Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility Around the World

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June 23, 2014

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Abstract

This paper examines data from 45 world markets and shows that the previously-documented relation between mean returns and idiosyncratic volatility arises because of biases in volatility estimates that we can attribute to the bid-ask bounce in trade prices. We show that no significant relation exists between mean returns and idiosyncratic volatility estimated from quote-midpoint returns. Further, there is no significant relation between mean returns and the portion of transaction-price based idiosyncratic volatility that is orthogonal to bid-ask spreads. The pricing of idiosyncratic volatility is due to the negative pricing of the bid-ask spread.

Keywords: Cross-Sectional Return, International Markets, Idiosyncratic Volatility, Bid-Ask Spread

I Introduction

Fundamental to asset pricing and investments is the trade-off between risk and return. The capital asset pricing model, assuming frictionless markets and complete market diversification, does not price idiosyncratic volatility (Sharpe (1964) and Lintner (1965)). In relaxing the complete market diversification assumption, Merton (1987) and Malkiel and Xu (2004) develop asset pricing models where expected returns are positively related to idiosyncratic volatility due to the lack of diversification across all assets. The pricing of idiosyncratic volatility arises because investors require a premium for bearing idiosyncratic risk in non-diversified portfolios.

Contrary to these theoretical models and predictions, more recent evidence documents a negative relation between realized idiosyncratic volatility and future mean returns. For example, Ang, Hodrick, Xing, and Zhang (2006), (2009) present compelling evidence that realized idiosyncratic volatility is negatively priced in the cross-section[1] in the U.S. market and across 23 developed international markets. Ang et al. (2009) demonstrate that standard risk factors or liquidity cannot explain the pricing of idiosyncratic volatility in the international markets.

In this paper, we investigate the importance of measurement errors in the transaction price-based estimate of idiosyncratic volatility and on its pricing ability across 45 world markets. One potential source of measurement error in transaction prices is the bid-ask bounce[2] (Blume and Stambaugh (1983) and Kaul and Nimalendran (1990)). We show that when we use quote midpoint-based returns to control for this measurement error (Han and

[1]Guo and Savickas (2008) also demonstrate a significant negative pricing ability for idiosyncratic volatility in aggregate market returns for G7 countries.

[2]This bid-ask bounce in prices is particularly relevant because we use daily security returns spanning one month to estimate realized idiosyncratic volatility. The consequence of the bid-ask bounce in price is that idiosyncratic volatility may contain a liquidity component (Han and Lesmond (2011)).

Lesmond (2011)) in estimating idiosyncratic volatility, the resulting estimate of idiosyncratic volatility has no pricing ability across these world markets. We further show that the portion of the transaction price-based idiosyncratic volatility that is orthogonal to the bid-ask spread is not priced in future returns.

Our analysis is related to, but quite distinct from that of Asparouhova, Bessembinder, and Kalcheva (2010), (2013). They study biases that arise in asset pricing applications because mean returns estimated from transaction prices are overstated when the prices contain microstructure noise. They show that these biases arise even if we measure all explanatory variables without error, but that using certain weighting mechanisms, including value-weighting, can correct these errors. We base our results on value-weighted returns. Therefore, our results are not attributable to the issues they assess. Instead, we are concerned with biases that develop because an explanatory variable, idiosyncratic volatility, is measured with error.

Lacking detailed liquidity information across international markets, Ang et al. (2009) provide comprehensive tests on whether liquidity can explain the pricing ability of idiosyncratic volatility, but by focusing only on the U.S. market. However, they reject liquidity as a possible explanation for the pricing ability of idiosyncratic volatility. We substantively broaden the scope of the liquidity examination by gathering all available bid-ask quote information for each of the 45 world markets to comprehensively gauge the impact of measurement errors in price on the pricing ability of idiosyncratic volatility. We show that the pricing of the transaction price-based estimate of idiosyncratic volatility is dependent on the pricing of the underlying bid-ask spread. In effect, the transaction price-based estimate of idiosyncratic volatility contains a bid-ask spread component; an estimate of idiosyncratic volatility that is free of this bid-ask spread component is not priced in returns.

Consistent with Ang et al. (2009), we find that the transaction price-based estimate of idiosyncratic volatility is negatively and significantly related to one-month ahead returns across world markets. Highlighting the importance of the measurement errors in price, we also find that the bid-ask spread is negatively and significantly priced with one-month ahead returns. For example, in value-weighted sort tests, the transaction price-based idiosyncratic volatility estimate across 23 developed markets shows a significant alpha of -0.717% per month, consistent with the findings of Ang et al. (2009).

For the same markets, value-weighted bid-ask spread sort tests also demonstrate a significant alpha of -0.884% per month. The finding of a negative relation between the bid-ask spread and future returns is quite surprising, but we find corroboration in these results from Brennan and Subrahmanyam (1996) and Easely, Hvidkjaer, and O'Hara (2002) who document a negative relation between the bid-ask spread[3] and returns for the U.S. market. The findings of Easely et al. (2002) are particularly relevant because the negative significance for the bid-ask spread is principally found in weighted regression tests and all of our results are weighted by firm size.

Controlling for the measurement error in price by using quote midpoint-based returns (Han and Lesmond (2011)), we find no pricing ability for the resulting quote midpoint-based estimate of idiosyncratic volatility. For instance, across 23 developed markets, the quote midpoint-based idiosyncratic volatility estimate shows an insignificant alpha of -0.160% per month in the value-weighted sort tests. We obtain similar results when we extend the analysis to value-weighted Fama and MacBeth (1973) regressions.

For robustness, we alternatively orthogonalize the bid-ask spread effect on idiosyncratic volatility by regressing the transaction price-based estimate of idiosyncratic volatility on the bid-ask spread. This orthogonalization directly controls for the bid-ask spread effect on the transaction price-based estimate of idiosyncratic volatility. Using the residual from

[3]Eleswarapu and Reinganum (1993) shows no pricing for the bid-ask spread in any month other than January while Chen and Kan (1996) argue that the positive findings of Amihud and Mendelson (1986) and others are due to mis-specification of risk.

this regression, we find no evidence of pricing ability for idiosyncratic volatility. We further demonstrate that controlling for a return reversal explanation on the pricing ability of idiosyncratic volatility (Huang, Liu, Rhee, and Zhang (2009)) by using two-month ahead returns finds significantly negative pricing ability of the transaction price-based estimate of idiosyncratic volatility. However, the quote midpoint-based estimate of idiosyncratic volatility is not significantly priced in two-month ahead returns.

These results are important for the following reasons. First, the literature is increasingly focusing on the factor specification in the global return generating process (Fama and French (1998), Griffin (2002), and Hou, Karolyi, and Kho (2011)). Our results that indicate the importance of liquidity in the return generating process across world markets would posit for a priced liquidity factor, consistent with the findings of Lee (2011).

Second, idiosyncratic stock return volatility varies across countries, as well as through time. Morck, Yeung, and Yu (2000) focus on cross-country differences in R^2s of the market model, and show that stock return R^2s are high in countries with opaque information environments. Moreover, Bartram, Brown, and Stulz (2012) find that the percentage of zero returns, a liquidity proxy (Lesmond, Ogden, and Trzcinka (1999)), explains the differences in R^2s between emerging markets and the U.S. market. This link between the bid-ask spread and idiosyncratic volatility will better focus the discussion on how liquidity costs reflect an opaque information environment, and how liquidity costs affect price co-movements across international markets.

Third, Bekaert, Hodrick, and Zhang (2012) show that growth opportunities, total market volatility, and the variance premium can explain the bulk of the variation in idiosyncratic volatility in international markets. Our results would argue for research that directly examines the impact of the bid-ask spread on returns and the consequent effect on the pricing of aggregate idiosyncratic volatility around the world.

Finally, the results of this paper can relate the various issues raised in the literature with idiosyncratic volatility and returns in the U.S. market, but with implications for international markets. With regard to economic advancement and financial market innovation, Brown and Kapadia (2007) claim that the increase in idiosyncratic risk is related to more volatile firms being listed through initial public offerings, while Irvine and Pontiff (2009) argue that idiosyncratic volatility and a firm's cash volatility are related. George and Hwang (2012) demonstrate that idiosyncratic volatility has predictive power well beyond the standard one-month horizon in the U.S. market. We conjecture that, given the link between idiosyncratic volatility and the bid-ask spread this paper establishes, we can recast all of these issues in a liquidity framework.

The paper is organized as follows. Section II outlines the estimation of the idiosyncratic volatility and the various control variables. Section III presents summary statistics, and Section IV presents the bid-ask spread quintile sort pricing tests. Section V reports quintile sort and Fama-MacBeth regression tests for both the transaction price-based and the quote midpoint-based estimate of idiosyncratic volatility. Section VI presents a robustness check on our results by using sorts of the residual of idiosyncratic volatility on liquidity as an alternative means of testing the liquidity hypothesis. Section VII concludes the paper. An Appendix contains a test that controls for a return reversal explanation for the pricing of idiosyncratic volatility.

II Idiosyncratic Volatility Estimation, Return Calculations, and Firm Attribute Controls

In all of our specifications, we implicitly assume that these world markets are integrated. Bekaert, Harvey, and Lumsdaine (2002) report that early in 1990, many small emerging markets liberalized, with subsequent integration. All of our empirical tests for the emerging markets are subsequent to this general liberalization date.

A Estimating World-Based Idiosyncratic Volatility

Following Ang et al. (2009), we estimate idiosyncratic volatility relative to the three-factor Fama-French model by first constructing local value and size factors. For the U.S. market, we use the factors from Ken French's website.[4] For the remaining developed markets, we follow Fama and French (1998) and determine the breakpoints for the book-to-market and firm-size portfolios as of the beginning of January each year. We use value-weighted returns to form the country-based high-minus-low (HML) value factor and the small-minus-big (SMB) size factor for each country; we then aggregate these factors into a world value-weighted HML and SMB factor. We rely on the MSCI developed market index for the market return.

We use daily returns over one month to estimate idiosyncratic volatility, using the annualized standard deviation of the residual from the Fama-French three-factor model for developed markets, and relative to a single factor model (using the world MSCI index) for the emerging markets.

For all of our tests, we use two definitions for the daily stock return, r_i, in the estimation of idiosyncratic volatility. We take this approach to provide a comparison to the findings of Ang et al. (2009) and to reflect the theory of Han and Lesmond (2011). Hence, we use transaction price-based returns and quote midpoint-based returns to provide two estimates of idiosyncratic volatility.

We use CRSP exclusively for the U.S. market and Datastream for the remaining markets as our primary sources of daily transaction price information.[5]

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[4] $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french$

[5] Datastream's RI measure leads to return calculations that differ from those that CRSP employs. When trading volume is zero, Datastream does not adjust the RI measure to the quote midpoint as CRSP does with the daily price. Datastream "carries over" the daily RI measure from the prior day(s) RI measure that did experience some trading volume. This feature affects our model's prediction with respect to the bias. Given zero trading volume, the stated price will be yesterday's price, but the price does not reflect the

Importantly, we find that Datastream[6] does *not* report the actual closing transaction price for the English market from 1986 to 2008. Rather they report an indicative price that is set to some level within the prevailing quote. Hence, we employ the Thomson Reuters Tick History (TRTH) intra-day data to determine the end-of-day bid and ask quotes as well as the last trade price of the day for the English market. Accurate closing prices from TRTH commence in 1996 for the English market.

We also adopt the data filter that Ince and Porter (2006) advocated when we use daily return data from Datastream. Specifically, we set daily returns to missing if the following condition is satisfied: $(1 + R_{i,d})(1 + R_{i,d-1}) <= 1.5$, where $R_{i,d}$ and $R_{i,d-1}$ are the stock returns of firm i on day d and $d - 1$, respectively, with at least one return greater than 100%. Finally, we impose the following U.S. dollar-based price limits for firms. For the G7 countries, we delete firms with prices less than \$5.00, and for the remaining developed markets we delete firms with prices less than \$3.00. For the emerging markets, we delete firms with prices less than \$1.00. These price thresholds ensure a sufficient number of firms across all markets, while eliminating outliers in the prices.

Finally, we convert all returns and local market factors from local currency prices into U.S. dollars for the non-U.S. markets. We accomplish this conversion by using the daily exchange rate for each country as provided by Datastream.

B Quote Midpoint-Based Returns

We use the Trades and Quotes (TAQ) and the Institute for the Study of Security Markets (ISSM) databases to obtain the daily end-of-day quotes for all NYSE/Amex/NASDAQ

bid-ask quote midpoint.

[6]We find the same results if we use Bloomberg as a source for closing price, bid quote, and ask quote information. We believe that we are the first to disclose this failure, by both Datastream and Bloomberg, to provide the actual closing price for the London Stock Exchange.

stocks. We calculate the quote midpoint return in an identical manner as CRSP, by using end-of-day prices. We specifically correct for stock splits and dividends in calculating quote-midpoint returns.

For the remaining 22 developed markets, except England, and 22 emerging markets we rely on both Datastream and Bloomberg for bid and ask quotes. We use both Datastream and Bloomberg to provide a comprehensive sample of firms with available bid-ask quotes and also to provide internal consistency with our bid-ask estimates. However, the availability of bid and ask quotes is not uniform; beginning dates vary considerably across countries.

If the bid or ask quotes are missing for a particular day, we retain the prior day's bid or ask quote. This step is particularly important for firms in international markets that are susceptible to thin trading volumes.

Finally, for our Fama-MacBeth regression tests, we employ various control variables that the literature[7] has shown to be associated with future returns. These control variables include return reversal, six-month momentum, book-to-market, and firm size. CRSP is the source for the U.S. firm-level information and Datastream is the source for the non-U.S. firm-level information.

Table 1 is here.

[7] These controls span contemporaneous world market index factor or Fama-French risk factors, one-month lagged returns (Huang et al. (2009)) and six-month momentum returns (Jegadeesh and Titman (1993)), book-to-market (Daniel and Titman (1997)), skewness (Barberis and Huang (2008)), and firm size. Value-weighted regressions are performed extensively by Ang et al. (2009).

III Summary Statistics of Idiosyncratic Volatility and the Bid-Ask Spread

Table 1 presents summary statistics for book-to-market, firm size, and liquidity costs for each of the 23 developed markets and 22 emerging markets for firms with available bid-ask spread information. We separate the world markets into the G7 countries in Panel A, the non-G7 developed countries in Panel B, and the emerging markets in Panel C. In each panel, we show the start date that corresponds to the availability of the bid-ask spread information.

Table 1 shows that the bid-ask quote information generally begins in late 1980 to early 1990 for the G7 countries and in the early-to-mid 1990s for the non-G7 developed countries. The bid-ask quote information for emerging markets begins in 1992 for Malaysia, the Philippines, Taiwan, and Thailand. But for the majority of the emerging markets, the quote information begins in the middle 1990s to early 2000, causing the quote information to be relatively sparse for the emerging markets.

The liquidity profiles for each country illustrate some surprising characteristics. First, the profiles show no apparent evidence that the G7 countries have the most complete spread information or the lowest liquidity costs in comparison with non-G7 countries. While the U.S. has the most expansive and complete spread information, followed by France that begins in 1988:07, Germany has spread data that begins as late as 1996:12. Although the Swiss market has complete spread information beginning in 1988:07, well before the German market, it has few firms for the early time periods. Note that a substantial number of emerging markets have spread information dated well before the German market. These emerging markets include the following countries: China, Greece, Indonesia, Korea, Malaysia, Mexico, the Philippines, South Africa, Taiwan, and Thailand.

England and France exhibit some of the highest spread costs among the developed countries, with average costs of 5.87% and 5.65%, respectively. Generally, as would be expected, the emerging markets experience the highest spread costs across all the countries of the world. Brazil, that exhibits a proportional spread of 16.38%, is evidence of this finding. However, China, Taiwan, and Turkey experience proportional spreads of less than 1.0%, a level far lower than those of any of the other countries we examined in this paper. The emerging market spread information, and in particular the low spread costs that China and Taiwan exhibit are consistent with Lesmond (2005).

Apparently, the U.S. has one of the highest spread costs among the G7 countries, and even among the other developed and emerging markets. The U.S., on average, exhibits a proportional spread of 3.78%, which is markedly higher than the proportional spread of some of the other G7 countries, notably Italy, or of non-G7 countries. We conjecture that this difference occurs for several reasons. First, the U.S. market has bid-ask spread information that preceded regulatory changes that dramatically reduced the level of the proportional spread. The move to 1/16 quotes (from 1/8 quotes) for NYSE/Amex firms beginning in 1997, and the decimalization of quotes that commence in 2001:04 (Bekaert, Harvey, and Lundblad (2007)) significantly reduced the quoted spreads. Second, the U.S. has a far more expansive equity market than does any other world market. For instance, the bid-ask spread information exists for over 5,964 firms in the U.S. market, but only for 190 firms for the Italian market.

Also evident in Table 1 is that the transaction price-based estimate of idiosyncratic volatility is usually larger than the quote midpoint-based estimate of idiosyncratic volatility. Higher levels of idiosyncratic volatility are usually associated with higher levels in the bid-ask spread, consistent with the findings of Han and Lesmond (2011) for the U.S. market. However, we note that for a number of countries (see, for example, France and Germany), the quote midpoint-based estimate of idiosyncratic volatility is higher than the transaction price-based estimate of idiosyncratic volatility. The Blume and Stambaugh (1983) model, which forms the basis for the theory of Han and Lesmond (2011), assumes that transaction prices bounce between the bid and ask quotes. However, we notice that while transaction prices remain unchanged from day-to-day, the ask or bid (or both) quotes are changing more frequently. Thus, while the transaction price-based return is zero, the matching quote midpoint-based return is non-zero. This situation leads to greater variability in the quote midpoint-based return relative to the variability in the transaction price-based return. The result is a high quote midpoint-based estimate of idiosyncratic volatility, relative to the transaction price-based estimate of idiosyncratic volatility.

Finally, Panel D of Table 1 shows the statistics for the various regional aggregations that our study comprises. As Panel D illustrates, grouping into the regional aggregations of the G7 countries, the 23 developed markets, and the emerging markets now shows that the transaction price-based estimates of idiosyncratic volatility are consistently larger than are the quote midpoint-based estimates of idiosyncratic volatility. Grouping by regions lessens the impact of country-specific effects.

IV Bid-Ask Spread Quintile Sort Results for World Markets

Since Amihud and Mendelson's (1986) seminal paper that demonstrated a positive relation between the bid-ask spread and future returns, the presumptive assumption is that the bid-ask spread and future returns are positively related. However, Han and Lesmond's (2011) theoretical model implies that if the bid-ask spread can explain the pricing of idiosyncratic volatility, then the bid-ask spread and future returns may be negatively related.

We first set out to determine the pricing ability of the bid-ask spread by using quintile sorts[8] that have become the standard in asset pricing tests. We use value-weighted sorts to correlate these findings to those tests that assess the pricing ability of idiosyncratic volatility.

[8]While not reported, we find very similar results for association of the bid-ask spread and one-month ahead returns, using Fama-MacBeth regression tests.

Every month, we place stocks into quintile–sorted portfolios, based on their daily average bid-ask spreads estimated over a one-month period. We employ value-weighted quintile sort tests, using firm size as the weight, that are standard in pricing tests of idiosyncratic volatility. We hold the portfolios for one month and then re–balance them. We difference the portfolio with the highest bid-ask spread (High) and the portfolio with the lowest bid-ask spread (Low). To estimate the alpha, we regress the value-weighted quintile portfolio High-Low returns against the three-factor Fama-French model. We determine significance by using Newey and West (1987)[9] robust test statistics. We focus on particular regions that we identify as the world, the world without the U.S., the developed markets, the developed markets without the U.S., the G7 countries, the G7 countries without the U.S., the U.S. market separately, and the emerging markets.

Table 2 is here.

As Table 2 shows, negative and significant pricing is evident in the High-Low alpha across all regional aggregations except for the emerging markets. For example, the world markets show a significant alpha of -0.903% per month, while the G7 country markets show a significant alpha of -0.897%. Remarkably, the significance of the negative pricing of the bid-ask spread is also evident in the U.S. market, with a robust alpha of -0.609%. We also note that the alpha is generally decreasing across the bid-ask spread quintiles. The economic interpretation is that low bid-ask spreads earn *high* value-weighted future returns and high bid-ask spreads earn *low* value-weighted future returns. These results suggest that the pricing of idiosyncratic volatility is dependent on the pricing ability of the underlying bid-ask spread. We do note that emerging markets exhibit little pricing ability. We would

[9]Ferson, Sarkissian, and Simin (2003) use a rule where the number of lags chosen is the minimum lag length at which no higher order autocorrelation is larger than two standard errors, where two standard errors is defined as $\frac{2}{\sqrt{T}}$. T is the sample length. The number of lags is chosen based on the number of statistically significant residual autocorrelations.

expect that the lack of pricing ability for the bid-ask spread would predict little pricing ability for idiosyncratic volatility across emerging markets.

These results show clearly that the sign and significance of the bid-ask spread's association with future returns is not positive as postulated by Amihud and Mendelson (1986), but rather, negative. These results stem, in part, due to the value-weighting of the sort tests that form the basis of tests for the pricing of idiosyncratic volatility. Regardless, this surprising result finds support in a host of related research in the U.S. market. As Easley and O'Hara (2003) note,

> Amihud and Mendelson (1986) find a significant positive effect of bid-ask spreads on stock returns and their results are supported by Eleswarapu (1997). However, Chen and Kan (1996) and Eleswarapu and Reinganum (1993) conclude[10] the opposite, as does research by Easely et al. (2002) who find no direct link between spreads and returns for the period 1983–1998. Indeed, Chen and Kan (1996) argue that the positive findings of Amihud and Mendelson (1986) and others are due to mis-specification of risk; and that when returns are not "properly" adjusted for risk, variables that are functions of the most recently observed price of a stock, such as size, dividend yield, and the relative bid-ask spread, are often found to possess explanatory power on the cross-sectional difference in the risk-adjusted return.

Brennan and Subrahmanyam (1996) corroborate these results. They find that the bid-ask spread and returns are negatively related using cross-sectional GLS regressions. Interestingly, Easely et al. (2002) find bid-ask spreads are *negatively* related to returns in weighted Fama-MacBeth regressions for the period 1984–1998. The positive relation between liquidity and

[10] Eleswarapu and Reinganum (1993) find that the association between bid/ask spreads and stock returns is mainly confined to the month of January, a result hard to reconcile with the underlying Amihud and Mendelson (1986) arguments.

returns most often found in the literature (see, for example, Amihud (2002) and Acharya and Pedersen (2005)) is often predicated on the price impact estimate of Kyle's lambda, most notably Amihud's measure.

V Quintile Sort and Fama-MacBeth Regression Results for World Markets

We now directly compare the pricing ability of idiosyncratic volatility that we estimate by using either the transaction price or the quote midpoint across world markets. The sort procedure is the same as performed in the bid-ask spread pricing tests. We compare the performance between the portfolio with the highest idiosyncratic volatility (High) and the portfolio with the lowest idiosyncratic volatility (Low). We eliminate any firm-month that lacks available spread information to ensure comparability of our transaction price and quote midpoint-based idiosyncratic volatility results. For the U.S. market, we also add a momentum factor to the standard three-factor Fama-French model in testing significance of the alpha. This is shown in Han and Lesmond (2011) to be important in potentially explaining the pricing of idiosyncratic volatility for the U.S. market. To accurately compare our prior results that show the pricing ability for the bid-ask spread with the pricing of idiosyncratic volatility, we also present the average bid-ask spread that corresponds to each idiosyncratic volatility quintile. All t-statistics are Newey and West (1987) corrected.

Table 3 is here.

A Transaction price-based estimates of idiosyncratic volatility

Table 3 presents the transaction price-based estimate of idiosyncratic volatility. As Table 3 shows, several trends are apparent. First, we see near monotonicity in the alphas across the idiosyncratic volatility quintiles across all regions. For instance, across the world markets, the low idiosyncratic volatility quintile shows an insignificant alpha of -0.006% per month and the high idiosyncratic volatility quintile shows a highly significant alpha of -0.805% per month. However, equally evident is the fact that ranking by idiosyncratic volatility also maintains the relative ranking of the bid-ask spread.

As we previously demonstrate for world markets, the low idiosyncratic volatility quintile is matched with the lowest average bid-ask spread, recorded at 0.608%, while the high idiosyncratic volatility quintile is matched with the highest average bid-ask spread, recorded at 1.746%. The implication is that ranking by idiosyncratic volatility also produces a monotonic ranking in the bid-ask spread. Given that our prior results demonstrate significant, negative pricing ability for the bid-ask spread, this information is further evidence that the pricing of the underlying bid-ask spread drives the pricing ability of idiosyncratic volatility.

Second, the High-Low investment portfolio results in Table 3 show consistent and significant pricing ability for idiosyncratic volatility, except for the emerging markets. The alphas evidence remarkable consistency, regardless of whether we include or exclude the U.S. market, or examine the U.S. alone. For instance, the world markets register a significant High-Low alpha of -0.798% per month, while the world without the U.S. demonstrates a High-Low alpha[11] of -0.724% per month. It should be stressed that the U.S. market alone is significant even after controlling for either Fama-French three-factor model, or including the Carhart factor in the tests for alpha.

Finally, the 22 emerging markets demonstrate no pricing ability, with an insignificant High-Low alpha of -0.408%. Coupled with the insignificance in the bid-ask spread sort tests that appear in Table 2, the lack of pricing ability for idiosyncratic volatility simply reflects

[11]These results are maintained if we incorporate the momentum factor in our pricing tests for non-U.S. firms.

the lack of pricing ability for the underlying bid-ask spread.[12]

Table 4 is here.

B Quote midpoint-based estimates of idiosyncratic volatility

We now turn to quote midpoints to control for the measurement errors in price that affect returns. As Table 4 shows, the effect on abnormal performance using quote midpoint-based idiosyncratic volatility is striking. Controlling for the microstructure noise in the computed return shows that *none* of the separate regional or world markets remains significantly different from zero. The emerging markets also demonstrate no significance in idiosyncratic volatility when we use quote midpoint-based returns.

The U.S. market alone remains significant at the 5% level, using the three-factor Fama-French model. However, Han and Lesmond (2011) find that in the U.S. market, using an additional momentum (Carhart) factor removes the significance in the pricing of idiosyncratic volatility. Consistent with Han and Lesmond (2011), including the momentum factor reduces alpha to insignificance.

The reduced pricing ability of the quote midpoint-based estimate of idiosyncratic volatility is due to a weakening of the monotonicity in alpha across the idiosyncratic volatility quintiles. For instance, the world market's alpha for the extreme high and low idiosyncratic volatility quintiles are -0.307% and -0.580% per month, respectively, while quintiles two through four are always greater than these extreme values. The highest levels of alpha in the idiosyncratic volatility quintiles are also matched with the highest bid-ask spreads. Sorting by the quote midpoint-based estimate of idiosyncratic volatility effectively resorts the stocks such that the relatively high spread firms now dominate the extreme quintiles.

[12]In unreported results, if we exclude the three lowest spread markets (China Turkey, and Taiwan), we find significance in the pricing of idiosyncratic volatility for the 19 remaining emerging markets.

The abnormal performance demonstrated by the quote midpoint-based idiosyncratic volatility estimates shows no clear pattern across the quintiles. With these quote midpoint-based estimates of idiosyncratic volatility, we can now clearly judge the pricing ability of idiosyncratic volatility without the liquidity influence. In so doing, we show that although the relation between idiosyncratic volatility and future returns is still negative, it is now largely insignificant.

The results support the hypothesis that the bid–ask bounce exerts a considerable influence on the estimate of idiosyncratic volatility and, most importantly, the bid-ask bounce alters the the subsequent performance of idiosyncratic volatility in predicting future returns. By using quote midpoint-based returns to estimate idiosyncratic volatility, hence controlling for the bid-ask bounce in the estimate of idiosyncratic volatility, we can eliminate the pricing ability of idiosyncratic volatility.

We conclude by constructing a long-short portfolio[13] that goes long the transaction price-based High-Low portfolio and short the quote midpoint-based High-Low portfolio. This test is a statistical test of the difference in pricing between these two High-Low idiosyncratic volatility portfolios.

As the last column of Table 4 shows, the alpha difference represents the pricing of the transaction price-based estimate of idiosyncratic volatility in excess of that earned by the quote midpoint estimate of idiosyncratic volatility. We see significance in the difference in alphas for all the regional aggregations, except for the G6 countries and the emerging markets. The lack of significance for the G6 countries is due to the weak significance of the transaction price-based estimate of idiosyncratic volatility shown in Table 3. This observation extends to the emerging markets where no significance is reported. The results are largely confirmatory that what is priced in the transaction price-based measure of idiosyncratic volatility is the embedded bid-ask spread.

[13] We thank an anonymous referee for suggesting this test.

C Fama-MacBeth Value-Weighted Regressions

The prior sort tests are one means of assessing the pricing ability of idiosyncratic volatility. However, they focus only on the extreme portfolios. We now present value-weighted Fama-MacBeth regressions of monthly returns on idiosyncratic volatility that we estimated using returns based either on the transaction price or on the quote midpoint for the separate regional aggregations. We use firm size as of the beginning of the month, converted to U.S. dollars, as the weight. We include control variables that Ang et al. (2009) employed. These variables pertain to the contemporaneous Fama-French risk factor betas, the six-month momentum return, book-to-market, and firm size. In addition, we include the prior month's return (Jegadeesh (1990)) that is associated with the pricing of idiosyncratic volatility (Huang et al. (2009)). We lag book-to-market by six months prior to estimating idiosyncratic volatility. We also include the bid-ask spread as an exogenous liquidity variable.

Table 5 is here.

As in the sort tests, we include and then exclude the U.S. market to control for the largest equity market on the pricing of idiosyncratic volatility. We convert all values to U.S. dollars, using daily exchange rates for each country. To assess significance, Newey and West (1987) robust test statistics are used. The regression is generally stated as:

$$
\begin{aligned}
\text{(1)}\quad \text{Return}_{i,t} &= \alpha_0 + \alpha_1 \text{Idiosyncratic Volatility}_{i,t-1} + \alpha_2\beta_{mkt,t} + \alpha_3\beta_{hml,t} + \alpha_4\beta_{smb,t} \\
&+ \alpha_5 \text{Ln(Book-to-Market)}_{i,t-7} + \alpha_6 \text{Six-Month Momentum}_{i,t-2} \\
&+ \alpha_7 \text{Ln(Firm Size)}_{i,t-1} + \alpha_8 \text{One-Month Return}_{i,t-1} + \alpha_9 \text{Liquidity}_{i,t-1} + \epsilon_{i,t}
\end{aligned}
$$

where the subscript i represents the firm and t represents the current month. Table 5 presents the regression results with the 23 developed markets and the G7 countries shown in Panels A and B, respectively.

First, focusing on the 23 developed markets (with the U.S.), Panel A of Table 5 reports robust significance for the transaction price-based estimate of idiosyncratic volatility with a coefficient of -0.0114. Including the spread does not affect the significance level of the idiosyncratic volatility. The quote midpoint estimate of idiosyncratic volatility, however, is not significant; it shows a coefficient of only -0.0044, with a t-statistic of only -1.20. The decline in the significance levels and magnitudes between the transaction price and the quote midpoint-based idiosyncratic volatility coefficients clearly illustrates the influence of the microstructure bias.

When we exclude the U.S. market, the pricing ability of the transaction price-based estimate of idiosyncratic volatility strengthens, as demonstrated by the increased significance level. As we observe in the base regression, the coefficient for idiosyncratic volatility increases to -0.0144, with a robust t-statistic of -2.78. Again, including liquidity does little to control for the pricing ability of idiosyncratic volatility. Also of note is that the bid-ask spread is now significant, but the sign is negative. The quote midpoint estimate of idiosyncratic volatility, is not significant, showing a coefficient of only -0.0023 with a t-statistic of only -0.56.

When we focus the analysis on the G7 countries in Panel B of Table 5, we find very similar results to those of the 23 developed markets with and without the U.S. market. However, the results are much stronger for the G6 countries than for the G7 countries. As shown for the G7 countries, we obtain significance, at the 5% level, for idiosyncratic volatility regardless of the liquidity control. However, the quote midpoint-based estimate of idiosyncratic volatility is only -0.005, showing no significance in its association with future returns. The G6 countries also show significance in the pricing for the transaction price-based estimate of idiosyncratic volatility, but no significance in the pricing of the quote midpoint-based estimate of idiosyncratic volatility.

Finally, we separate the U.S. market from the other markets to perform separate examinations and these results appear in Panel C of Table 5. Given the size and scope of the number of firms listed in the U.S. market, we include the dispersion of the analyst forecasts in the regressions. George and Hwang (2012) demonstrate the importance of the dispersion in analyst forecast in the pricing of idiosyncratic volatility. Panel C of Table 5 illustrates that for the U.S. market, including analyst dispersion as a control variable reduces the level in the pricing ability of idiosyncratic volatility, but it remains significant at the 5% level. However, the pricing ability of the quote midpoint-based estimate of idiosyncratic volatility is insignificant.

The evidence when using the bid-ask spread indicates that a limits-to-arbitrage argument cannot explain the pricing ability of idiosyncratic volatility. In particular, the bid-ask spread appears to be particularly ineffective at removing the pricing ability of idiosyncratic volatility for any market aggregation. This phenomenon is especially true of the market aggregations without the U.S. Unfortunately, these regions are precisely where the pricing ability of the transaction price-based estimate of idiosyncratic volatility is most in evidence. Indeed, the consistently negative sign for the bid-ask spread indicates that large future returns are associated with low costs to immediacy, a result opposite to the limits-to-arbitrage argument. This evidence is consistent with Ang et al.'s (2009); they show that including liquidity as an exogenous variable cannot explain the pricing ability of idiosyncratic volatility. Spiegel and Wang (2005) clearly articulate this point when they argue that while idiosyncratic volatility and liquidity are related, the relation between idiosyncratic volatility and future returns is stronger[14] than is the relation between liquidity and future returns.

[14]Han and Lesmond (2011) theorize that the difference in variance estimated using the transaction price and the quote midpoint-based returns is related to the square of the bid-ask spread. The relation is non-linear and consequently, the transaction price-based estimate of idiosyncratic volatility will contain linear and non-linear bid-ask spread components. Because of the non-linear bid-ask component embedded in the transaction price-based estimate of idiosyncratic volatility, including only a linear bid-ask spread term as an additional regressor will not drive out the significance of idiosyncratic volatility. In unreported results, we also performed sort tests on the fitted values of the regression of idiosyncratic volatility on the spread and the squared spread. The resulting sort results are demonstrably strengthened relative to those reported in

Overall, these results are consistent with Han and Lesmond (2011), who posit that price movements between the bid and ask quotes inflate the measured returns resulting in a variance inflation. Consequently, a liquidity bias drives the reported pricing ability of idiosyncratic volatility, and controlling for this bias by using quote midpoint-based returns reduces the pricing ability of idiosyncratic volatility to insignificance. This evidence is persistent in both quintile sort and Fama-MacBeth regression tests and across any of the regional aggregations.

VI Robustness Check

The prior sort and regression tests highlight the role that liquidity plays in estimating idiosyncratic volatility and on its relation with future returns. We now examine a robustness check on the pricing ability of idiosyncratic volatility.

We directly control for a bid-ask spread effect on the pricing ability of idiosyncratic volatility by regressing the transaction price-based idiosyncratic volatility estimate on the spread and the squared spread and then taking the residual of this regression. We incorporate both the spread and the square of the spread[15] to operationalize the theory of Han and Lesmond (2011).

We then use this residual idiosyncratic volatility in sort tests for the ability of idiosyncratic volatility to predict future returns. We can construe this residual as the "true" id-

the bid-ask spread sorts of Table 2. The fitted value sort results highlight the importance of the nonlinear bid-ask spread element in the pricing of bid-ask spread. Idiosyncratic volatility is picking up both the linear and non-linear elements of the bid-ask spread; thus demonstrating more power than only the linear bid-ask spread, and explaining why idiosyncratic volatility drives out the significance of the bid-ask spread.

[15]We do not attempt to find the best fit for the transaction price-based estimate of idiosyncratic volatility and we obtain stronger results using the square root of the spread. The key idea is that the relation is non-linear and we represent that idea generally with a square term.

iosyncratic volatility according to the theory of Han and Lesmond (2011). Johnson (2004), Nagel (2005), and Fama and French (2008) have used this regression residual approach to "orthogonalize" highly related variables in a Fama–MacBeth setting. The residual measures the pricing ability of idiosyncratic volatility that is orthogonal to the bid-ask spread. This procedure is an alternative, but more direct, method of controlling for the liquidity bias in estimating idiosyncratic volatility.

Table 6 is here.

Each month, we sort stocks into quintiles according to 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. Table 6 reports the results for world markets.

As Table 6 shows, *none* of the High-Low alphas are significant. Even the U.S. market alone, which previously demonstrated some pricing with the quote midpoint with the Fama-French factors, is now insignificant in the residual sort. Again, higher levels of the bid-ask spread are evident in the extreme idiosyncratic volatility quintiles that also experience the largest negative levels in alpha. However, neither the alpha of each idiosyncratic volatility portfolio nor the average bid-ask spread demonstrates any monotonicity across the quintiles. The lack of a monotonic ordering for the bid-ask spread across the idiosyncratic volatility quintiles explains the lack of significance in the pricing ability for the idiosyncratic volatility component that is orthogonal to the bid-ask spread.

VII Conclusions

Ang et al. (2006), (2009) present compelling evidence that realized idiosyncratic volatility is priced in security returns. We find that the pricing ability of idiosyncratic volatility depends critically on the underlying bid-ask spread. The premise of our finding is a measurement error in price argument (Blume and Stambaugh (1983) and Kaul and Nimalendran (1990)) that conjectures that the bid-ask bounce leads to a measurement error (liquidity bias) in estimating idiosyncratic volatility. In conjunction with the negative relation that idiosyncratic volatility and future returns exhibits, we find that the bid-ask spread and returns are negatively related across the developed markets around the world, a result that runs counter to the conventional wisdom, but a result that is very consistent with the empirical evidence for the U.S. market (Brennan and Subrahmanyam (1996) and Easely et al. (2002)). These results suggest that testing for the pricing ability of idiosyncratic volatility is, in fact, testing for the pricing ability of the underlying bid-ask spread.

We provide a means for controlling for the measurement error in price by using quote midpoints to estimate idiosyncratic volatility as Han and Lesmond (2011) argued. Across world markets, we find that the transaction price-based estimate of idiosyncratic volatility is negatively and significantly related to one-month ahead returns. Conversely, we find that the quote midpoint-based estimate of idiosyncratic volatility is not priced. We directly control for the bid-ask spread effect by orthogonalizing idiosyncratic volatility and the spread and we find that the orthogonal component is not priced in future returns.

In addition, we use two-month ahead returns to demonstrate that these results withstand tests that control for reversal effects induced by the bid-ask bounce. The transaction price-based estimate of idiosyncratic volatility remains largely significant, but the quote midpoint-based estimate of idiosyncratic volatility is insignificant in its relation to two-month ahead future returns.

This work has implications for international asset pricing. Hou et al. (2011) have put forth the notion that firm-level characteristics should be important drivers in global asset pricing. Our results indicate that firm-level liquidity, as opposed to the firm-level idiosyncratic volatility characteristic, should be the focus of international asset pricing research, echoing the findings of Lee (2011). This suggested focus extends to examining the determinants of idiosyncratic volatility, analyzing their time trends, and exploring whether trends exist in the behavior of those determinants, as Brandt, Brav, Graham, and Kumar (2010) and Bekaert et al. (2012) examine. This line of research should consider the effects of the bid-ask spread on the behavior of idiosyncratic volatility. We raise the issue whether the test of the pricing ability of idiosyncratic volatility is essentially a test of the pricing ability of the underlying bid-ask spread. Future work should incorporate this issue.

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A Appendix: Return Reversal Test

If stock returns are positively correlated with idiosyncratic volatility in the ranking month, and if the month-end price of the ranking month from which the next month's return is calculated is more likely at the ask quote than at the bid quote, then the resulting price reversal leads to a negative relation between idiosyncratic volatility and returns in the month immediately following the ranking. We control for any potential liquidity effects on the reported monthly returns by excluding the month immediately following the estimation of idiosyncratic volatility. Also, we use this robustness test to control for a return reversal effect (Huang et al. (2009)) on pricing. Table 7 shows these results.

Table 7 is here.

As Panel A of Table 7 shows, excluding the month immediately following the estimation of idiosyncratic volatility still produces significance in the pricing ability of idiosyncratic volatility for world markets (both with and without the U.S.), the 23 developed markets, the G7 countries, and the U.S. market, but no significance in the pricing of idiosyncratic volatility is evident for the developed markets without the U.S. and for the G6 countries. In contrast, as Panel B of Table 7 shows, the quote midpoint-based estimate of idiosyncratic volatility does not demonstrate any pricing ability with the two-month ahead returns, regardless of market aggregation.

These results indicate that the pricing ability of idiosyncratic volatility does not depend on a bid-ask bounce effect on future monthly returns or a return reversal effect. Rather, the pricing ability of idiosyncratic volatility depends critically on the bid-ask bounce in daily security returns that affects the estimation of idiosyncratic volatility, and controlling for the bid-ask bounce by using quote midpoints reduces the pricing ability of idiosyncratic volatility to insignificance.

Table 1
Summary Statistics

We present summary statistics for all markets around the world, segregated by developed and emerging market classifications. We further separate the developed markets into G7 countries and other developed markets. The G7 markets are in Panel A, the other developed markets are in Panel B, and the emerging markets are in Panel C. Panel D presents the summary statistics for the regional aggregations that our study comprises. For the regional aggregations in Panel D, all of our empirical tests will span 246 months for the 22 developed markets (from 1988:07 to 2008:12), 300 months for market aggregations that include the U.S. market (from 1984:01 to 2008:12), and 177 months for the emerging markets (from 1992:04 to 2008:12). We present variables on a monthly basis with individual starting dates outlined for each market. Dates are presented in Year:Month format. The number of months is a count from the beginning date of the bid-ask spread to the end of December 2008. We take book-to-market and firm size from Datastream for all markets except the U.S. market. For the U.S. market, all data stem from either CRSP or the Compustat quarterly databases, and we first compute book-to-market using the quarterly Compustat book equity and then convert it to a monthly book-to-market, using the monthly firm size. All values are in U.S. dollars, using daily exchange rates provided by Datastream. Firm size is in millions of U.S. dollars. The spread is the proportional bid-ask spread. We present two idiosyncratic volatility estimates; we base the first estimate on the transaction price-based returns and the second estimate on the quote midpoint-based returns. Each of the idiosyncratic volatility estimates is derived relative to the three-factor Fama-French model. We take the market factor from the MSCI world index that comprises both developed and emerging markets.

		Firm Characteristics				Liquidity Characteristics		
Country	Beginning Spread Date	Book to Market	Firm Size	Number of Firms	Transaction Price Idiosyncratic Volatility	Number of Months	Spread (%)	Quote Midpoint Idiosyncratic Volatility
Panel A: G7 Countries								
Canada	1989:10	0.79	915	949	52.23	231	3.56	45.47
England	1996:01	0.66	2352	931	36.21	156	5.87	30.12
France	1988:07	0.83	2142	540	38.67	246	5.65	44.37
Germany	1996:12	2.04	1653	633	48.32	145	4.69	48.88
Italy	1994:01	0.82	2023	190	31.61	180	1.21	31.75
Japan	1990:03	0.99	595	2606	40.63	226	3.83	35.91
U.S.	1984:01	0.71	1243	5964	58.12	300	3.78	45.12

		Firm Characteristics				Liquidity Characteristics		
Country/Region	Beginning Spread Date	Book to Market	Firm Size	Number of Firms	Transaction Price Idiosyncratic Volatility	Number of Months	Spread (%)	Quote Midpoint Idiosyncratic Volatility
Panel B: Other Developed Markets								
Australia	2001.07	0.66	1742	969	38.89	90	2.91	33.29
Austria	2001.07	1.22	1225	71	27.54	90	4.66	20.91
Belgium	1995:01	0.82	1866	124	28.91	168	3.33	22.44
Denmark	1989:12	0.92	451	130	28.00	240	3.43	25.28
Finland	1994:08	0.73	1488	109	35.73	173	2.96	29.63
Greece	1995:07	0.75	458	207	43.20	162	2.21	31.88
Hong Kong	1992:03	0.96	3658	610	41.08	202	1.61	40.26
Ireland	1995:03	0.80	1735	31	33.62	166	3.11	27.87
Netherlands	1996:01	0.70	2923	98	30.19	156	2.77	27.21
New Zealand	1992:04	0.63	639	75	29.81	201	2.46	27.56
Norway	1992:04	1.05	1057	99	38.44	201	4.38	36.21
Portugal	1994:03	0.86	1288	40	31.35	178	2.83	25.32
Singapore	1992:04	0.76	2205	333	29.98	201	1.97	28.18
Spain	1991:12	0.69	3725	76	28.00	205	1.15	25.68
Sweden	1992:04	0.83	1265	259	42.47	201	2.69	38.08
Switzerland	1988:07	1.19	2732	168	28.73	246	2.35	25.03
Panel C: Emerging Markets								
Argentina	1997:08	0.61	872	19	34.14	138	7.24	31.58
Brazil	1995:02	1.38	1602	310	43.94	167	16.38	38.75
Chile	2002:07	0.72	900	80	20.25	78	14.13	19.96
China	1996:07	0.23	934	1191	44.79	150	0.20	42.09
Colombia	1999:01	1.09	1569	11	26.71	119	7.77	11.27
Hungary	1999:12	1.15	2097	7	40.41	109	8.70	23.19
India	2000:01	0.87	426	54	46.57	108	2.38	30.42
Indonesia	1994:01	0.73	638	66	36.54	180	7.23	29.06
Israel	1993:02	0.76	72	403	37.13	190	9.27	33.03
Korea	1996:01	1.21	60	805	59.36	156	4.75	49.15
Malaysia	1992:04	0.50	805	187	40.56	201	1.98	37.54
Mexico	1994:02	0.72	2403	44	31.11	179	6.21	24.58
Pakistan	2005:12	0.51	336	103	31.31	37	3.77	27.73
Peru	1997:11	0.97	451	66	29.63	134	9.27	22.38
Philippines	1992:04	1.02	566	24	32.49	201	7.37	26.47
Poland	1999:12	0.79	341	255	43.21	109	2.35	33.36
Russia	2001:01	0.55	172	42	31.15	88	13.47	19.12
South Africa	1994:02	0.70	1242	37	34.71	179	4.45	29.50
Sri Lanka	2006:04	2.83	44	57	33.54	33	21.85	30.68
Taiwan	1992:05	0.45	1693	104	39.80	200	0.81	23.66
Thailand	1992:04	0.84	645	83	35.23	201	4.90	27.90
Turkey	2002:06	0.89	286	116	44.11	79	0.91	26.29
Panel D: Regional Aggregations								
45 World Markets	1984:01	0.93	1326	20187	47.76	300	3.94	41.12
World w/o U.S.	1988.07	1.08	1055	14267	44.79	246	4.17	39.57
G7 Countries	1984:01	0.88	1500	11743	43.94	300	3.93	38.71
G7 w/o U.S.	1988:07	1.11	1203	5823	41.16	246	4.39	39.11
23 Developed Markets	1984:01	0.91	1466	15142	41.13	300	4.11	38.12
Developed w/o U.S.	1988:07	1.09	1232	9222	40.11	246	4.58	37.21
22 Emerging Markets	1992:04	0.93	343	3961	49.17	201	6.02	42.54

Table 2
Bid-Ask Spread Sort Tests

We sort stocks into quintiles according to the bid-ask spread and we estimate the alpha by using the three-factor Fama-French model. We segregate the results across the 45 world markets, across 23 developed markets, by the G7 countries, and across all 22 emerging markets. We break out the U.S. market alone which covers the NYSE/Amex/NASDAQ markets. Where applicable, we both include and exclude the U.S. market. We convert all returns to U.S. dollars to provide a common currency for testing across the market aggregations. The column labeled High-Low refers to the abnormal performance (alpha) between the portfolios in the highest and the lowest bid-ask spread quintiles. We value-weight all of these results. At the beginning of the month, we use market capitalization converted to U.S. dollars as the weight. We also delete any observation with prices less than $5.00 for G7 countries, $3.00 for non-G7 country developed markets, and $1.00 for emerging markets. The start date for the world markets, the developed markets, and the G7 countries is 1984:01. The start date for the emerging markets is 1992:04. The end date is 2008:12. Newey-West robust t-statistics with nine lags are in parentheses. We denote significance at the 1%, 5%, and 10% levels by an ***, an **, or an *, respectively.

	FF Alpha					
	Low	2	3	4	High	High-Low
45 World Markets	0.009	-0.324**	-0.562***	-0.716***	-0.894***	-0.903***
	(0.071)	(-2.360)	(-4.668)	(-4.187)	(-4.171)	(-3.714)
World Markets w/o U.S.	-0.421***	-0.992***	-0.878***	-0.967***	-1.049***	-0.629**
	(-3.110)	(-5.041)	(-3.891)	(-3.798)	(-3.868)	(-2.300)
23 Developed Markets	0.017	-0.311**	-0.506***	-0.699***	-0.867***	-0.884***
	(0.138)	(-2.240)	(-4.253)	(-4.090)	(-4.305)	(-3.879)
Developed Markets w/o U.S.	-0.411***	-0.911***	-0.930***	-0.842***	-1.018***	-0.606**
	(-3.304)	(-4.737)	(-4.489)	(-3.373)	(-4.033)	(-2.305)
G7 Countries	0.053	-0.302**	-0.563***	-0.652***	-0.845***	-0.897***
	(0.422)	(-2.201)	(-4.414)	(-3.464)	(-3.982)	(-3.713)
G7 Countries w/o U.S.	-0.487***	-1.087***	-1.074***	-1.095***	-1.298***	-0.810**
	(-3.246)	(-5.013)	(-4.209)	(-4.079)	(-3.928)	(-2.439)
U.S. Market	0.274*	-0.007	-0.211	-0.188	-0.336	-0.609***
	(1.735)	(-0.036)	(-1.112)	(-0.882)	(-1.356)	(-3.039)
22 Emerging Markets	-1.223**	-1.385***	-1.024*	-1.014*	-0.637	0.586
	(-2.046)	(-2.650)	(-1.948)	(-1.709)	(-1.095)	(1.109)

Table 3
Transaction Price Idiosyncratic Volatility Sort Tests

We estimate idiosyncratic volatility using the (market closing) transaction price-based returns. This approach is the common return definition used in the literature. We employ the transaction price return to estimate idiosyncratic volatility using the daily returns over one-month and then rank them into quintiles. At the beginning of the month, we convert market capitalization to U.S. dollars to use as the weight and we measure the abnormal performance of each of the portfolios by using either the three-factor Fama-French model, shown in Panel A, or with the Carhart momentum factor, shown in Panel B. The column labeled High-Low refers to the abnormal performance (alpha) between the portfolios in the highest and the lowest idiosyncratic volatility quintiles. We also provide the average bid-ask spread that corresponds to each of the idiosyncratic volatility quintiles. We segregate the results across the 45 world markets, across 23 developed markets, by the G7 countries, and across all 22 emerging markets. Where applicable, we both include and exclude the U.S. market. The start date for the world markets, the 23 developed markets, and the G7 countries is 1984:01. The start date for the emerging markets is 1992:04. The end date is 2008:12. Newey-West robust t-statistics with nine lags are in parentheses. We denote significance at the 1%, 5%, and 10% levels by an ***, an **, or an *, respectively.

		Low	2	3	4	High	High-Low
		Panel A: Fama-French Three-Factor Alpha					
45 World Markets	FF Alpha	-0.006	-0.163	-0.267**	-0.462***	-0.805***	-0.798***
		(-0.048)	(-1.449)	(-2.506)	(-2.957)	(-3.153)	(-2.978)
	Spread	0.608	0.809	1.092	1.319	1.746	1.138
World Markets w/o U.S.	FF Alpha	-0.452***	-0.692***	-0.828***	-0.878***	-1.177***	-0.724**
		(-2.945)	(-5.640)	(-4.514)	(-3.365)	(-3.664)	(-2.095)
	Spread	1.069	1.349	1.658	2.002	2.404	1.335
23 Developed Markets	FF Alpha	-0.005	-0.158	-0.286**	-0.289*	-0.722***	-0.717***
		(-0.039)	(-1.447)	(-2.579)	(-1.793)	(-2.885)	(-2.840)
	Spread	0.607	0.814	1.080	1.327	1.746	1.139
Developed Markets w/o U.S.	FF Alpha	-0.384**	-0.581***	-0.929***	-0.751***	-1.088***	-0.704**
		(-2.558)	(-5.215)	(-5.564)	(-3.126)	(-4.110)	(-2.441)
	Spread	1.081	1.321	1.604	1.934	2.365	1.283
G7 Countries	FF Alpha	-0.012	-0.121	-0.265**	-0.265	-0.724***	-0.712***
		(-0.101)	(-1.071)	(-2.138)	(-1.599)	(-2.844)	(-2.847)
	Spread	0.634	0.839	1.114	1.343	1.770	1.135
G7 Countries w/o U.S.	FF Alpha	-0.691***	-0.742***	-1.010***	-0.721***	-1.182***	-0.491*
		(-4.380)	(-5.321)	(-6.150)	(-2.597)	(-4.189)	(-1.918)
	Spread	1.330	1.508	1.830	2.111	2.580	1.250
U.S. Market	FF Alpha	0.175	0.088	0.118	0.099	-0.538*	-0.713***
		(1.235)	(0.503)	(0.637)	(0.457)	(-1.835)	(-2.790)
	Spread	0.536	0.641	0.792	1.001	1.481	0.944
22 Emerging Markets	FF Alpha	-0.926*	-0.939**	-0.956*	-1.428**	-1.334**	-0.408
		(-1.828)	(-1.982)	(-1.761)	(-2.243)	(-2.021)	(-0.867)
	Spread	1.297	1.170	1.251	1.436	2.449	1.152
		Panel B: Carhart Four-Factor Alpha					
U.S. Market	Carhart Alpha	0.178	0.150	0.280	0.214	-0.350	-0.527*
		(1.086)	(0.797)	(1.290)	(0.878)	(-1.063)	(-1.864)

Table 4
Quote Midpoint Idiosyncratic Volatility Sort Tests

We estimate idiosyncratic volatility by using the quote midpoint-based returns, and using the world three-factor Fama-French model. We sample the closing bid and ask quotes from Bloomberg and Datastream to compute the quote midpoint-based daily return. At the beginning of the month, we convert market capitalization to U.S. dollars to use as the weight and we measure the abnormal performance of each of the portfolios by using either the three-factor Fama-French model, that appears in Panel A, and then with the Carhart momentum factor, that appears in Panel B. The column labeled High-Low refers to the abnormal performance (alpha) between the portfolios in the highest and the lowest idiosyncratic volatility quintile. We also provide the average bid-ask spread for each of the idiosyncratic volatility quintiles. The last column presents a portfolio that is long the High-Low transaction price (TP) idiosyncratic volatility and short the High-Low quote midpoint (QM) idiosyncratic volatility. We segregate the results across the 45 world markets, the 23 developed markets, the G7 countries, and the 22 emerging markets. Where applicable, we both include and exclude the U.S. market. The start date for the world markets is 1984:01 and the start date for the emerging markets is 1992:04. The end date is 2008:12. Newey-West robust t-statistics with nine lags are in parentheses. We denote significance at the 1%, 5%, and 10% levels by an ***, an **, or an *, respectively.

		Low	2	3	4	High	High-Low	$\alpha_{TP} - \alpha_{QM}$
		Panel A: Fama-French Three-Factor Alpha						
World Markets	FF Alpha	-0.307**	-0.066	-0.213	-0.245*	-0.580**	-0.273	-0.525***
		(-2.083)	(-0.546)	(-1.604)	(-1.670)	(-2.476)	(-0.928)	(-2.789)
	Spread	1.130	0.654	0.710	0.932	1.715	0.585	
World Markets w/o U.S.	FF Alpha	-0.688***	-0.653***	-0.748***	-0.897***	0.896***	-0.208	-0.516*
		(-3.553)	(-3.940)	(-4.106)	(-4.582)	(-2.784)	(-0.537)	(-1.850)
	Spread	1.823	1.503	1.147	1.261	2.603	0.780	
Developed Markets	FF Alpha	-0.294**	-0.071	-0.218	-0.144	-0.454**	-0.160	-0.557***
		(-2.014)	(-0.567)	(-1.580)	(-1.005)	(-1.985)	(-0.573)	(-2.784)
	Spread	1.141	0.660	0.711	0.929	1.690	0.549	
Developed Markets w/o U.S.	FF Alpha	-0.667***	-0.618***	-0.836***	-0.700***	-0.655***	0.012	-0.715***
		(-3.428)	(-3.818)	(-5.562)	(-3.615)	(-2.812)	(0.041)	(-2.734)
	Spread	1.853	1.575	1.257	1.191	2.363	0.509	
G7 Countries	FF Alpha	-0.271*	-0.100	-0.175	-0.111	-0.465**	-0.193	-0.519**
		(-1.888)	(-0.760)	(-1.236)	(-0.775)	(-1.981)	(-0.687)	(-2.533)
	Spread	1.182	0.683	0.726	0.949	1.704	0.522	
G7 Countries w/o U.S.	FF Alpha	-0.723***	-0.730***	-1.048***	-0.628***	-0.855***	-0.132	-0.359
		(-3.399)	(-4.277)	(-5.724)	(-2.788)	(-3.328)	(-0.516)	(-1.302)
	Spread	2.028	1.676	1.648	1.415	2.520	0.492	
U.S. Market	FF Alpha	0.148	0.115	0.056	0.162	-0.371	-0.519**	-0.194*
		(1.001)	(0.721)	(0.297)	(0.898)	(-1.343)	(-2.172)	(-1.862)
	Spread	0.591	0.569	0.661	0.808	1.274	0.682	
Emerging Markets	FF Alpha	-1.004**	-0.955*	-1.262**	-1.136	-0.998	0.006	-0.355
		(-2.296)	(-1.905)	(-2.168)	(-1.594)	(-1.499)	(0.012)	(-1.320)
	Spread	1.170	1.150	1.285	1.623	2.542	1.372	
		Panel B: Carhart Four-Factor Alpha						
U.S. Market	Carhart Alpha	0.142	0.178	0.148	0.306	-0.195	-0.337	-0.190*
		(0.870)	(0.999)	(0.704)	(1.447)	(-0.633)	(-1.221)	(-1.813)

Table 5
Value-Weighted Fama-MacBeth Regressions

We present value-weighted Fama-MacBeth regressions using the prior month's firm size, converted to U.S. dollars, as the weight. We estimate the transaction price (TP) based idiosyncratic volatility and the quote midpoint (QM) based idiosyncratic volatility using the Fama-French three-factor model. We delete any observation without comparable bid-ask spread information. For each of these classifications we include and then exclude the U.S. market to demonstrate the sensitivity in the pricing of idiosyncratic volatility. The start date (shown as year:month) is relative to the available spread information. We include the three contemporaneous Fama-French risk factors, the log scaled book-to-market, the lagged one-month monthly return to control for reversal effects, and the six-month momentum return. We measure book-to-market seven months before the monthly return. We also include the bid-ask spread. For the U.S. market results, we include the dispersion in analyst forecasts. Panel A refers to the 23 developed markets, Panel B refers to the G7 countries, and Panel C refers to the U.S. alone. We show Newey-West t-statistics with nine lags in parentheses. The R^2 statistic reports the average of the cross-sectional adjusted R^2 statistics. We denote significance at the 1%, 5%, and 10% levels by an ***, an **, and an *, respectively.

Panel A: 23 Developed Markets

	With U.S.			Without U.S.		
Intercept	0.0017	0.0049	0.0005	-0.0235	-0.0201	-0.0283*
	(0.16)	(0.43)	(0.04)	(-1.62)	(-1.44)	(-1.90)
TP Idiosyncratic Volatility	-0.0114**	-0.0112**		-0.0144***	-0.0130**	
	(-2.53)	(-2.47)		(-2.78)	(-2.54)	
QM Idiosyncratic Volatility			-0.0044			-0.0023
			(-1.20)			(-0.56)
β_{rm}	-0.0004	-0.0003	-0.0005	-0.0028	-0.0027	-0.0031
	(-0.27)	(-0.21)	(-0.31)	(-1.34)	(-1.32)	(-1.51)
β_{hml}	-0.0001	-0.0001	-0.0001	0.0004	0.0005	0.0005
	(-0.11)	(-0.14)	(-0.05)	(0.73)	(0.76)	(0.79)
β_{smb}	0.0001	-0.0001	0.0001	0.0017*	0.0017*	0.0019*
	(0.09)	(-0.01)	(0.04)	(1.71)	(1.70)	(1.90)
Log B/M	0.0007	0.0007	0.0008	0.0032***	0.0031***	0.0033***
	(0.76)	(0.77)	(0.90)	(3.84)	(3.84)	(3.84)
Six-Month Momentum	0.0066**	0.0064**	0.0063**	0.0078*	0.0081*	0.0084**
	(2.13)	(2.12)	(2.03)	(1.83)	(1.93)	(1.98)
Firm-Size	0.0004	0.0003	0.0004	0.0015**	0.0013**	0.0016**
	(0.93)	(0.63)	(0.91)	(2.32)	(2.19)	(2.55)
One-Month Reversal	-0.0002***	-0.0002***	-0.0002***	-0.0004***	-0.0004***	-0.0005***
	(-3.11)	(-3.27)	(-3.55)	(-3.17)	(-3.30)	(-3.74)
Bid-Ask Spread		-0.0052	-0.0080		-0.0007**	-0.0008**
		(-0.87)	(-1.06)		(-2.23)	(-2.47)
Start Date		1984:01 (300)			1988:07 (246)	
adj. R^2	0.134	0.138	0.137	0.195	0.199	0.197

Panel B: G7 Countries

	With U.S.			Without U.S.		
Intercept	0.0029	0.0064	0.0023	-0.0134	-0.0063	-0.0130
	(0.26)	(0.55)	(0.19)	(-0.82)	(-0.38)	(-0.76)
TP Idiosyncratic Volatility	-0.0115**	-0.0114**		-0.0176***	-0.0150***	
	(-2.57)	(-2.54)		(-3.53)	(-3.14)	
QM Idiosyncratic Volatility			-0.0050			-0.0058
			(-1.34)			(-1.41)
β_{rm}	-0.0003	-0.0001	-0.0003	-0.0020	-0.0020	-0.0023
	(-0.17)	(-0.10)	(-0.18)	(-0.94)	(-0.91)	(-1.07)
β_{hml}	0.0001	-0.0001	0.0001	0.0006	0.0006	0.0006
	(0.01)	(-0.02)	(0.05)	(0.86)	(0.88)	(0.84)
β_{smb}	0.0001	-0.0001	-0.0001	0.0015	0.0016	0.0017*
	(0.01)	(-0.11)	(-0.07)	(1.58)	(1.63)	(1.76)
Log B/M	0.0006	0.0006	0.0007	0.0032***	0.0029***	0.0028***
	(0.62)	(0.64)	(0.74)	(3.78)	(3.58)	(3.20)
Six-Month Momentum	0.0071**	0.0070**	0.0069**	0.0090**	0.0091**	0.0096**
	(2.20)	(2.20)	(2.13)	(2.10)	(2.11)	(2.17)
Firm-Size	0.0004	0.0002	0.0004	0.0010	0.0007	0.0009
	(0.78)	(0.48)	(0.73)	(1.37)	(0.92)	(1.19)
One-Month Reversal	-0.0003***	-0.0003***	-0.0003***	-0.0005***	-0.0005***	-0.0006***
	(-3.32)	(-3.46)	(-3.78)	(-3.68)	(-3.74)	(-4.10)
Bid-Ask Spread		-0.0053	-0.0081		-0.0013*	-0.0014*
		(-0.88)	(-1.07)		(-1.72)	(-1.96)
Start Date		1984:01 (300)			1988:07 (246)	
adj. R^2	0.136	0.140	0.140	0.207	0.212	0.210

Panel C: U.S. Market			
Intercept	0.0239**	0.0272**	0.0262**
	(2.01)	(2.21)	(2.09)
TP Idiosyncratic Volatility	-0.0099**	-0.0098**	
	(-1.98)	(-1.96)	
QM Idiosyncratic Volatility			-0.0063
			(-1.48)
β_{rm}	0.0007	0.0006	0.0005
	(0.41)	(0.40)	(0.34)
β_{hml}	0.0001	0.0001	0.0001
	(0.01)	(0.04)	(0.15)
β_{smb}	-0.0003	-0.0003	-0.0003
	(-0.51)	(-0.50)	(-0.46)
Log B/M	0.0003	0.0004	0.0004
	(0.25)	(0.34)	(0.37)
Six-Month Momentum	0.0076*	0.0072*	0.0071*
	(1.93)	(1.86)	(1.81)
Firm-Size	-0.0005	-0.0006	-0.0006
	(-1.00)	(-1.17)	(-1.09)
One-Month Reversal	-0.0002***	-0.0002***	-0.0002***
	(-2.99)	(-3.04)	(-3.16)
Analyst Dispersion	-2.4248***	-2.4826***	-2.6260***
	(-3.53)	(-3.82)	(-4.08)
Bid-Ask Spread		-0.0111	-0.0160
		(-1.48)	(-1.60)
Start Date		1984:01 (300)	
adj. R^2	0.145	0.147	0.146

Table 6
Sort Tests of the Residual Idiosyncratic Volatility on Liquidity

We estimate the residual of a Fama–MacBeth regression of idiosyncratic volatility on the spread, and the squared spread. We rank the firms into quintiles to form residual idiosyncratic volatility portfolios each month. The column labeled High-Low refers to the abnormal performance (alpha) between the portfolios in the highest and the lowest residual idiosyncratic volatility quintiles. We also provide the average bid-ask spread for each of the residual idiosyncratic volatility quintiles. We measure the abnormal performance of each of the portfolios using the three-factor Fama-French alpha. We segregate the results across the 45 world markets, across 23 developed markets, and by the G7 countries. For the developed markets, the sample period runs from 1984:01 to 2008:12 (300 monthly observations), while for the world markets without the U.S., the sample periods runs from 1988:07 to 2008:12 (246 monthly observations). Newey and West (1987) robust t-statistics with nine lags are in parentheses and we denote significance at the 1%, 5%, and 10% level is given by an ***, an **, and an *, respectively.

		Low	2	3	4	High	High-Low
45 World Markets	FF Alpha	-0.243*	-0.081	-0.117	-0.208	-0.373*	-0.130
		(-1.752)	(-0.662)	(-0.920)	(-1.474)	(-1.764)	(-0.560)
	Spread	1.482	0.668	0.677	0.820	1.206	-0.276
World Markets w/o U.S.	FF Alpha	-0.685***	-0.517***	-0.702***	-0.889***	-1.002***	-0.317
		(-3.865)	(-3.848)	(-4.414)	(-4.612)	(-3.653)	(-0.983)
	Spread	2.270	1.201	1.286	1.489	1.797	-0.473
23 Developed Markets	FF Alpha	-0.281**	-0.021	-0.213	-0.144	-0.419**	-0.138
		(-2.118)	(-0.169)	(-1.618)	(-1.037)	(-2.028)	(-0.611)
	Spread	1.488	0.666	0.668	0.822	1.214	-0.275
Developed Markets w/o U.S.	FF Alpha	-0.633***	-0.531***	-0.775***	-0.829***	-0.932***	-0.299
		(-3.257)	(-3.993)	(-5.585)	(-4.657)	(-3.439)	(-1.005)
	Spread	2.270	1.212	1.290	1.476	1.811	-0.459
G7 Countries	FF Alpha	-0.237*	-0.044	-0.194	-0.091	-0.374*	-0.137
		(-1.888)	(-0.361)	(-1.375)	(-0.605)	(-1.711)	(-0.597)
	Spread	1.487	0.677	0.682	0.839	1.232	-0.255
G7 Countries w/o U.S.	FF Alpha	-0.947***	-0.731***	-0.882***	-0.830***	-1.087***	-0.140
		(-4.716)	(-4.906)	(-5.543)	(-4.102)	(-3.819)	(-0.518)
	Spread	2.487	1.362	1.459	1.682	2.033	-0.454
U.S. Market	FF Alpha	0.122	0.118	0.190	0.151	-0.172	-0.294
		(0.852)	(0.694)	(1.114)	(0.780)	(-0.639)	(-1.231)
	Spread	0.964	0.600	0.575	0.652	0.823	-0.142

Table 7
Two-Month Ahead Return Sort Tests

For this test, we exclude the month directly following the idiosyncratic volatility estimation and use the two-month ahead monthly returns when we examine the pricing ability of idiosyncratic volatility. This test eliminates a potential bid-ask bias in the computed monthly returns. We estimate idiosyncratic volatility using the transaction price-based returns in Panel A, and by computing daily returns using the quote midpoint prices in Panel B. We measure the abnormal performance of each of the portfolios using the three-factor Fama-French alpha. The column labeled High-Low refers to the abnormal performance (alpha) between the portfolios in the highest and in the lowest idiosyncratic volatility quintiles. We segregate the results across the world markets, the developed markets, the G7 countries, and the U.S. market alone. Where necessary, we both include and then exclude the U.S. market for each of these regional classifications. e convert market capitalization to U.S. dollars and then use it to weight each regression. The end date is 2008:12. Newey-West robust t-statistics with nine lags are in parentheses. We denote significance at the 1%, 5%, and 10% levels by an ***, an **, or an *, respectively.

	FF Alpha					
	Low	2	3	4	High	High-Low
Panel A: Transaction Price Estimated Idiosyncratic Volatility						
45 World Markets	-0.046	-0.065	-0.218*	-0.322*	-0.787***	-0.741**
	(-0.354)	(-0.551)	(-1.776)	(-1.822)	(-2.814)	(-2.508)
World Markets w/o U.S.	-0.431**	-0.413**	-0.678***	-0.923***	-1.113***	-0.682*
	(-2.423)	(-2.335)	(-3.956)	(-4.265)	(-3.222)	(-1.946)
Developed Markets	-0.039	-0.060	-0.208*	-0.258	-0.664**	-0.626**
	(-0.298)	(-0.478)	(-1.707)	(-1.540)	(-2.442)	(-2.106)
Developed Markets w/o U.S.	-0.473***	-0.420**	-0.654***	-0.860***	-0.951***	-0.478
	(-2.631)	(-2.471)	(-4.672)	(-4.076)	(-3.233)	(-1.424)
G7 Countries	-0.009	-0.031	-0.188	-0.246	-0.698***	-0.689**
	(-0.068)	(-0.251)	(-1.472)	(-1.370)	(-2.604)	(-2.451)
G7 Countries w/o U.S.	-0.618***	-0.481**	-0.798***	-0.852***	-0.982***	-0.364
	(-2.969)	(-2.567)	(-4.179)	(-2.930)	(-3.124)	(-1.090)
U.S. Market	0.105	0.248	0.216	0.116	-0.508*	-0.613**
	(0.725)	(1.456)	(1.096)	(0.477)	(-1.655)	(-2.140)
Panel B: Quote Midpoint Estimated Idiosyncratic Volatility						
45 World Markets	-0.238	-0.069	-0.106	-0.201	-0.490*	-0.253
	(-1.622)	(-0.614)	(-0.721)	(-1.315)	(-1.907)	(-0.852)
World Markets w/o U.S.	-0.797***	-0.555***	-0.533***	-0.717***	-0.893***	-0.096
	(-3.775)	(-2.835)	(-2.902)	(-3.460)	(-2.753)	(-0.272)
Developed Markets	-0.226	-0.059	-0.100	-0.145	-0.389	-0.163
	(-1.542)	(-0.472)	(-0.708)	(-0.957)	(-1.548)	(-0.542)
Developed Markets w/o U.S.	-0.728***	-0.513***	-0.622***	-0.506**	-0.800***	-0.071
	(-3.710)	(-2.604)	(-3.563)	(-2.499)	(-2.894)	(-0.212)
G7 Countries	-0.170	-0.064	-0.096	-0.098	-0.335	-0.165
	(-1.194)	(-0.489)	(-0.667)	(-0.621)	(-1.303)	(-0.563)
G7 Countries w/o U.S.	-0.704***	-0.565***	-0.812***	-0.587**	-0.995***	-0.290
	(-3.259)	(-2.748)	(-3.890)	(-2.357)	(-3.867)	(-1.068)
U.S. Market	-0.728***	-0.514***	-0.622***	-0.505**	-0.800***	-0.073
	(-3.709)	(-2.610)	(-3.561)	(-2.496)	(-2.897)	(-0.216)