 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 idiosyncratic volatility. Second, it expressly examines the incremental ability of idiosyncratic volatility in predicting returns after controlling for liquidity influences on the estimation of idiosyncratic volatility itself. Our microstructure theory posits that the estimated idiosyncratic volatility is upward biased due to microstructure noise and this regression test will highlight that hypothesis.

To be entirely consistent with Ang, Hodrick, Xing, and Zhang (2009), we employ a value-weighted Fama-MacBeth regression using firm size at the beginning of the month as the weight.

The general specification is given as:

$$
\begin{aligned}
\text{Return}_{i,t} = \alpha_0 &+ \alpha_1 \text{Idiosyncratic Volatility}_{i,t-1} + \alpha_2 \beta_{mkt,t} + \alpha_3 \beta_{smb,t} + \alpha_4 \beta_{hml,t} \\
&+ \alpha_5 \text{Lagged Return}_{i,t-1} + \alpha_6 \text{Momentum Return}_{i,t-6} + \alpha_7 \text{Ln(Book-to-Market)}_{i,t-1} \\
&+ \alpha_8 \text{Ln(Firm Size)}_{i,t-1} + \alpha_9 \text{Coskewness}_{i,t-1} + \alpha_{10} \text{Dispersion}_{i,t-1} + \alpha_{11} \text{Inst. Holdings}_{i,q-1} \\
&+ \alpha_{12} \text{Leverage}_{i,t-1} + \alpha_{13} \text{Liquidity}_{i,t-1} + \epsilon,
\end{aligned}
\tag{18}
$$

where the subscript t represents the month for each variable and q represents the quarter for the institutional holdings reflecting the frequency of observation. We employ four separate idiosyncratic volatility estimates. These include the idiosyncratic volatility computed from CRSP-closing returns, the residual idiosyncratic volatility, the idiosyncratic volatility estimated using the quote midpoint, or the residual idiosyncratic volatility using the quote midpoint based idiosyncratic volatility. Liquidity represents Amihud's measure, the proportional spread, the percentage zero returns, the squared spread, and an interaction term for the zero returns and the spread. The regression results are presented in Table 8 for NYSE/Amex/NASDAQ exchange listed firms.

The reversal effect (lagged return) is measured using the one month return occurring over the estimation period of idiosyncratic volatility or during t-1. The six-month return is the cumulative return accruing from month t-6 to t-2 so as not to overlap with the lagged return. Book-to-market is calculated by dividing the book equity (following Fama and French (1993)) from the quarterly Compustat by the market value of equity each month from CRSP. Leverage is defined as the sum of long and short term debt divided by the sum of debt and market value of equity consistent with that used by Johnson (2004).

The first prominent result in Table 8 is that the CRSP closing return based idiosyncratic volatility remains significantly related to future returns regardless of the controls included. The estimated marginal effect of idiosyncratic volatility on future returns ranges between 15 and 22 basis points depending on the control variables included in the regression. Contrary to Fu (2009) or Huang, Qianqiu, Rhee, and Zhang (2009), the reversal effect (lagged return) does *not* control for the pricing ability of idiosyncratic volatility. Including institutional holdings, dispersion in analyst forecasts, and leverage noticeably reduces the pricing ability of idiosyncratic volatility. The momentum effect, so prominent in the sort results with the Carhart alpha, is significant in the CRSP based idiosyncratic volatility results, but insignificant in any of the liquidity based idiosyncratic volatility estimates.

Consistent with the results of Spiegel and Wang (2005), idiosyncratic volatility appears to dominate liquidity in its relation to future returns regardless of how liquidity is defined (i.e. using the price of immediacy (spread), price impact (Amihud's measure), or a very general liquidity cost measure (percentage of zero returns)). In fact, the spread even has the wrong sign, although value-weighting could possibly affect these inferences. These results are telling because they point to the multicollinearity bias that is evident in Spiegel and Wang (2005) and illustrate the importance of modeling the spread effect on the idiosyncratic volatility before testing is performed.

This is brought into sharper focus by using the residual of the regression specified in Equation (17) that reports far different results for the pricing ability of idiosyncratic volatility. These results are shown in columns six, seven, and eight of Table 8. Now the residual of CRSP closing return based idiosyncratic volatility (labeled "CRSP Residual Idiosyncratic Volatility") 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 idiosyncratic volatility and liquidity allows for a specification that specifically tests whether idiosyncratic volatility alone (without the liquidity influence) is associated with future returns. The residual coefficient would indicate that the marginal effect of the pure idiosyncratic volatility (i.e. without the liquidity influence) is now only 10.5 basis points and insignificant. This represents a 35% reduction in the incremental influence indicating that liquidity represents a very large influence on the estimate of idiosyncratic volatility. Removing liquidity's influence on idiosyncratic volatility also removes the significance of idiosyncratic volatility in predicting future returns.

We also focus on the quote midpoint as a basis of estimating the idiosyncratic volatility (labeled "MidQuote Return Idiosyncratic Volatility"). This result is shown in the column seven of Table 8.

As is shown, the change in the marginal effect of idiosyncratic volatility on future returns is dramatic. The incremental effect of idiosyncratic volatility is now only 8 basis points. Moreover, the significance level of the resultant association is greatly reduced. We would argue that this insignificant result, in conjunction with the residual idiosyncratic volatility results, demonstrates that the pricing power of idiosyncratic volatility is subject to the underlying liquidity costs embedded in idiosyncratic volatility.

Finally, we use the midquote residual idiosyncratic volatility in the last column of Table 8. This specification for idiosyncratic volatility controls for the percentage of zero returns observed even though quote midpoint returns are used to estimate the idiosyncratic volatility. As is shown, the incremental effect of idiosyncratic volatility is reduced to a mere 7 basis points. That is less than half the incremental effect without the liquidity correction on the estimated idiosyncratic volatility. The liquidity bias corrected idiosyncratic volatility results highlight the power of the spread and zero returns, and their influence on returns, to alter the ability of idiosyncratic volatility to predict future returns.

7.5 Sub-period Fama-MacBeth regression tests

The idiosyncratic volatility pricing effect has been shown to be weakening to insignificance from 1997 to 2008; a period that corresponds to regulatory changes instituted subsequent to 1997. However, as shown in Figure 1, a gradual reduction in both the zero returns and the spread subsequent to 1992 can be observed. We have no economic rationale why the liquidity costs declined subsequent to 1992, but a natural question arises whether the reduction in zero returns and spread costs has affected the pricing ability of idiosyncratic volatility. We will extend the sub-period analysis to the period from 1984 to 1992 for completeness and where idiosyncratic volatility is significant, we will determine if the quote midpoint return based idiosyncratic volatility can reduce the pricing ability to insignificance. We present these results based on a Fama-MacBeth specification and utilize all the previous control variables except institutional holdings, dispersion in analyst forecast, and leverage. We are using a parsimonious regression specification to maximize the idiosyncratic volatility effect on future returns. The results are presented in Table 9.

As shown in Table 9, consistent with our prior sort results, the period from 1997 to 2008 and from 2001 to 2008 all show insignificant pricing ability of idiosyncratic volatility. However, the period from 1992 to 2008 also demonstrates no significant pricing ability of idiosyncratic volatility that corresponds exactly with the decline in both the zero returns and the spread. This result indicates that the spread and zero return effect on the pricing of idiosyncratic volatility is not a general market efficiency notion as postulated by Chordia, Roll, and Subramanyman (2008). They postulate that the tick size reduction in 1997 and 2001 led to a marked improvement in market efficiency, or return predictability from past information that is short lived. The tick size did not change until 1997, while the pricing ability of idiosyncratic volatility has been diminished to insignificance five years prior to the conversion to sixteenth based quotes and ten years prior to the decimalization date.

Finally, Table 9 shows the pricing ability of idiosyncratic volatility concentrated in the period from 1984 to 1992. The incremental effect of 44 basis points is highly significant. However, estimating the idiosyncratic volatility on a quote midpoint basis drastically reduces the pricing ability of idiosyncratic volatility to insignificance. The incremental effect is now reduced to a mere 12 basis points. This result further shows that the pricing ability of idiosyncratic volatility is highly dependent on the underlying liquidity costs that affect returns. These liquidity costs, embodied by the bid-ask spread and the zero returns, bias the idiosyncratic volatility estimate leading to spurious pricing ability.

8 Conclusions

We analyze the empirical relation between cross-sectional idiosyncratic volatility and expected stock returns. The literature has presented a very vexing set of results with Ang, Hodrick, Xing, and Zhang (2006) finding that idiosyncratic volatility 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 frictions (short-sale constraint), and liquidity, while others question the robustness of the findings.

We show that microstructure influences are fundamental to the estimation of idiosyncratic volatility and in the value-weighted idiosyncratic volatility'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 idiosyncratic volatility leading to the observed negative relation with future returns. In effect, the idiosyncratic volatility estimated from the standard methodology has an embedded liquidity component. We find that controlling for the liquidity cost effect on idiosyncratic volatility estimation, either by examining the returns derived from quote midpoints or by filtering by the zero returns, can significantly reduce idiosyncratic volatility'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 idiosyncratic volatility in predicting future returns.

The importance of the findings lies in the link to existing microstructure influences clearly noted 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 idiosyncratic volatility is complete. We raise the issue whether the estimation of idiosyncratic volatility 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 idiosyncratic volatility 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 idiosyncratic volatility's ability to predict future returns is premature.

More telling is the recent work by Ang, Hodrick, Xing, and Zhang (2009) 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 presumably much higher than in the US, we suspect that the strong relation between idiosyncratic volatility 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 idiosyncratic volatility should account for the bid-ask bounce in returns before concluding that idiosyncratic volatility is priced, rather than testing for a liquidity cost effect after the estimation of idiosyncratic volatility. 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 using the CRSP-based closing returns each month. Lagged return (reversal) is the prior month return and six month momentum is the return measured from t-6 to t-2. Book-equity is taken from the quarterly Compustat and monthly book-to-market is calculated using firm size each month. Firm size is month-end price multiplied by the shares outstanding. Co-skewness 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). Analyst dispersion is the standard deviation of the one-year ahead earnings forecast provided by I/B/E/S and is measured monthly. Institutional holdings are 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. Finally, leverage is the total debt divided by total debt plus the market value of equity and is taken from Compustat and CRSP. Our sample period runs from 1984:1 to 2008:6 for a total of 294 months and this period encapsulates the bid-ask spread observations. High - Low is the difference between the highest (High) quintile and the lowest (Low) quintile for each respective variable. Significance at the 1% level and 5% level is given by an ** and an *, respectively.

Rank	%Zeros	Idiosyncratic Volatility (%)	Spread(%)	B/M	Size	Lagged Return(%)	6-month Momentum(%)	Co-Skewness	Analyst Dispersion	Institutional Holdings	Leverage
Low	5.062**	2.778**	1.704**	0.563**	3287.972**	2.151**	11.185**	-0.010**	0.042**	50.637**	0.225**
	(6.56)	(23.51)	(11.66)	(33.51)	(10.90)	(6.34)	(7.38)	(-4.43)	(3.24)	(30.33)	(36.84)
2	13.570**	3.811**	3.287**	0.739**	1098.064**	4.101**	2.693	-0.008	0.061**	36.289**	0.264**
	(9.88)	(26.29)	(22.70)	(37.55)	(9.06)	(5.89)	(1.60)	(-1.75)	(23.42)	(33.65)	(51.96)
3	19.613**	3.580**	3.831**	0.739**	845.532**	1.194**	4.332**	-0.018**	0.061**	32.623**	0.271**
	(9.59)	(23.97)	(11.32)	(30.05)	(5.00)	(4.08)	(3.29)	(-7.11)	(10.36)	(16.92)	(37.40)
4	28.683**	3.965**	5.318**	0.817**	394.569**	0.686*	1.345	-0.018**	0.098**	24.586**	0.291**
	(10.43)	(24.81)	(12.08)	(25.75)	(4.01)	(2.04)	(0.94)	(-7.54)	(4.92)	(15.98)	(35.92)
High	49.839**	3.801**	10.232**	0.906**	114.669**	-0.442	-0.571	-0.015**	0.664	15.409**	0.307**
	(11.02)	(21.20)	(8.88)	(31.30)	(4.39)	(-1.68)	(-0.44)	(-8.06)	(1.51)	(11.42)	(39.77)
High - Low	44.777**	1.023**	8.527**	0.343**	-3173.303**	-2.593**	-11.756**	-0.004*	0.622	-35.228**	0.083**
	(11.78)	(8.41)	(7.97)	(11.31)	(-10.95)	(-9.78)	(-10.45)	(-2.21)	(1.45)	(-45.65)	(8.67)

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 sorted portfolios. For each liquidity measure, the spread and the percentage of zero returns, we perform double sorts by first sorting on the liquidity measure and then, within these partitions, further sorting on idiosyncratic volatility. Panel A reports the sort results using the proportional bid-ask spread and Panel B reports the sort results using the percentage of zero returns. "%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 idiosyncratic volatility (High) quintile and the lowest idiosyncratic volatility (Low) quintile. Significance at the 1% level and 5% level is given by an ** and an *, respectively.

	Rank of Idiosyncratic Volatility					
	Low	2	3	4	High	High - Low
Panel A: Carhart Alpha - Double Sort with Spread						
Spread Low	0.086	0.019	-0.042	0.119	0.008	-0.079
	(1.12)	(0.28)	(-0.52)	(1.10)	(0.04)	(-0.30)
Spread 2	-0.043	0.003	-0.220	-0.226	-0.855**	-0.811*
	(-0.32)	(0.03)	(-1.55)	(-1.66)	(-3.86)	(-2.57)
Spread High	0.256	0.073	-0.164	-0.414	-1.438**	-1.694**
	(1.46)	(0.44)	(-0.67)	(-1.23)	(-3.90)	(-4.69)
Panel B: Carhart Alpha - Double Sort with %Zeros						
%Zeros Low	0.011	-0.054	-0.045	-0.039	-0.539*	-0.550
	(0.15)	(-0.82)	(-0.46)	(-0.25)	(-2.33)	(-1.94)
%Zeros 2	0.172	0.096	0.216	-0.353	-0.309	-0.481
	(1.60)	(0.82)	(1.12)	(-1.41)	(-0.89)	(-1.30)
%Zeros High	0.122	0.201	-0.042	-0.204	-0.314	-0.436
	(1.00)	(0.88)	(-0.26)	(-0.80)	(-0.81)	(-1.14)

Table 3: Idiosyncratic Volatility Estimated from CRSP Returns and MidQuote Prices

We estimate idiosyncratic volatility using both the CRSP provided closing returns in Panel A and by computing daily returns using the midquote 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 rank them into quintiles. Attached to each idiosyncratic volatility portfolio are the percentage of zero returns, the spread, and the monthly excess return. The sample period runs from 1984:1 to 2008:6 for 294 monthly observations. The row labeled High-Low refers to the difference between the portfolio in the highest quintile and the lowest quintile for each variable. The abnormal performance of each of the portfolios is measured using the three factor Fama-French Alpha or using the four-factor Carhart Alpha (Carhart, 1997). 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	Idiosyncratic Volatility(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: CRSP Closing Price Estimated Idiosyncratic Volatility						
Low	1.048**	7.028**	0.596**	0.707**	0.111	0.050
	(27.08)	(9.29)	(11.93)	(3.58)	(1.81)	(0.71)
2	1.737**	6.762**	0.812**	0.586*	-0.088	-0.011
	(31.30)	(9.11)	(12.49)	(2.29)	(-1.10)	(-0.16)
3	2.534**	8.082**	1.139**	0.576	-0.081	0.029
	(29.57)	(8.82)	(11.80)	(1.79)	(-0.77)	(0.33)
4	3.668**	10.040**	1.767**	0.170	-0.445**	-0.210
	(28.65)	(8.67)	(9.89)	(0.40)	(-2.82)	(-1.40)
High	6.416**	13.240**	3.564**	-0.575	-1.227**	-0.783**
	(29.40)	(8.90)	(9.04)	(-1.17)	(-5.14)	(-3.38)
High - Low	5.368**	6.213**	2.969**	-1.283**	-1.338**	-0.834**
	(28.48)	(7.62)	(7.94)	(-3.06)	(-4.75)	(-3.04)
Panel B: MidQuote Price Estimated Idiosyncratic Volatility						
Low	0.886**	6.101**	0.623**	0.648**	0.079	0.035
	(25.01)	(8.35)	(12.14)	(3.26)	(1.23)	(0.50)
2	1.418**	4.121**	0.695**	0.658**	0.022	0.072
	(27.91)	(8.73)	(12.92)	(2.86)	(0.39)	(1.39)
3	2.063**	4.673**	0.894**	0.555	-0.104	0.041
	(27.30)	(8.77)	(13.29)	(1.75)	(-0.97)	(0.40)
4	2.987**	6.175**	1.206**	0.443	-0.169	0.020
	(27.73)	(8.22)	(12.11)	(1.10)	(-1.14)	(0.14)
High	5.367**	9.265**	2.152**	-0.300	-0.864**	-0.475
	(30.73)	(8.08)	(10.19)	(-0.61)	(-3.52)	(-1.95)
High - Low	4.481**	3.164**	1.529**	-0.948*	-0.943**	-0.510
	(30.38)	(4.84)	(8.01)	(-2.28)	(-3.34)	(-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 2008:6 and from 2001 to 2008:6 that have been shown to experience significant reductions in liquidity costs due to regulatory changes. These periods coincide with the NYSE/Amex/NASDAQ move to sixteenth pricing and the decimalization in quotes, respectively. We rank into quintiles according to the CRSP closing return based idiosyncratic volatility estimated using a Fama-French three factor model. The row labeled High-Low refers to the difference between the portfolio with the highest idiosyncratic volatility (High) and the portfolio with the lowest idiosyncratic volatility (Low). The remaining columns are defined as follows: %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolio. The abnormal performance is based on the three-factor Fama-French Alpha and on the four-factor Carhart Alpha (Carhart, 1997). 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	Idiosyncratic Volatility(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: From 1997:06 to 2008:06						
Low	1.119**	1.886**	0.492**	0.443	0.096	0.028
	(14.47)	(8.04)	(4.71)	(1.55)	(0.85)	(0.22)
2	1.800**	1.688**	0.623**	0.239	-0.159	-0.052
	(16.65)	(7.28)	(4.80)	(0.59)	(-1.18)	(-0.41)
3	2.575**	1.879**	0.619**	0.324	-0.088	0.013
	(15.51)	(6.08)	(5.47)	(0.60)	(-0.62)	(0.10)
4	3.668**	2.260**	0.682**	0.176	-0.204	0.015
	(14.98)	(5.88)	(5.79)	(0.22)	(-0.87)	(0.06)
High	6.199**	3.337**	1.157**	-0.346	-0.895*	-0.417
	(15.70)	(6.16)	(6.02)	(-0.37)	(-2.53)	(-1.44)
High - Low	5.080**	1.451**	0.665**	-0.789	-0.991*	-0.445
	(15.79)	(4.13)	(4.62)	(-0.99)	(-2.31)	(-1.21)
Panel B: From 2001:04 to 2008:06						
Low	0.935**	1.179**	0.225**	0.197	-0.002	-0.009
	(15.66)	(18.84)	(3.26)	(0.58)	(-0.02)	(-0.09)
2	1.545**	1.019**	0.289**	0.082	-0.291**	-0.295**
	(17.55)	(18.84)	(3.36)	(0.16)	(-2.88)	(-2.99)
3	2.192**	1.064**	0.311**	0.279	-0.145	-0.139
	(15.27)	(18.71)	(3.99)	(0.47)	(-0.93)	(-0.86)
4	3.118**	1.314**	0.375**	0.289	-0.115	0.058
	(14.13)	(15.87)	(4.83)	(0.35)	(-0.42)	(0.18)
High	5.372**	1.987**	0.700**	0.245	-0.286	0.019
	(13.56)	(15.37)	(4.70)	(0.23)	(-0.84)	(0.06)
High - Low	4.437**	0.808**	0.475**	0.048	-0.284	0.028
	(13.10)	(5.69)	(4.77)	(0.06)	(-0.72)	(0.07)

Table 5: Idiosyncratic Volatility and Liquidity Regressions

We present regression results of the idiosyncratic volatility, estimated using a three-factor Fama-French model, 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 idiosyncratic volatility. We include the spread and the the square of the spread. These two terms control for the first and second order effects on the idiosyncratic volatility estimate. We also include an interaction effect between the %zero returns and the bid-ask spread. Finally, we separately include Amihud's price impact measure for completeness. The sample period runs from 1984 to 2008. Each of these microstructure controls are estimated contemporaneously with the idiosyncratic volatility measurement. T-statistics are in parentheses and significance at the 1% level and 5% level is given by an ** and an *, respectively.

	Idiosyncratic Volatility					
	1	2	3	4	5	6
Intercept	3.388**	2.041**	2.554**	2.354**	1.800**	1.780**
	(25.40)	(18.51)	(21.47)	(24.92)	(15.10)	(15.69)
Amihud	1.882**					
	(6.79)					
Spread		41.370**	46.980**	65.410**	70.850**	76.120**
		(11.67)	(13.34)	(20.47)	(37.67)	(30.53)
%Zeros			-3.840**	-4.967**	-1.795**	-2.442**
			(-15.23)	(-16.14)	(-7.32)	(-7.85)
Sq. Spread				-110.500**		-83.290**
				(-4.84)		(-3.38)
%Zeros×Spread					-58.820**	-44.780**
					(-13.12)	(-9.35)
N	1724502	1368375	1368172	1368172	1368172	1368172
adj. R^2	0.082	0.329	0.360	0.413	0.465	0.469

Table 6: Sort Performance of Idiosyncratic Volatility Residuals

The base idiosyncratic volatility is estimated relative to Fama and French (1993) using daily returns over a one-month interval. Panel A presents the sort results of the residual of idiosyncratic volatility using the spread, the squared spread, the percentage of zero returns, and the interaction between the spread and the %zero returns. Panel B focuses on the quote midpoint return based idiosyncratic volatility estimate using a linear and non-linear specification for the percentage of zero returns. The sample period runs from 1984 to 2008. High-Low refers to the difference between the highest (High) and lowest idiosyncratic volatility (Low) categories. The remaining columns are defined as follows: %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios. Abnormal performance is measured using the three-factor Fama-French model and using the four-factor Carhart (Carhart, 1997) 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	Residual Idiosyncratic Volatility(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: Residual Idiosyncratic Volatility (%Zeros, Spread, Sq. Spread, %Zeros×Spread)						
Low	-1.413**	7.712**	1.329**	0.632**	0.012	0.027
	(-19.2)	(7.70)	(9.91)	(3.07)	(0.16)	(0.32)
2	-0.872**	6.773**	0.655**	0.575**	-0.006	-0.027
	(-18.0)	(9.22)	(12.8)	(2.66)	(-0.10)	(-0.46)
3	-0.371**	7.342**	0.655**	0.525	-0.057	-0.020
	(-17.5)	(9.17)	(12.9)	(1.86)	(-0.83)	(-0.24)
4	0.326**	7.719**	0.779**	0.583	0.091	0.167
	(15.5)	(9.17)	(12.5)	(1.62)	(0.72)	(1.42)
High	1.943**	8.645**	1.166**	0.129	-0.399	-0.245
	(23.0)	(9.28)	(11.9)	(0.27)	(-1.77)	(-1.14)
High - Low	3.356**	0.933	-0.163	-0.504	-0.411	-0.272
	(21.4)	(1.88)	(-1.71)	(-1.23)	(-1.59)	(-1.08)
Panel B: Residual MidQuote Idiosyncratic Volatility (%Zeros, Sq. %Zeros)						
Low	-1.939**	10.80**	0.753**	0.631**	0.061	0.037
	(-26.8)	(7.89)	(12.4)	(3.21)	(0.99)	(0.56)
2	-1.288**	6.795**	0.707**	0.578*	-0.018	0.031
	(-24.5)	(8.74)	(12.6)	(2.44)	(-0.34)	(0.50)
3	-0.660**	6.231**	0.825**	0.608	0.006	0.109
	(-21.3)	(9.29)	(12.1)	(1.82)	(0.06)	(0.91)
4	0.207**	6.752**	1.119**	0.411	-0.195	0.002
	(7.81)	(9.35)	(11.8)	(1.00)	(-1.27)	(0.01)
High	15.47**	8.729**	3.237**	-0.032	-0.585**	-0.312
	(3.04)	(9.42)	(4.70)	(-0.07)	(-2.85)	(-1.49)
High - Low	17.41**	-2.066**	2.484**	-0.663	-0.647**	-0.349
	(3.40)	(-3.17)	(3.69)	(-1.72)	(-2.67)	(-1.41)

Table 7: Sort Performance of Amihud Idiosyncratic Volatility Residuals

The base idiosyncratic volatility is estimated relative to Fama and French (1993) using daily returns over a one-month interval. The first specification, shown in Panel A, is a residual of idiosyncratic volatility on Amihud's measure and the square of Amihud's measure. The second specification, shown in Panel B, uses the prior specification for the trade difficulty, but includes the percentage of zero returns. Both of these specifications mimic the prior tables using the spread and the %zeros. The sample period runs from 1984 to 2008. High-Low refers to the difference between the portfolios with the highest residual idiosyncratic volatility (High) and the lowest residual idiosyncratic volatility (Low). The remaining columns are defined as follows: %Zeros is the proportion of zero returns; Spread is the proportional bid-ask spread; Return is the monthly excess returns of the portfolios. Abnormal performance is measured by the three factor Fama-French Alpha and by the four factor Carhart Alpha (Carhart, 1997). 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	Residual Idiosyncratic Volatility(%)	%Zeros	Spread(%)	Return(%)	Alpha(%)	
					Fama-French	Carhart
Panel A: Residual Idiosyncratic Volatility (Amihud, Sq. Amihud)						
Low	-2.129**	7.069**	0.591**	0.716**	0.127	0.058
	(-29.8)	(9.34)	(12.0)	(3.65)	(1.91)	(0.82)
2	-1.471**	6.724**	0.798**	0.586*	-0.094	-0.033
	(-26.9)	(9.11)	(12.4)	(2.32)	(-1.18)	(-0.49)
3	-0.711**	7.935**	1.112**	0.593	-0.072	0.044
	(-27.1)	(8.81)	(11.9)	(1.88)	(-0.69)	(0.50)
4	0.352**	9.752**	1.684**	0.206	-0.416**	-0.201
	(20.6)	(8.64)	(10.0)	(0.50)	(-2.68)	(-1.33)
High	2.883**	12.58**	3.251**	-0.437	-1.094**	-0.680**
	(30.0)	(8.80)	(8.97)	(-0.89)	(-4.52)	(-3.06)
High - Low	5.013**	5.510**	2.660**	-1.153**	-1.221**	-0.738**
	(30.2)	(7.26)	(7.75)	(-2.83)	(-4.34)	(-2.82)
Panel B: Residual Idiosyncratic Volatility (Amihud, Sq. Amihud, %Zeros)						
Low	-2.100**	7.545**	0.599**	0.690**	0.104	0.035
	(-29.6)	(9.18)	(12.0)	(3.51)	(1.73)	(0.55)
2	-1.449**	6.406**	0.768**	0.501*	-0.179*	-0.145*
	(-27.4)	(8.94)	(12.5)	(2.00)	(-2.47)	(-2.20)
3	-0.703**	7.400**	1.053**	0.586	-0.064	0.045
	(-27.2)	(8.61)	(12.3)	(1.87)	(-0.69)	(0.52)
4	0.350**	9.207**	1.591**	0.220	-0.380*	-0.212
	(21.0)	(8.45)	(10.4)	(0.53)	(-2.56)	(-1.48)
High	2.847**	12.07**	3.128**	-0.479	-1.113**	-0.699**
	(30.3)	(8.73)	(9.19)	(-0.97)	(-4.65)	(-3.11)
High - Low	4.947**	4.529**	2.530**	-1.169**	-1.218**	-0.735**
	(30.4)	(6.30)	(7.92)	(-2.84)	(-4.27)	(-2.71)

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 294 months in our sample that span from 1984:1 to 2008:6. We estimate the idiosyncratic volatility using the Fama-French three factor model for all firms listed on the NYSE/Amex/NASDAQ exchanges. We employ all three Fama-French risk factors measured contemporaneously. Lagged return (reversal) is the prior month return and six-month momentum is the return measured from t-6 to t-2. Book-equity is taken from the quarterly Compustat and monthly book-to-market is calculated using firm size each month. Firm size is month-end price multiplied by the shares outstanding. Co-skewness 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). Analyst dispersion is the standard deviation of the one-year ahead earnings forecast provided by I/B/E/S and is measured monthly. Institutional holdings are 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. Leverage is the total debt divided by total debt plus the market value of equity and is taken from Compustat and CRSP. Our liquidity variables are the proportional spread (ask minus bid divided by the quote midpoint), the percentage of zero returns, and Amihud's measure. We use the CRSP-closing return idiosyncratic volatility estimated relative to the Fama and French (1993) model as a baseline comparison. The CRSP residual idiosyncratic volatility is the residual of a regression of the baseline CRSP-closing return idiosyncratic volatility on the spread, the squared spread, the %zero returns, and the spread times the %zero returns. The midquote return idiosyncratic volatility uses the quote midpoint to estimate the idiosyncratic volatility. Finally, the midquote residual idiosyncratic volatility uses the residual of a regression of the midquote estimated idiosyncratic volatility on the %zero returns. 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 (%)							
	1	2	3	4	5	6	7	8
Intercept	2.480**	2.040**	2.050**	2.170**	2.140**	1.400*	1.620*	1.240
	(3.46)	(2.97)	(2.89)	(3.28)	(3.11)	(2.14)	(2.38)	(1.85)
CRSP Closing Return	-0.214**	-0.149*	-0.158*	-0.156*	-0.156*			
Idiosyncratic Volatility	(-3.04)	(-2.05)	(-2.15)	(-2.13)	(-2.13)			
CRSP Residual						-0.105		
Idiosyncratic Volatility						(-1.51)		
MidQuote Return							-0.084	
Idiosyncratic Volatility							(-1.44)	
MidQuote Residual								-0.078
Idiosyncratic Volatility								(-1.43)
β_{mkt}	0.155	0.148	0.162	0.160	0.163	0.125	0.153	0.139
	(0.90)	(0.87)	(0.93)	(0.93)	(0.94)	(0.72)	(0.90)	(0.83)
β_{smb}	-0.101*	-0.113*	-0.114*	-0.107*	-0.115*	-0.114*	-0.102	-0.103
	(-1.99)	(-2.08)	(-2.11)	(-2.00)	(-2.13)	(-2.07)	(-1.87)	(-1.83)
β_{hml}	-0.009	0.021	0.007	0.010	0.008	0.030	0.005	0.018
	(-0.09)	(0.22)	(0.07)	(0.10)	(0.08)	(0.30)	(0.05)	(0.19)
Lagged Return	-2.030**	-2.490**	-2.230**	-2.250**	-2.320**	-2.350**	-2.270**	-2.400**
	(-3.54)	(-4.25)	(-3.77)	(-3.78)	(-3.97)	(-3.92)	(-4.01)	(-4.18)
6-Month Momentum	0.781*	0.630	0.672*	0.663*	0.685*	0.632	0.632	0.581
	(2.52)	(1.84)	(2.02)	(2.04)	(2.11)	(1.82)	(1.89)	(1.64)
Ln(Firm Size)	-0.073	-0.068	-0.070	-0.074	-0.075	-0.043	-0.045	-0.035
	(-1.79)	(-1.52)	(-1.53)	(-1.69)	(-1.67)	(-0.97)	(-1.00)	(-0.76)
Ln(B/M)	0.124	0.166	0.145	0.149	0.151	0.169	0.138	0.159
	(1.38)	(1.62)	(1.45)	(1.48)	(1.54)	(1.65)	(1.40)	(1.57)
CoSkewness	-0.143	-0.117	-0.126	-0.124	-0.119	-0.115	-0.167	-0.166
	(-1.14)	(-0.94)	(-0.98)	(-0.97)	(-0.94)	(-0.92)	(-1.29)	(-1.32)
Inst. Holdings($\times$100)		0.786**	0.741**	0.775**	0.735**	0.819**	0.752**	0.817**
		(3.07)	(2.97)	(3.20)	(2.97)	(3.25)	(2.99)	(3.16)
Leverage		-0.504	-0.420	-0.426	-0.419	-0.500	-0.383	-0.460
		(-1.58)	(-1.37)	(-1.38)	(-1.37)	(-1.57)	(-1.22)	(-1.42)
Analyst Dispersion($\times$0.01)		-1.591**	-1.560**	-1.637**	-1.435**	-1.993**	-1.728**	-1.924**
		(-3.27)	(-3.44)	(-3.43)	(-3.58)	(-3.45)	(-3.47)	(-3.21)
Amihud					0.081			
					(0.03)			
Spread			-2.110	-9.750				
			(-0.38)	(-0.83)				
%Zeros				0.324				
				(0.39)				
Sq. Spread($\times$0.01)				-1.154				
				(-0.35)				
%Zeros$\times$Spread				10.100				
				(0.11)				
N	1331479	701362	728664	728643	752591	677068	714839	664004
adj. R^2	0.137	0.164	0.163	0.167	0.160	0.165	0.161	0.165

Table 9: Sub-Period Fama-MacBeth Regressions

We regress the monthly return against lagged control variables that comprise risk, return reversal and momentum, and information environment variables. Each of the regressions is value-weighted using lagged firm size as the weight. Four separate periods are examined. The period from 1997 to 2008 and the period from 2001 to 2008 correspond to regulatory changes that caused a sharp drop in liquidity costs. The period from 1992 to 1997 also shows a gradual reduction in liquidity costs, although for no explicit exogenous reason. Finally, for completeness, we also include the period from 1984 to 1992. We measure the idiosyncratic volatility using the Fama-French three factor model for all firms listed on the NYSE/Amex/NASDAQ exchanges. We employ all three Fama-French risk factors measured contemporaneously. Lagged returns (reversal) and six-month momentum measure the prior period return effects. Book-to-market (B/M) is log scaled and measures value versus growth effects, log scaled firm size measures extraneous risk effects, while co-skewness measures downside risk. We also include the quote midpoint return based idiosyncratic volatility estimate for the period (1984 to 1992), where the closing return based idiosyncratic volatility proved significant, to illustrate the importance of liquidity costs on the estimation of idiosyncratic volatility. 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.

	1984:01 - 1991:12		1992:01 - 2008:06	1997:06 - 2008:06	2001:04 - 2008:06
	Return(%)	Return(%)	Return(%)	Return(%)	Return(%)
Intercept	2.920*	1.740	2.270*	2.810*	2.930*
	(2.56)	(1.35)	(2.50)	(2.19)	(2.53)
CRSP Closing Return Idiosyncratic Volatility	-0.440**		-0.105	-0.085	-0.085
	(-5.62)		(-1.19)	(-0.69)	(-0.50)
MidQuote Return Idiosyncratic Volatility		-0.124			
		(-1.70)			
β_{mkt}	0.517**	0.493**	-0.020	-0.099	-0.204
	(3.22)	(3.03)	(-0.09)	(-0.29)	(-0.74)
β_{smb}	-0.224**	-0.214**	-0.042	-0.054	0.017
	(-3.25)	(-3.18)	(-0.66)	(-0.60)	(0.18)
β_{hml}	-0.092	-0.091	0.031	0.014	0.001
	(-1.67)	(-1.62)	(0.21)	(0.06)	(0.01)
Lagged Return	-1.930	-2.030	-2.070**	-2.150*	-2.060
	(-1.74)	(-1.83)	(-3.13)	(-2.58)	(-1.74)
6-Month Momentum	0.295	0.112	1.020*	1.430**	1.040
	(0.66)	(0.21)	(2.55)	(2.90)	(1.61)
Ln(Firm Size)	-0.106	-0.060	-0.057	-0.098	-0.110
	(-1.56)	(-0.70)	(-1.13)	(-1.45)	(-1.88)
Ln(B/M)	-0.008	-0.078	0.189*	0.180	0.229
	(-0.04)	(-0.34)	(1.99)	(1.51)	(1.97)
CoSkewness	0.085	-0.027	-0.253	-0.384	-0.542**
	(0.43)	(-0.11)	(-1.66)	(-1.93)	(-2.66)

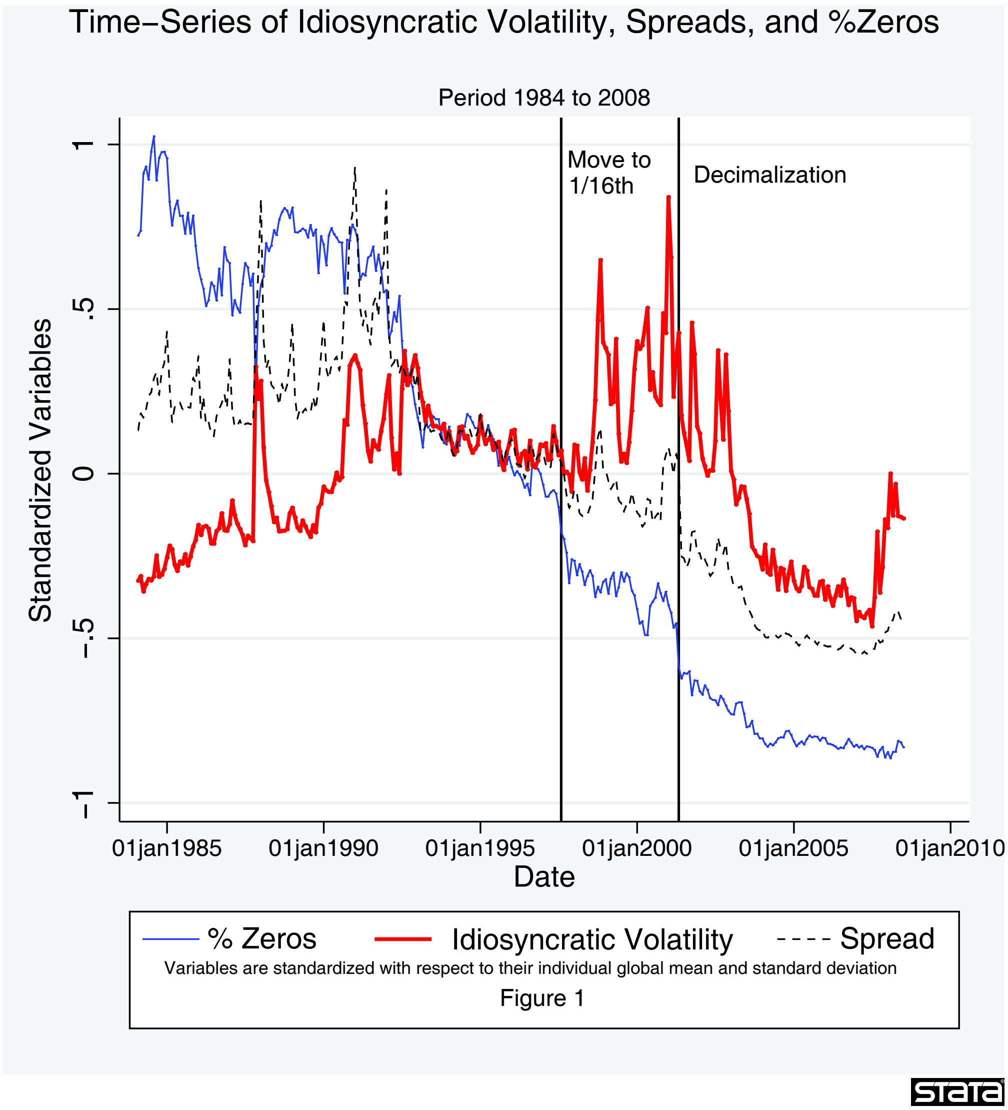
Time−Series of Idiosyncratic Volatility, Spreads, and %Zeros
Period 1984 to 2008
Standardized Variables
1
.5
0
−.5
−1
Move to
1/16th
Decimalization
01jan1985
01jan1990
01jan1995
01jan2000
01jan2005
01jan2010
Date
% Zeros
Idiosyncratic Volatility
Spread
Variables are standardized with respect to their individual global mean and standard deviation

Figure 1