Journal of Banking & Finance 34 (2010) 2562–2571

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Liquidity skewness

Richard Roll, Avanidhar Subrahmanyam *

Anderson School of Management, University of California at Los Angeles, Los Angeles, CA 90095, USA

ARTICLE INFO

Article history:
Received 23 February 2010
Accepted 22 April 2010
Available online 27 April 2010

JEL classification:
G12
G14

Keywords:
Liquidity
Market efficiency
Trading

ABSTRACT

Bid–ask spreads in equities have declined on average but have become increasingly right-skewed. This finding holds across exchanges as well as size, price, and volume quartiles. Higher right-skewness is consistent with more competition among market makers; which may reduce cross-subsidization across periods of high and low asymmetric information, unlike a monopolistic regime that can maintain a relatively constant spread. Confirming this intuition, proportional differences in spreads between earnings announcements and normal periods have increased considerably even as trading costs have declined on average. Skewness also is cross-sectionally related to information proxies such as institutional holdings and analyst following.

© 2010 Elsevier B.V. All rights reserved.

1. Introduction

Liquidity is an intrinsic feature of financial markets. The importance of this attribute is magnified because trading costs affect required returns (Amihud and Mendelson, 1986; Amihud, 2002; Chan et al., 2008) and thus corporate costs of capital. In addition, understanding liquidity dynamics could improve the efficacy of active investment management. Further, given the recent financial turmoil, a better comprehension of liquidity dynamics could also help restore investor confidence in financial markets.

Despite the importance of liquidity, we have yet to fully understand the behavior of trading costs over time. For example, while there have been dramatic increases in liquidity in recent years, and trading costs appear to have a common component (e.g., Jones, 2002; Chung and Hrazdil, 2010; Gibson and Mougeot, 2004; Fernando et al., 2008), we still do not know much about how the nature of fluctuations in spreads for a given firm has changed. Do spreads move about a central value more or less symmetrically? Or have they become more skewed in one direction or another? This issue is relevant because agents who need to trade at random time points could benefit from a better understanding of the distribution of trading costs. Would they be more likely to face relatively larger spread observations in the right tails? Or is it the case that spreads fluctuate within a narrow band about the smaller means? From an academic viewpoint, right- or left-skewed distributions, and shifts in these distributions, may imply a shift in the economic forces governing trading costs, and rationalizing the observed pattern would then be of considerable interest.

While there is no explicit model of the distribution of liquidity, Glosten and Milgrom (1985) (also referenced and discussed in Glosten, 1989) offer a few pointers on how one would expect liquidity skewness to change as the market maker faces more competition. The idea is that a monopolistic specialist has more flexibility in setting the bid–ask spread than a competitive one. Thus, the monopolist is able to raise spreads in periods of low asymmetric information (AI) to partially compensate for the increased losses to informed agents during high AI periods. However, competition from other market makers requires the specialist to breakeven on each transaction over time, and thus reduces the ability of the market maker to cross-subsidize across periods of high and low AI. Hence one may observe more large spreads (relative to the mean) during illiquid periods (possibly periods of high asymmetric information), and a clustering of observations in the left tail due to increased competition and a lowered tick size (Bessembinder, 2003) in recent years.

The previous argument relies on the optimizing behavior of the market maker. However, the per trade profit to agents that assist the specialist, such floor brokers, may also have reduced over time due to increased competition and a lower minimum price increment. Such agents could step away from taking order flow during high AI periods, reducing the risk-bearing capacity of the market and causing the designated dealer in the stock to be more exposed during these periods. This could naturally cause unusually wide spreads during some periods, and increase skewness.

* Corresponding author. Tel./fax: +1 310 825 5355.
E-mail addresses: rroll@anderson.ucla.edu (R. Roll), subra@anderson.ucla.edu (A. Subrahmanyam).

0378-4266/$ - see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.jbankfin.2010.04.012

Our analysis confirms these conjectures. We find that average annual skewness in bid–ask spreads has indisputably increased in recent years. For the full sample, even as average spreads at the end of the sample falls to a tenth to what they were at the beginning of the sample, skewness increases seven-fold. The increase is apparent in NYSE/Amex as well as Nasdaq stocks, and across size-, price-, and volume-based quartiles. We confirm the skewness increase both for CRSP-based closing bid–ask quotes as well as TAQ data filtered for outliers.

We shed empirical light on specific mechanisms by which skewness may have increased in recent years. Our arguments suggest that as the market maker loses monopoly power, spreads in periods of high asymmetric information widen relative to those in normal periods even as the mean spread declines. We show that the spread prior to earnings announcements has indisputably increased in recent years relative to the spread during other periods, supporting this reasoning. We show that increases in skewness are correlated with increases in spreads around earnings announcements as well as on extreme negative return days (when illiquidity is generally lower, viz. Chordia et al., 2001).

We find that skewness is cross-sectionally related to information proxies such as return volatility and institutional holdings. We find that skewness is inversely related to analyst following, which is consistent with the notion that analysts imply greater production of public information and thus less information asymmetry (Easley et al., 1998).

To our knowledge, this is the first paper to consider skewness in trading costs; as such, it is largely descriptive in nature. We leave a detailed analysis of what types of events result in extreme illiquidity that, in turn, affect skewness, for future research. However, we believe the third moment of liquidity, while hitherto unexplored, may capture important features of securities markets, especially during episodes that potentially affect liquidity, such as the recent financial crisis. Further analysis of macroeconomic conditions that influence liquidity skewness would also be a worthwhile area of research.

It is important to clarify that we are not asserting anything about investor welfare. Thus, the average spread has declined considerably even though the skewness in bid–ask spreads has increased substantially. The sign of the shift in overall investor welfare remains an open question and we believe that future theoretical work would shed further light on the subject.

The paper is organized as follows: Section 2 provides a simple example to show how skewness in spreads can increase with a reduction in the minimum tick size and increased competition. Section 3 describes the data and documents our main descriptive results about liquidity skewness. Section 4 discusses a potential explanation for the increased skewness. Section 5 discusses cross-sectional determinants of liquidity skewness. Section 6 concludes.

2. An example

We provide a stylized example of how spread skewness can increase as the minimum tick size is reduced and as the specialist loses monopoly power due to electronic networks (ECNs) and off-floor trading (viz. Stoll, 2006). The example is inspired by the arguments of Glosten and Milgrom (p. 75) (also referenced by Glosten, 1989; p. 212) as well as the specialist's obligation to maintain a "fair and orderly market" (NYSE Rule 104.10).

Table 1 provides an example where there are eight periods (in chronological order). Five periods are "normal" and the other three are characterized by low, moderate, and high periods of asymmetric information (AI). The period-by-period breakeven (zero expected profit) spreads appear in the first column. The second column represents spreads that may prevail in a regime with a high (1/8) tick size and high monopoly power, and the last column represents the spreads that may exist in a regime with the opposite attributes. There is one transaction of one share per period.

Table 1
An example of changes in spread skewness across market environments. Hypothetical spreads are presented across five normal periods (with a breakeven spread of 0.01) and three periods corresponding to low, medium, and high asymmetric information, with breakeven spreads of 0.05, 0.25, and 0.080, respectively). Regime 1 is characterized by a large minimum tick size and low competition, and regime 2 has the opposite attributes.

Breakeven spread	Spread in regime 1	Spread in regime 2
0.01	0.125	0.01
0.01	0.125	0.01
0.01	0.125	0.01
0.01	0.125	0.01
0.01	0.125	0.01
0.05	0.125	0.05
0.25	0.250	0.25
0.80	0.250	0.80
Mean	0.156	0.144
Skewness	1.440	2.408

Since this is primarily an empirical investigation, we take the spreads in the table as representing observed outcomes in the market and provide plausible economic justifications for these outcomes, as opposed to formally modeling the outcomes. However, the objective that yields the observed spread in the first regime is simply the notion that the specialist sets the lowest spread that ensures a non-negative cumulative profit across all periods to date. (The lowest spread restriction may be rationalized by the obligation to maintain a fair and orderly market.) In the second regime, competition requires that the spread be set to breakeven in each period.

In the first (monopolistic) regime, the spread is 0.125 in the five normal periods, as well as in the period with low asymmetric information. In all of these periods the specialist charges more than the breakeven spread. The spread jumps to 0.25 in the period with moderate asymmetric information as that is the breakeven spread in this period. However, due to the ability to charge spreads greater than the breakeven level of the spread during normal periods, the specialist is able to quote a spread of 0.25 that is below the breakeven spread of 0.8 in the high AI period. This allows him to meet an affirmative obligation to provide a fair and orderly market and also earn positive expected profits across the eight periods.

The spread in the second regime behaves differently. Because of competition, the spread is at the breakeven level in each period. Thus, the quoted spread is one penny for the five normal periods, and is also at the breakeven level in the low and moderate AI periods. Even in the high AI period, the specialist sets the spread at the breakeven level of 0.80, since the cross-subsidy from spreads in other periods is no longer available. As can be seen, regime 1 has a high mean and low skewness whereas regime 2 has the opposite attributes.

The basic hypothesis we test in the following sections is based on the observation that the market environment has more closely come to resemble regime 2, as opposed to 1. This implies that spreads (whose means are already known to have decreased – e.g., Jones, 2002) should also exhibit increased skewness in recent years.

3. Data and summary statistics

Our data mainly come from CRSP end-of-day closing bid–ask quotes that are available from 1993 onwards. We use these data instead of ISSM or TAQ data because they are less prone to errors.

However, later we add a robustness check using filtered TAQ data. The data include NYSE/Amex and Nasdaq stocks and are later stratified by size, price, and trading volume.

3.1. Summary statistics for the full sample

Table 2 presents annual equal-weighted averages of mean, standard deviation, and skewness of individual firm bid–ask spreads within the year. We present statistics for both the quoted spread as well as the proportional quoted spread, which is defined as the ask quote minus the bid quote divided by the mid-point of the quotes. We drop all quotes with negative ask–bid spreads and require the recorded ask and bid prices to be strictly positive. No other filters are imposed on the CRSP data. The sample size starts at 8126 firms, peaks at 9927 in 1997 during the tech stock boom, and declines to 7611 by 2007.

Panel A presents statistics for proportional quoted spreads, whereas Panel B reports the same results for unscaled spreads. The average annual proportional spread declined from over 3% to 0.35% over the sample period. This decline is fairly gradual, and not obviously related to specific events such as the changes in tick size in 1997 and 2001. Of course, Jones (2002) and Chordia et al. (2008) also document the general decline in spreads. On average, the standard deviation within a year of individual firm spreads has also declined (to roughly a third of its beginning value).

Table 2
Annual quoted spread statistics, all stocks. Summary statistics for bid–ask proportional spreads[a] and unscaled quoted spreads are calculated for all stocks listed on the CRSP database. The statistics are first calculated for each stock during each year. Then annual equally-weighted averages of the resulting individual firm statistics are computed and presented in the table.

Year	Mean	Standard deviation	Skewness	Number of firms
Panel A: Proportional quoted spreads				
1993	0.0311	0.0110	0.5258	8126
1994	0.0294	0.0105	0.5483	8697
1995	0.0284	0.0105	0.4349	9089
1996	0.0254	0.0097	0.5629	9686
1997	0.0240	0.0105	0.6451	9927
1998	0.0234	0.0119	1.1925	9785
1999	0.0220	0.0107	1.1235	9453
2000	0.0200	0.0111	1.4082	9160
2001	0.0182	0.0130	2.1901	8441
2002	0.0140	0.0099	1.5388	7741
2003	0.0090	0.0066	1.6772	7304
2004	0.0047	0.0034	2.1914	7185
2005	0.0042	0.0030	2.4163	7246
2006	0.0033	0.0023	2.6364	7321
2007	0.0035	0.0031	3.5393	7611
2007–1993	−0.0276	−0.0079	3.0135	
(*p*-value)	(<0.001)	(<0.001)	(<0.001)	
Panel B: Quoted spreads				
1993	0.4787	0.1446	0.3759	8126
1994	0.4659	0.1365	0.3919	8697
1995	0.4662	0.1416	0.2404	9089
1996	0.4857	0.1587	0.3982	9686
1997	0.4683	0.1768	0.5892	9927
1998	0.4348	0.1912	1.0162	9785
1999	0.3986	0.1838	1.1250	9453
2000	0.3820	0.2218	1.3767	9160
2001	0.2820	0.2387	2.2961	8441
2002	0.1977	0.1450	1.5303	7741
2003	0.1499	0.1237	1.6097	7304
2004	0.1389	0.1250	2.2262	7185
2005	0.1238	0.0862	2.4328	7246
2006	0.1081	0.0770	2.6799	7321
2007	0.1447	0.1397	3.5021	7611
2007–1993	−0.3340	−0.0049	3.126	
(*p*-value)	(<0.001)	(0.44)	(<0.001)	

[a] (Ask–bid)/[(Ask + Bid)/2].

In contrast, skewness has increased substantially, from 0.53 to 3.54, which is almost a seven-fold shift. A simple difference in means test confirms that the growth from 1993 to 2007 is significant with a *p*-value of less than 1%. In addition, skewness generally shows a steady, though, not monotonic, increase, which is particularly apparent in the post-decimal period. Thus, the skewness increase is not an artifact of any specific year in the sample period. Fig. 1 plots the spread skewness and clearly shows how this quantity has steadily increased on average over the past years.

Panel B of Table 2 indicates that the mean of the unscaled quoted decreases from 48 cents to about 15 cents. The skewness of quoted spreads increases from 0.38 to 3.50, and the magnitude of this increase is very similar to that of the proportional quoted spread. From this point on, while we mainly use the proportional quoted spread in our analysis since it is an economically sensible measure of trading cost, similar results are obtained with the raw (unscaled) spread, as we later point out.

In order to provide some additional perspective on how the distribution of liquidity has shifted over time, we now consider the empirical distribution of spreads for a representative stock, IBM. The actual mean spreads for IBM in 1993 and 2007 are about 0.19% and 0.04%, respectively, whereas the corresponding skewness values are 0.87 and 4.36. Thus, just as for the entire sample, the mean spread for IBM decreases, whereas skewness increases. These increases are, of course, statistically significant. In Fig. 2, we plot the frequency distribution of the spread for IBM for the first and last years of the sample. The figure demonstrates how the mean spread has decreased simultaneously with increased skewness. Basically, while the bulk of the 2007 observations are clustered around the low mean, there also are large excursions from the mean that contribute to the high skewness in 2007.

The remainder of this section stratifies this phenomenon of a shift in the skewness of bid–ask spreads by exchange and firm size. For convenience, from this point on, the term "skewness" should be understood as skewness in bid–ask spreads unless otherwise stated.

3.2. Liquidity skewness by exchange and other attributes

It is conceivable that skewness may differ across exchanges, given differences in market making protocols. For example, an exchange like the NYSE confers monopoly power on specialists, which may give them flexibility to cross-subsidize spreads in conditions of low liquidity with higher spreads during conditions of high liquidity (Glosten, 1989).

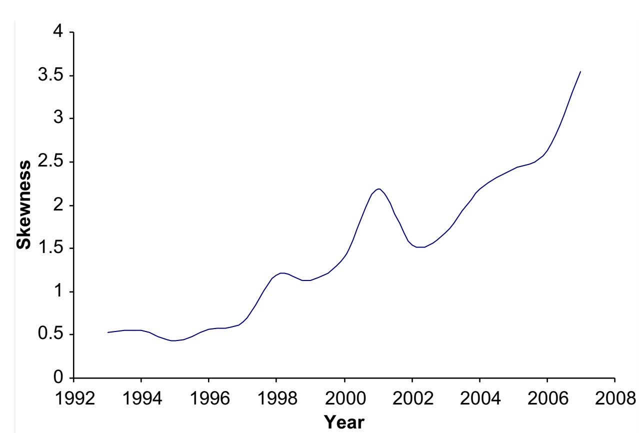

Fig. 1. Annual quoted proportional spread skewness. Skewness for bid–ask proportional spreads is calculated for all stocks listed on the CRSP database. The skewness is first calculated for each stock during each year. Then annual equally-weighted averages of the resulting values for individual firm skewness are computed and plotted in the figure.

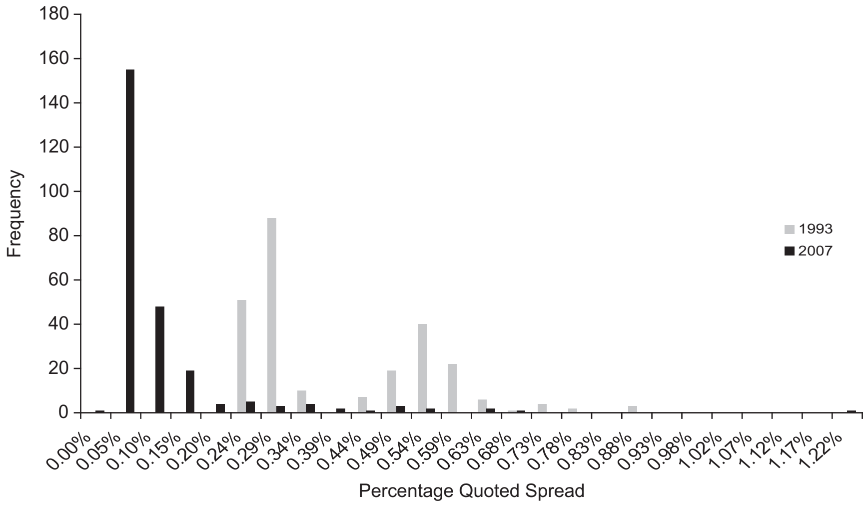

Fig. 2. IBM spreads, first and last years of the sample. This figure provides the frequency distributions of the daily proportional quoted spreads for IBM, in 1993 and 2007.

To shed light on this issue, Panels A and B of Table 3 present the results separately for NYSE/Amex and Nasdaq stocks. The mean NYSE/Amex proportional spread declines from 1.5% to 0.3%, but the skewness of spreads increases quite dramatically from 0.7 to 4.2. Similarly the mean spread for Nasdaq decreases from 4% to 0.5%, but again, the skewness increases from 0.4 to 2.7. The increase in skewness is statistically significant on both exchanges with a p-value of less than 1%.

Table 3
Summary statistics for proportional spreads, by exchange. Summary statistics for bid–ask proportional spreads[a] are calculated for all stocks listed on the CRSP database. The statistics are first calculated for each stock during each year. Then annual equally-weighted averages of the resulting individual firm statistics are computed and presented in the table.

Year	Mean	Standard deviation	Skewness	Number of firms
Panel A: Annual proportional spread statistics, NYSE/Amex				
1993	0.0145	0.0056	0.7001	3272
1994	0.0141	0.0054	0.7861	3460
1995	0.0170	0.0061	0.3729	3551
1996	0.0167	0.0064	0.6967	3733
1997	0.0184	0.0073	0.6877	3884
1998	0.0228	0.0086	1.0563	3951
1999	0.0265	0.0101	0.8534	3876
2000	0.0239	0.0102	1.0839	3821
2001	0.0161	0.0113	1.5697	3643
2002	0.0109	0.0078	1.5616	3577
2003	0.0067	0.0052	1.8816	3547
2004	0.0034	0.0023	2.8805	3643
2005	0.0030	0.0024	3.3249	3764
2006	0.0024	0.0018	3.6095	3892
2007	0.0025	0.0022	4.2296	4111
2007–1993	−0.0120	−0.0031	3.5295	
(p-value)	(<0.001)	(<0.001)	(<0.001)	
Panel B: Annual proportional spread statistics, Nasdaq				
1993	0.0420	0.0144	0.4031	4936
1994	0.0393	0.0137	0.3872	5314
1995	0.0354	0.0131	0.4663	5638
1996	0.0304	0.0116	0.4724	6092
1997	0.0273	0.0124	0.6080	6175
1998	0.0238	0.0140	1.2677	5938
1999	0.0190	0.0110	1.3018	5662
2000	0.0172	0.0118	1.6268	5408
2001	0.0196	0.0142	2.6482	4841
2002	0.0165	0.0117	1.5117	4214
2003	0.0112	0.0078	1.4805	3789
2004	0.0061	0.0044	1.4761	3567
2005	0.0054	0.0037	1.4308	3508
2006	0.0041	0.0029	1.5168	3462
2007	0.0046	0.0040	2.6746	3455
2007–1993	−0.0374	−0.0104	2.2715	
(p-value)	(<0.001)	(<0.001)	(<0.001)	

[a] (Ask–bid)/[(Ask + Bid)/2].

Overall, the difference in exchange protocol does not appear to have much bearing on the skewness pattern. One must note that Nasdaq dealers' oligopolistic power to manage spreads (Christie and Schultz, 1999) may cause their behavior to resemble that of the NYSE specialist.

Next, we examine liquidity skewness across size quartiles. This is to check whether the results are driven by a few small-cap companies experiencing extremely illiquid conditions on certain days. We assign stocks to four groups based on market capitalization as of the end of the previous year and then compute cross-sectional average statistics for each group. The results appear in Table 4, Panel A.

The skewness increase is evident in every size quartile, though the changes are not monotonic. Note the particularly large skewness in 2001 relative to surrounding years, likely the outcome of the turmoil following September 2001. Overall, the table reveals that skewness in the last year increases for every size quartile by a factor of about six or more relative to that in the first year of the sample, and all increases are statistically significant.

In Panels B and C of Table 4, we present annual liquidity skewness for trading volume and price level quartiles. This allows us to ascertain whether thinly traded and/or low-priced stocks experienced different skewness behavior relative to other stocks. We construct the trading volume quartiles using annual trading volume as of the previous year, whereas the price quartiles use the price as of the end of the previous year.

The results reveal that in each price and trading volume quartile, skewness shows a significant increase across the sample period. Indeed, the point estimate of the increase in skewness across the first and last years of the sample is largest for the most active, highest-priced stocks. Thus, the increase in skewness is not a phenomenon confined to small, thinly traded, or low-priced, stocks.

3.3. Liquidity skewness using intraday averages from TAQ data

Up to this point, we mainly have used CRSP closing bid–ask quotes. We prefer these to standard TAQ data, because the latter

Table 4
Skewness in proportional spread, by market capitalization, volume, and price. Skewness in bid–ask proportional spreads[a] is calculated for all stocks listed on the CRSP database after assigning each stock to a size quartile based on market capitalization as of the end of the previous year (Panel A), the previous year's trading volume (Panel B), and the end of the previous year price (Panel C). Skewness is first calculated for each stock during each year. Then annual equally-weighted averages of the resulting individual firm skewnesses are computed and presented in the table.

Year	Size quartile			
	Smallest	2	3	Largest
Panel A: Liquidity skewness by market capitalization				
1993	0.5302	0.4507	0.5485	0.6544
1994	0.4834	0.4835	0.5816	0.7022
1995	0.5359	0.4030	0.2928	0.5275
1996	0.5605	0.4673	0.4898	0.8627
1997	0.6229	0.4289	0.4664	1.0682
1998	1.1150	1.1274	1.1416	1.4439
1999	1.0417	0.9980	1.0117	1.4432
2000	1.1622	1.1443	1.3534	1.9637
2001	1.8410	2.0817	2.2641	2.7036
2002	1.4633	1.6785	1.7967	1.2459
2003	1.4535	1.7854	1.9885	1.5500
2004	1.4499	1.6855	2.4564	3.3812
2005	1.5750	2.0895	2.6689	3.4982
2006	1.6910	2.2601	3.0788	3.7683
2007	3.0503	3.3425	3.7158	4.2618
2007–1993	2.5201	2.8918	3.1673	3.6074
(*p*-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Volume quartile			
Panel B: Liquidity skewness by volume				
1993	0.2748	0.5772	0.6434	0.6439
1994	0.2763	0.5973	0.6773	0.6721
1995	0.2351	0.4165	0.4548	0.6390
1996	0.3052	0.5527	0.6559	0.8393
1997	0.2927	0.4486	0.7531	1.0551
1998	0.8913	1.0956	1.2941	1.5174
1999	0.7343	0.9930	1.1522	1.5393
2000	0.9624	1.1330	1.4665	1.9991
2001	1.4864	2.0341	2.3511	2.9252
2002	1.6014	1.6608	1.5810	1.3620
2003	1.5405	1.8995	1.8232	1.5142
2004	1.4802	1.9182	2.6487	2.8071
2005	1.7024	2.4644	2.8338	2.7662
2006	1.9140	2.5636	3.0772	3.1715
2007	3.3144	3.6115	3.6022	3.8495
2007–1993	3.0396	3.0343	2.9588	3.2056
(*p*-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	Prize quartile			
Panel C: Liquidity skewness by price level				
1993	0.5835	0.5194	0.5399	0.5435
1994	0.5772	0.5201	0.5520	0.6013
1995	0.6188	0.3571	0.3009	0.4870
1996	0.6399	0.5242	0.4132	0.8066
1997	0.6799	0.4955	0.3880	1.0226
1998	1.1708	1.1992	1.0743	1.3870
1999	1.0876	1.0703	0.8841	1.4343
2000	1.2260	1.1515	1.2716	1.9862
2001	2.0488	2.1615	2.0583	2.6117
2002	1.4836	1.7241	1.6401	1.3401
2003	1.5343	1.8056	1.8881	1.5487
2004	1.5164	2.0644	2.5080	2.8784
2005	1.6067	2.3735	2.8440	3.0077
2006	1.7119	2.5989	3.0696	3.4055
2007	2.8379	3.5781	3.9662	4.0110
2007–1993	2.2544	3.0587	3.4263	3.4675
(*p*-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

[a] (Ask–bid)/[(Ask + Bid)/2].

have transcription errors that may be small as a percentage of the total number of data points but could still have a significant impact on the third moment. Nonetheless, as a robustness check, Table 5 presents the skewness of quoted and effective spreads extracted from TAQ/ISSM data from 1984 to 2007. Since these spreads are prone to data entry errors when recording numerous intradaily transactions, we apply additional error-detection filters (as detailed in Chordia et al., 2001).

Table 5
Skewness from TAQ data. Spread skewness is calculated for all stocks in the ISSM/TAQ database. First, average daily quoted and effective spreads are calculated for each firm using all quotes matched to a transaction in the database, after being filtered for errors. Next, spread skewness is calculated for the average daily spreads of each stock during each year. Then annual equally-weighted averages of the resulting individual firm skewnesses are computed and presented in the table.

Year	Quoted spread	Effective spread
1984	0.6037	1.1545
1985	0.7084	0.9468
1986	0.6705	1.1410
1987	0.9171	1.3104
1988	0.5911	0.8341
1989	0.5933	0.6160
1990	0.5057	0.8801
1991	0.6287	1.2756
1992	0.5695	0.9475
1993	0.6406	0.9960
1994	0.6990	1.0999
1995	0.8705	0.8159
1996	0.8514	0.6554
1997	0.6023	1.3034
1998	0.7839	1.6765
1999	0.7605	1.5317
2000	0.7844	1.5163
2001	1.3244	1.6936
2002	1.3075	1.6627
2003	1.2752	1.6335
2004	1.3720	1.7337
2005	1.4052	1.6722
2006	1.8169	2.0083
2007	1.6058	2.1128
2007–1984	1.002	0.958
(*p*-value)	(<0.001)	(<0.001)

We first average spreads daily within each stock, and then calculate summary statistics as in Tables 2–4. Since the data extraction is intense (the annual share turnover is 200% towards the end of the sample), and we are only using the ISSM/TAQ data for a robustness check, we confine the calculations to NYSE/Amex stocks only. Results appear in Table 5 and indicate that the skewness of both quoted and effective spreads increases significantly. There is more year-to-year variability in these numbers but the mean skewness for quoted spreads in the last five years of the sample almost doubles in comparison to the corresponding value in the first five years. The skewness of effective spreads also increases substantially. The increases in skewness for both quoted and effective spreads are statistically significant.

Fig. 3 contains the plots of skewness obtained from these TAQ spreads. There are significant deviations from the general trend, especially in the earlier years, presumably due to lower data quality than in the later years. However, the overall trend is positive and is especially evident in the later years. Overall, the TAQ results confirm the increase in skewness for both quoted and effective spreads.

In the remainder of the paper we revert to the CRSP data on closing bid and ask quotes since, as argued earlier, these data are more likely to be free of typographical errors than the intradaily TAQ data. Also, since the proportional quoted spread, which measures the percentage transaction cost, is a more economically meaningful measure than the unscaled spread, and also addresses discreteness in unscaled spreads, we will mainly focus on the proportional spread from this point on. Thus, henceforth the term "spread" will refer to "proportional spread" (unless otherwise noted).

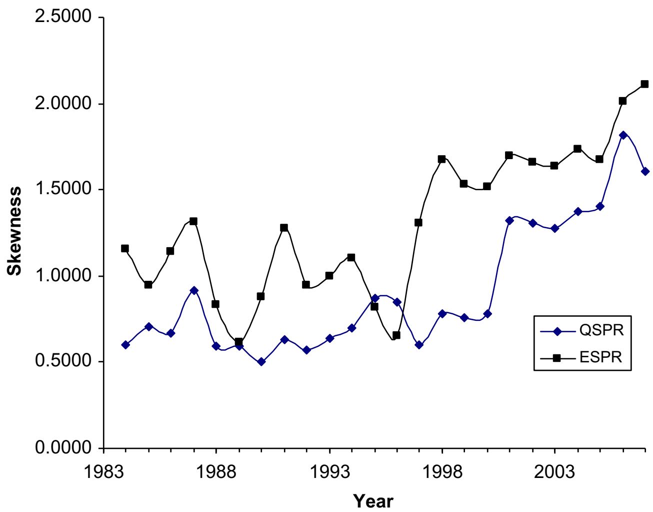

Fig. 3. Annual quoted and effective proportional spread skewness, TAQ data. Quoted and effective spread skewnesses are calculated for all stocks listed on the CRSP database. First, average daily quoted (QSPR) and effective (ESPR) spreads are calculated using all quotes matched to a transaction in the TAQ database, filtered for errors. Next, spread skewness is calculated for each stock in each year. Then, annual equally-weighted averages of these statistics are computed and plotted by year.

4. Why has skewness increased?

The previous section indicates that the cross-sectional average of the annual skewness has increased over time. This implies that successive annual time-series of spreads tend to have more extreme observations in the right tail. Why has this happened?

The first surmise might be that the phenomenon is mechanical and would be induced by a reduction in the mean of any right-skewed distribution. The spread is indeed bounded below at zero and its distribution is asymmetric. Its mean declines dramatically (Table 2). Could these two features be responsible for the observed skewness increase?

To shed some light on this question, we use as an example what is perhaps the best-known asymmetric distribution, the lognormal, and ask whether a decline in its mean is inextricably linked to a reduction in skewness. If $Y = \ln(X)$ and Y is normally distributed with mean μ and standard deviation σ, X is lognormal with the following expectation, variance, and skewness (Aitchison and Brown, 1963):

$$E(X) = \exp\left(\mu + \sigma^2/2\right),$$
$$\mathrm{Var}(X) = [E(X)]^2\eta^2,$$
$$\mathrm{Skewness} = E\left[(X-\mu)^3\right]\Big/\mathrm{Var}(X)^{3/2} = \eta^3 + 3\eta,$$
$$\text{where} \quad \eta^2 \equiv \exp(\sigma^2) - 1.$$

Note that a lognormal's skewness depends on σ but not on μ (the mean of Y). Hence, any connection between the skewness and the mean of X must be induced by σ. But the relation between skewness and σ is positive and monotonic, so a reduction in $E(X)$ induced by a reduction in σ would *decrease* rather than increase skewness.

The volatility and the mean of spreads both decrease while skewness increases (Table 2). Moreover, we have verified, in unreported results, that the volatility of the *logarithm* of spreads actually increases. This is analogous to a lognormal's η increasing but $\mathrm{Var}(X)$ decreasing because $E(X)$ has fallen more than η has increased.

Of course, there are other distributions that either have a positive or negative link between mean and skewness. For example, the gamma distribution's mean and skewness are inversely related to each other (Hogg and Craig, 1978). On the other hand, the skew-normal distribution can be left- or right-skewed but if it is right-skewed then its skewness is in fact *positively* related to its mean (Azzalini, 1985). Our objective is to simply argue that there is no *necessary* mechanical link between the mean of an empirically observed series and its skewness.

The preceding arguments provide counterpoints to the notion that a decline in the mean of a random variable with left bounded support can mechanically lead to an increase in its skewness. Rather than a mechanical explanation, we now explore an explanation based on economics. Specifically, we consider whether, in later sample years, spreads are higher relative to their means during periods of high asymmetric information. This is consistent with the arguments of Glosten and Milgrom (1985), which suggest that as the market maker loses monopoly power and a minimum guaranteed profit per transaction by way of a large tick size, he also will lose the ability to cross-subsidize spreads in periods of high asymmetric information by charging higher spreads in periods of low asymmetric information. The loss of the ability to cross-subsidize should result in larger right-tail observations.

We propose that periods prior to earnings announcements are likely to be periods of high asymmetric information. While there are undoubtedly many other periods where asymmetric information is likely to be significant, earnings announcement dates are in the public record and they assure numerous information events for most companies. Other public information events, such as merger announcements (viz. Aktas et al., 2008) could also be considered but are less numerous; we leave this for future research.

For each stock every year, we calculate an average spread over the five contiguous trading days ending on all earnings announcement dates. We then compare this average earnings announcement spread to the average spread on all other days during that year. We term the percentage difference of these two spreads as IE. We calculate the equally-weighted mean of IE along with its median and standard deviation are calculated across firms each year and reported in Table 6.

As can be seen, there is little doubt that pre-announcement spreads increase relative to spreads on other days during each year.

Table 6
Percentage differences between spreads just before earnings announcements and spreads on other days of the year. For each stock every year, an average spread is calculated over the five trading days ending on all earnings announcement dates. This average earnings announcement spread is then compared to the average spread on all other days during that year. The percentage difference of these two spreads is computed for each firm. Finally, the equally-weighted mean of the percentage difference along with its median and standard deviation are calculated across firms each year.

Year	Mean	Median
1993	0.446	−0.532
1994	1.039	0.560
1995	2.197	1.206
1996	1.970	1.380
1997	1.901	1.222
1998	2.111	0.733
1999	2.564	0.787
2000	6.589	3.917
2001	−2.190	−3.459
2002	1.132	−1.842
2003	1.346	−1.482
2004	6.345	1.264
2005	9.663	3.982
2006	9.303	4.018
2007	10.499	2.696
2007–1993	10.053	3.228
(p-value)	(<0.001)	(<0.001)

The increase in the mean percentage difference, from 0.45 in 1993 to more than 10.5 in 2007, is significant at any conventional level. Note the exception to the general pattern in 2001, where spreads during earnings announcements are on average smaller than in normal periods. This oddity notwithstanding, it is reasonable to conclude that investors now pay relatively more to transact in periods of high asymmetric information, (as proxied by periods around earnings announcements). This result indicates that even though trading costs decline dramatically over our sample period, trading costs around a significant informational event, namely, the release of earnings, increase relative to their mean values.

The evidence in Table 6 lends support to our argument that the skewness increase is at least partially due to a loss of market maker monopoly power, which results in relatively larger spreads during periods of high asymmetric information. It would be interesting to ascertain if this phenomenon is also present near other information events such as repurchase or acquisition/merger announcements, and other significant corporate events such as the launch of a new product line, or a change in management.

As a check to ascertain the relation between skewness shifts and IE, we calculate the average skewness and average IE for each firm in the 1993–2000 period, and the same quantities for each firm in the 2001–2007 period. We then calculate the change in skewness and IE for each firm that was present in both samples. The cross-sectional correlation between the change in skewness and change in IE is 0.072, with a p-value of 2%. The correlation is positive, suggesting that IE shifts and skewness shifts are positively related, just as hypothesized. However, the modest magnitude of the correlation suggests that the increase in average spreads during earnings announcements relative to those in normal periods is not wholly responsible for the increase in spread skewness.

We perform one more exercise to ascertain the causes of the skewness increase. Previous research (e.g., Chordia et al., 2001) indicates that liquidity is particularly low in down markets. This may happen because down markets affect market maker collateral requirements (Brunnermeier and Pedersen, 2009; Hameed et al., 2010). It may be that shifts in spread behavior within extreme down markets may be related to skewness.

To address the preceding idea, we perform the following exercise. For each stock in each year, we calculate the fifth percentile of the (signed) daily return. We then calculate the average proportional spread for all days in which the return is less than or equal to the fifth percentile. Finally, we compute the percentage difference between the spread on these days and the average spread on all other days. Let us term this quantity ER. While our initial prediction was that the aggregate ER would also generally be monotonically increasing through the sample period (as is IE), this is not the case. ER ranges from 19% in 1993 to 34% in 2001, and is at its low at about 11% in 2006.

This behavior of ER notwithstanding, it is still possible that in the cross-section, stocks with changes in ER may also have experienced corresponding changes in skewness. Thus, just as for IE above, we calculate the correlation as above between changes in ER and changes in skewness in the two subperiods (1993–2000 and 2001–2007). This cross-sectional correlation is 0.119 and is also significant. A simple cross-sectional regression of skewness shifts on IE shifts and ER shifts yields coefficients that are both significant with t-values of 2.42 and 4.00, respectively.

These two exercises suggest that spread skewness shifts are at least partially due to shifts in how spreads behave around informational events and in extreme down markets. However, the correlations between skewness shifts and changes in IE and ER are not overwhelmingly large, which implies that more needs to be done to uncover the causes of increases in skewness.

5. Cross-sectional determinants of skewness

We now turn to an analysis of the variables that are cross-sectionally related to skewness. Previously, we have argued that skewness arises because extreme informational events result in extreme right-tail spread observations. If this is the case then information asymmetry proxies should be significant determinants of skewness. Proximate variables related to information asymmetry include such candidates as size, return volatility, analyst following, and institutional holdings. Brief arguments in their favor are given below.

There is some reason to believe that larger, more visible firms should have less asymmetric information (Arbel and Strebel, 1983). Conversely, larger return volatility could be associated with greater asymmetric information because of greater profit potential to informed traders (Kyle, 1985). We therefore include market capitalization and a measure of return volatility in our regressions.

When more investment analysts follow a firm, there is presumably less potential to uncover private information (Easley et al., 1998). This suggests that more analysts should be associated with less informed trading. On the other hand, agents with ill-founded but strong beliefs might be more tempted to trade in stocks that are more widely followed. In addition, if analysts disseminate valuable private information to favored institutional clients (Green, 2006) such clients may be tempted to exploit this information. Thus, analysts may be positively or negatively related to information asymmetry. To explore the relative importance of these contrasting roles of security analysts, we consider analyst following as an explanatory variable.

Larger holdings by institutional investors could increase asymmetric information. Institutions often employ their own buy-side analysts, thereby increasing the potential for uncovering information. The role of institutions as information producers is discussed in Sarin et al. (1999), Rhee and Wang (2009), and Rubin and Smith (2009). Thus, we include institutional holdings as an explanatory variable. We also include the Herfindahl index of institutional holdings to measure institutional concentration as we hypothesize that large blockholders may be more likely to have inside information (Rubin, 2007).

Analyst following is proxied by the number of I/B/E/S analysts making one-year earnings forecasts as of December of the previous year, while return volatility is the daily return standard deviation in the previous year. Size is market capitalization as of the last trading day of the previous year. The institutional holdings data,

Table 7
Summary statistics for cross-sectional determinants of skewness. Possible determinants of liquidity skewness include institutional holdings, return volatility, analyst following, size, and information asymmetry proxies. This table provides summary statistics for these variables. For each calendar year, 1992–2006, HOLDINGS is the percentage of outstanding shares held by institutions in December, as reported by Thomson Financial. ANALYSTS is the number of IBES analysts making one-year earnings forecasts in December of the year. VOL is the daily return standard deviation during the previous year. SIZE is market capitalization at year end. HERF is the Herfindahl index of institutional concentration at year end. IE is the percentage difference in spreads around earnings announcements and other days. ASYNCH is the Hou and Moskowitz (2005) measure of information asymmetry during the year. ER is the percentage difference between spreads on extremely low return days and other days. A number with subscript k indicates that the number should be multiplied by 10^k, e.g., 1.30_{-2} is .0130.

	Mean	Standard deviation
HOLDINGS	25.2	24.7
ANALYSTS	4.17	5.73
VOL	1.30_{-2}	1.20_{-2}
SIZE	1.90_{6}	9.09_{6}
HERF	1.20_{-2}	2.47_{-2}
IE	0.446	7.810
ASYNCH	0.416	0.337
ER	0.360	0.480

Table 8
Regressions for cross-sectional determinants of skewness. Individual firm spread skewness during a given year is related to institutional holdings, return volatility, analyst following, size, and information asymmetry proxies during or at the end of the previous year. HOLDINGS is the percentage of outstanding shares held by institutions in December, as reported by Thomson Financial. ANALYSTS is the number of IBES analysts making one-year earnings forecasts in December. VOL is the daily return standard deviation during the year. SIZE is market capitalization at year end. HERF is the Hefindahl index of institutional concentration at year end. IE is the percentage difference in spreads around earnings announcements and other days. ASYNCH is the Hou and Moskowitz (2005) measure of information asymmetry during the year. ER is the percentage difference between spreads on extremely low return days and other days. SPREAD is the proportional spread averaged over the year. The dependent variable, liquidity skewness, is averaged for each firm in each of the year 1994 through 2007 while the explanatory variables are measured with a one-year lag over the period 1993 through 2006. A number with subscript k indicates that the number should be multiplied by 10^k, e.g., 1.30_{-2} is .0130.

Year	Firms	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
		HOLDINGS		ANALYSTS		VOL		SIZE		HERF		IE		ASYNCH		ER		SPREAD		Intercept	
1994	1616	1.28_{-4}	2.67	-2.96_{-3}	−0.57	0.738	0.32	-4.18_{-9}	−0.60	−0.462	−0.48	-2.76_{-3}	−1.19	0.173	0.92	−0.26	−1.23	-5.30_{-2}	−6.40	0.703	17.95
1995	1740	2.63_{-3}	2.02	1.15_{-2}	2.78	2.28	0.89	2.56_{-9}	0.44	8.99_{-2}	0.16	2.11_{-3}	1.08	−0.314	−1.57	0.144	0.84	-4.99_{-4}	−0.05	0.454	7.82
1996	1022	4.19_{-3}	1.35	5.19_{-3}	0.69	−8.55	−1.36	8.89_{-9}	1.40	0.618	0.49	1.50_{-3}	0.46	−0.162	−0.42	-4.51_{-2}	−0.14	-3.65_{-2}	−1.41	0.803	5.66
1997	1054	4.99_{-3}	0.83	1.53_{-2}	2.01	6.21	0.81	1.76_{-8}	3.60	1.29	1.14	-3.65_{-4}	−0.09	−0.419	−1.16	−0.364	−1.26	−0.2	−5.11	1.26	9.19
1998	1047	6.34_{-3}	1.70	1.18_{-2}	1.42	−4.35	−0.66	-2.96_{-9}	−0.76	−1.17	−1.05	1.36_{-3}	0.33	−0.509	−1.47	0.78	2.72	−0.121	−3.11	1.47	10.17
1999	983	-1.71_{-3}	−0.69	4.18_{-2}	4.24	6.54	1.21	1.03_{-8}	3.11	0.77	0.54	5.30_{-3}	1.27	−0.638	−1.71	-5.30_{-2}	−0.20	-8.99_{-2}	−2.75	1.47	9.23
2000	883	4.30_{-3}	0.75	2.57_{-2}	2.73	9.93	1.64	-1.21_{-9}	−0.48	−1.63	−1.01	1.77_{-3}	0.45	−1.18	−3.17	0.254	0.80	−0.209	−6.03	2.03	11.73
2001	831	3.91_{-3}	1.48	-9.11_{-3}	−0.85	−7.24	−1.09	-2.72_{-10}	−0.10	−0.748	−0.63	3.66_{-3}	1.04	0.618	1.50	0.936	3.42	-5.02_{-2}	−1.60	1.66	7.88
2002	822	-4.72_{-3}	−1.91	-2.72_{-2}	−3.72	−3.29	−0.75	8.36_{-10}	0.45	0.435	0.23	-1.70_{-3}	−1.16	0.333	1.38	8.95_{-2}	0.83	0.181	3.54	1.09	7.89
2003	838	-3.76_{-3}	−1.75	-3.31_{-2}	−4.73	4.79	1.51	1.27_{-10}	0.06	0.665	0.66	-3.01_{-4}	−0.21	0.526	2.43	0.353	2.84	0.113	2.55	1.59	14.24
2004	824	1.79_{-2}	5.35	-3.64_{-2}	−2.54	−7.18	−0.76	-1.68_{-8}	−4.49	−2.20	−0.98	2.83_{-3}	1.23	−0.613	−1.29	0.227	1.19	−0.728	−4.85	3.73	13.38
2005	871	8.37_{-3}	3.82	-7.02_{-2}	−6.90	−12.1	−1.20	-1.13_{-8}	−3.94	0.238	0.13	2.28_{-3}	1.17	0.409	1.04	−0.151	−1.24	−1.71	−9.60	4.6	25.94
2006	1502	2.08_{-2}	2.53	-4.88_{-2}	−3.75	−35.4	−3.05	-1.53_{-8}	−4.22	−0.201	−0.09	1.39_{-3}	0.73	0.454	1.02	0.272	1.80	−0.361	−2.87	1.99	20.65
2007	1798	9.47_{-3}	0.04	-2.17_{-2}	−1.63	−27.1	−3.59	2.46_{-10}	0.07	1.03	0.49	1.12_{-3}	0.50	−0.388	−0.97	0.250	1.53	−0.590	−3.83	3.38	29.76

All years		Coefficient	*t*-Statistic
		2.08_{-2}	11.4
		-4.26_{-2}	−6.61
		13.8	3.57
		8.46_{-9}	2.84
		−2.44	−2.16
		-3.84_{-3}	−1.28
		−1.75	−9.85
		−0.386	−0.45
		−0.254	−22.6
		2.759	3.25

representing the percentage of outstanding shares held by institutions as of December of the previous year, are obtained from Thomson Financial for the years 1993–2007.

In addition to the previous variables, we include the IE and ER measures from the previous section, and an adaptation of asynchronicity measure of Hou and Moskowitz (2005), which is one minus the R^2 of the regression of individual stock returns on the value-weighted CRSP return index and the equal-weighted portfolio of stocks with the same 3-digit SIC code as the relevant stock. We require each stock to have at least 30 observations per stock per year for computation of this measure. To control for any possible industry effects, we include 47 industry dummies using the Fama and French (1997) industry categorizations, but the coefficients of these variables are not reported for brevity (in all of our regressions, none of the industry dummies are significant).

Finally, we also include the mean spread during the previous year as an explanatory variable, since the level of asymmetric information could be related to the spread itself. As mentioned above, all explanatory variables are measured as of the previous year to mitigate endogeneity concerns, as well as the "lookahead" concern arising from the fact that some of the variables are measured at the end of the year, whereas skewness is measured throughout the year.

Table 7 provides summary statistics for the explanatory variables. Among other statistics, the mean institutional holdings amount to 25%, whereas the mean number of analysts is about four. The mean value of the Hou and Moskowitz (2005) measure is about 42%. The mean daily standard deviation is about 0.013, corresponding to an annualized standard deviation of about 16%.

We run annual cross-sectional regressions with skewness as the dependent variable, and the results are reported in Table 8. While many variables are not consistently significant, it is worth noting that holdings are positively and significantly related to skewness in three of the four most recent years, whereas the opposite is true of analyst following and firm size. The coefficient signs are consistent with the notion that firms with greater information asymmetry have more extreme episodic events and spread skewness is greater for such firms. These results generally are consistent with the notion that skewness may have become more sensitive to information asymmetry events in recent years as specialists and dealers face increasing competition.

Also, IE and ER are largely insignificant, suggesting that the while the time-series shift in these variables may be relevant for explaining time-series changes in skewness, there is no reliable cross-sectional relation between the variables and skewness.

In the last row of Table 8, we also present a single regression that uses averages of all variables for each stock across all years. Interestingly, the measure of Hou and Moskowitz (2005) is negatively related to skewness for the full sample, which is a puzzling result deserving future study. Note that the full sample results confirm the relation of skewness with holdings and analyst following pointed out in the discussion of the year-by-year regressions.

The mean spread itself is negatively related to skewness in the regression. This goes against the usual presumption that more right-skewed distributions have large means (relative to medians). However, since the distribution here is cross-sectional, the usual intuition does not seem to apply. Apparently, after adjusting for the other control variables, firms with lower trading costs on average, which implies lower profits for market makers, experience much larger deviations of trading costs from the average when asymmetric information arrives.

For a perspective on economic significance, we consider the coefficients in Table 8, Panel B. We find that the average annual standard deviation of skewness in the cross-section is 1.46, whereas the overall mean skewness is 1.51. Using the relevant numbers in Table 7 and the relevant regression coefficients, a one-standard deviation move in holdings implies a change in skewness of 0.51, whereas an analogous shift in analyst following is associated with a skewness shift of -0.24. Compared to the means and standard deviations of skewness, these magnitudes are economically substantial. We leave it for the reader to perform such calculations for other variables of interest.

6. Conclusion

Stock bid–ask spreads are increasingly right-skewed in recent years. This finding holds across exchanges, and across firms stratified by size, trading volume, and price. The result could indicate that as specialists and dealers increasing competition over time, they are less able to cross-subsidize spreads between periods of high and low asymmetric information. This may lead to larger spreads during periods where private information is more material, and, in turn, increasing right-skewness under a competitive market making regime. Consistent with this observation, the percentage difference between spreads prior to earnings announcements and other periods experiences a considerable increase in recent years. Liquidity skewness is cross-sectionally related to information proxies such as institutional holdings and analyst following, which are associated with the proportion of traders with privileged information.

Further research is required to pin down the causes of liquidity skewness. While we find that spreads during periods of high asymmetric information are larger relative to their mean in recent years, it remains to be known whether this is associated with high funding constraints for market maker inventories (Brunnermeier and Pedersen, 2009). Market makers constrained by competition may not be able to provide adequate liquidity during periods with high financing costs since they cannot recoup their losses in those periods by charging higher spreads during normal periods. This issue is worth exploring. It also is worth investigating whether co-skewness of individual stock spreads with aggregate spread is material for the cross-section of stock returns.

In closing, we reiterate that we document a decline in the average spread in recent times, indicating a lower mean cost of trading, in conjunction with an increase in spread skewness. The net effect of these phenomena on investors with varying preferences or utility functions appears to be a fertile and important arena for future work on liquidity.

References

Aitchison, J., Brown, J., 1963. The Lognormal Distribution. Cambridge University Press, Cambridge, UK.

Aktas, N., de Bodt, E., Van Oppens, H., 2008. Legal insider trading and market efficiency. Journal of Banking and Finance 32, 1379–1392.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid–ask spread. Journal of Financial Economics 17, 223–249.

Arbel, A., Strebel, P., 1983. Pay attention to neglected stocks. Journal of Portfolio Management (Winter), 37–42.

Azzalini, A., 1985. A class of distributions which includes the normal ones. Scandinavian Journal of Statistics 12, 171–178.

Bessembinder, H., 2003. Quote-based competition and trade execution costs in NYSE-listed stocks. Journal of Financial Economics 70, 385–422.

Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. Review of Financial Studies 22, 2201–2238.

Chan, J., Hong, D., Subrahmanyam, M., 2008. A tale of two prices: Liquidity and asset prices in multiple markets. Journal of Banking and Finance 32, 947–960.

Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. Journal of Finance 56, 501–530.

Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. Journal of Financial Economics 87, 249–268.

Christie, W., Schultz, P., 1999. The initiation and withdrawal of odd-eighth quotes among Nasdaq stocks: An empirical analysis. Journal of Financial Economics 52, 409–442.

Chung, D., Hrazdil, K., in press. Liquidity and market efficiency: A large sample study. Journal of Banking and Finance.

Easley, D., O'Hara, M., Paperman, J., 1998. Financial analysts and information-based trade. Journal of Financial Markets 1, 175–201.
Fama, E., French, K., 1997. Industry costs of equity. Journal of Financial Economics 43, 153–193.
Fernando, C., Herring, R., Subrahmanyam, A., 2008. Common liquidity shocks and market collapse: Lessons from the market for perps. Journal of Banking and Finance 32, 1625–1635.
Gibson, R., Mougeot, N., 2004. The pricing of systematic liquidity risk: Empirical evidence from the US stock market. Journal of Banking and Finance 28, 157–178.
Glosten, L., 1989. Insider trading, liquidity, and the role of the monopolist specialist. Journal of Business 62, 211–235.
Glosten, L., Milgrom, P., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71–100.
Green, C., 2006. The value of client access to analyst recommendations. Journal of Financial and Quantitative Analysis 41, 1–24.
Hameed, A., Kang, W., Viswanthan, S., 2010. Stock market declines and liquidity. Journal of Finance 65, 257–293.
Hogg, R., Craig, A., 1978. Introduction to Mathematical Statistics. Macmillan, New York.
Hou, K., Moskowitz, T., 2005. Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18, 981–1020.
Jones, C., 2002. A Century of Stock Market Liquidity and Trading Costs, Working Paper, Columbia University.
Kyle, A., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.
Rhee, S., Wang, J., 2009. Foreign institutional ownership and stock market liquidity: Evidence from Indonesia. Journal of Banking and Finance 33, 1312–1324.
Rubin, A., 2007. Ownership level, ownership concentration and liquidity. Journal of Financial Markets 10, 219–248.
Rubin, A., Smith, D., 2009. Institutional ownership, volatility and dividends. Journal of Banking and Finance 33, 627–639.
Sarin, A., Shastri, K., Shastri, K., 1999. Ownership Structure and Stock Market Liquidity, Working Paper, Santa Clara University.
Stoll, H., 2006. Electronic trading in stock markets. Journal of Economic Perspectives 20, 153–174.