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Institutional ownership and stock liquidity

Abstract

This paper examines how institutional ownership influences the cross-sectional differences in stock liquidity for a sample of stocks listed on the NYSE and the AMEX. The author finds that stocks with larger increases in the number of institutional investors tend to be more liquid than other stocks. Further analysis reveals that this effect tends to be stronger for stocks with more severe asymmetric information. Moreover, active institutional investors, such as independent advisors and mutual funds, exert larger impacts on stock liquidity than passive institutions do. These results are consistent with the theoretical prediction that information competition among institutional investors increases stock liquidity.

Keywords: stock liquidity, institutional investor, trading volume, asymmetric information, information competition.
JEL Classification: G12, G14, G20.

Introduction

This paper examines how institutional ownership influences the cross-sectional differences in individual stock liquidity. Illiquidity, defined as the price impact caused by order flows (Kyle, 1985), is an invisible trading cost to investors[1]. Recent studies document that liquidity affects stock returns; stocks with lower liquidity generally have higher expected returns[2]. Given the importance of liquidity in asset pricing, several papers have been devoted to investigating the cross-sectional determinants of liquidity[3]. This paper focuses on how the number of institutional investors holding shares affects stock liquidity.

Institutions have grown increasingly important in the stock market. As shown in Figure 1, the average number of institutions holding one stock increases from less than 50 institutions at the beginning of 1980 to over 200 at the end of 2007. Institutional investors also trade very frequently and in large amounts. As reported by Grahl and Lysandrou (2006), institutions account for almost 80% of trading volume. Since liquidity is by definition related to investors' trading behavior, given the fact that institutional investors become the major traders in the market, it is possible that their behavior may affect liquidity.

Institutional investors are generally considered better informed than other investors[4]. Theoretical studies suggest that the information competition among informed traders increases stock liquidity. For example, Admati and Pfleiderer (1988) and Holden and Subrahmanyam (1992) develop models for how the number of informed traders affects liquidity. Both models assume that there are multiple privately informed traders who compete with each other strategically. Since these informed traders compete aggressively, their private information is revealed in the price very quickly. Therefore, more informed traders speed up the information revelation process and thus reduce the illiquidity associated with information asymmetry.

Using the liquidity measure proposed by Amihud (2002), I find that stocks with larger increases in the number of institutional investors are more liquid than other stocks for a sample of stocks on the NYSE and the AMEX from 1980 to 2007. Moreover, stocks with more severe asymmetric information, as measured by PIN values, show a larger and more significant improvement in liquidity than other stocks when the number of institutions increases. Further analysis on the types of institutions shows that active institutional investors, such as independent advisors or mutual funds, show a stronger effect in increasing stock liquidity than do passive institutional investors, i.e., bank trust departments, insurance companies, and etc. These results are consistent with the theoretical prediction that the information competition among informed traders increases stock liquidity.

This paper contributes to the literature in two aspects. First, I choose the number of institutional investors holding shares as a measure of institutional ownership rather than the fraction of shares held by institutions, a frequently used measure in previous studies. This is because, compared with the fraction of shares held by investors, the theoretical implication of how the number of institutions affects liquidity is clear if we consider that institutional investors are informed traders[5]. In addition, recent studies have recognized the important role of number of the institutions in affecting stock returns[6]. This paper

[1] See Treynor (1994).

[2] See, e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and Amihud (2002).

[3] For example, Breen, Hodrick, and Korajczyk (2002) find that stock characteristics such as market cap and dividend yield influence liquidity.

[4] See, for example, Grinblatt and Titman (1989, 1993), Parrino, Sias, and Starks (2003).

[5] Moreover, a larger fraction of shares held by institutions does not necessary indicate that competition among informed traders is more intense. An extreme case is that a stock has only one institutional investor who holds the majority fraction of shares.

[6] See, for example, Sias, Starks and Titman (2006) and Chen, Hong and Stein (2002).

adds to this line of literature on institutional investors by emphasizing the importance of the number of the institutions in influencing stock liquidity.

Second, this paper contributes to the literature by examining the effects of various types of institutional investors on liquidity. Previous papers generally treat institutions as a homogeneous group and consider its overall effect on liquidity. This paper proposes that since these five types are subject to different regulations and follow various investment objectives, their trading behavior may not be the same. As a result, their influences on liquidity are expected to be different.

The remainder of this paper is organized as follows. Section 1 describes the data and the methodology. Section 2 discusses the empirical results. The last section summarizes the major findings in this paper.

1. Data collection and methodology

The data used to construct the liquidity measure and the numbers of institutions are from two sources: CRSP and Thomson Financial CDA/Spectrum Institutional (13f) Holdings. Only stocks listed on the NYSE and the AMEX are included[1]. The CDA data are available at a quarterly frequency from the first quarter of 1980 to the third quarter of 2007.

The liquidity measure used in this paper is proposed by Amihud (2002). It is essentially a measure that follows Kyle's (1985) concept of illiquidity − that price response to order flows[2]. This measure is computed as the absolute price change per dollar of daily trading volume for each stock each day, $\frac{|R_{td}^i|}{\$VOL_{td}^i}$, where R_{td}^i is stock i's return on day d of quarter t and $\$VOL_{td}^i$ is the same-day dollar trading volume (measured in millions of dollars) of this stock. The quarterly illiquidity measure[3] for each stock is computed by averaging the daily measure within each quarter, $\frac{1}{D_t^i}\sum_{d=1}^{D_t^i}\frac{|R_{td}^i|}{\$VOL_{td}^i}$, where D_t^i is the number of days in quarter t for which data are available for stock i. It assesses the average daily price impact caused by a one-million-dollar trading volume for stock i in each quarter. The sample includes stocks that have return and volume data for more than 45 trading days during the quarter with prices greater than \$5 at the end of the quarter.

Table 1 reports the time-series average of the cross-sectional means and standard deviations of illiquidity denoted as "ILLIQ." As shown in the table, the cross-sectional average of ILLIQ is 0.1415 (Panel A) during the sample period, indicating that a one-million-dollar trading volume generally would cause prices to change by 14.15%.

The number of institutions, denoted as "Number," is defined as the number of aggregate institutions that hold the stock at the end of each quarter in CDA Spectrum. Figure 1 plots the cross-sectional average number of institutions holding shares each quarter. Table 1 reports that the average of the cross-sectional mean number of institutions is around 122 (Panel A) during the sample period.

Panel B of Table 1 reports the average of the mean number of institutions by type across the sample period. CDA Spectrum classifies institutions into five types: bank trust departments, insurance companies, mutual funds, independent investment advisors, and other institutional investors including pension funds, university endowments foundations. However, the classification is not proper in 1998 and beyond, according to Thomson Financial Ownership Data Manual. So, the sample period is up to the fourth quarter of 1997 when I consider the effects of different types of institutional investors on liquidity. Figure 2 provides a time-series pattern of the mean number of institutions by type. Similar to the numbers reported in Panel B of Table 1, stocks are mainly held by bank trust departments and independent investment advisors. Further evidence shows that the number of institutions for all five types increases over time − except the number of bank trust departments starts decreasing after 1990. In addition, the increase in the number of all institutions is mainly driven by the increase in the number of independent investment advisors, especially after 1990.

To avoid the potential multi-collinearity problem in the regressions due to the high correlation between the number of institutions and market cap, I work instead on the percentage changes in the number of institutions, denoted as $\%\Delta Number_{it}$. This measure is computed as $(Number_{it} - Number_{it\text{-}1})/Number_{it\text{-}1}$, where $Number_{it\text{-}1}$ and $Number_{it}$ are the numbers of institutions holding stock i at the end of quarter t-1 and quarter t, respectively. I use percentage changes rather than raw changes to make this measure comparable among stocks. Table 1 shows that the cross-sectional average of $\%\Delta Number_{it}$ is about 5.38%. Table 2 shows the correlation between $\%\Delta Number_{it}$, and the logarithm of market cap, denoted as "Size," is on average -0.055.

[1] NASDAQ stocks are excluded from the sample because unlike the volumes reported on the NYSE and the AMEX, the volumes on the NASDAQ include inter-dealer trades, which may result in artificially higher-volume figures for those stocks.

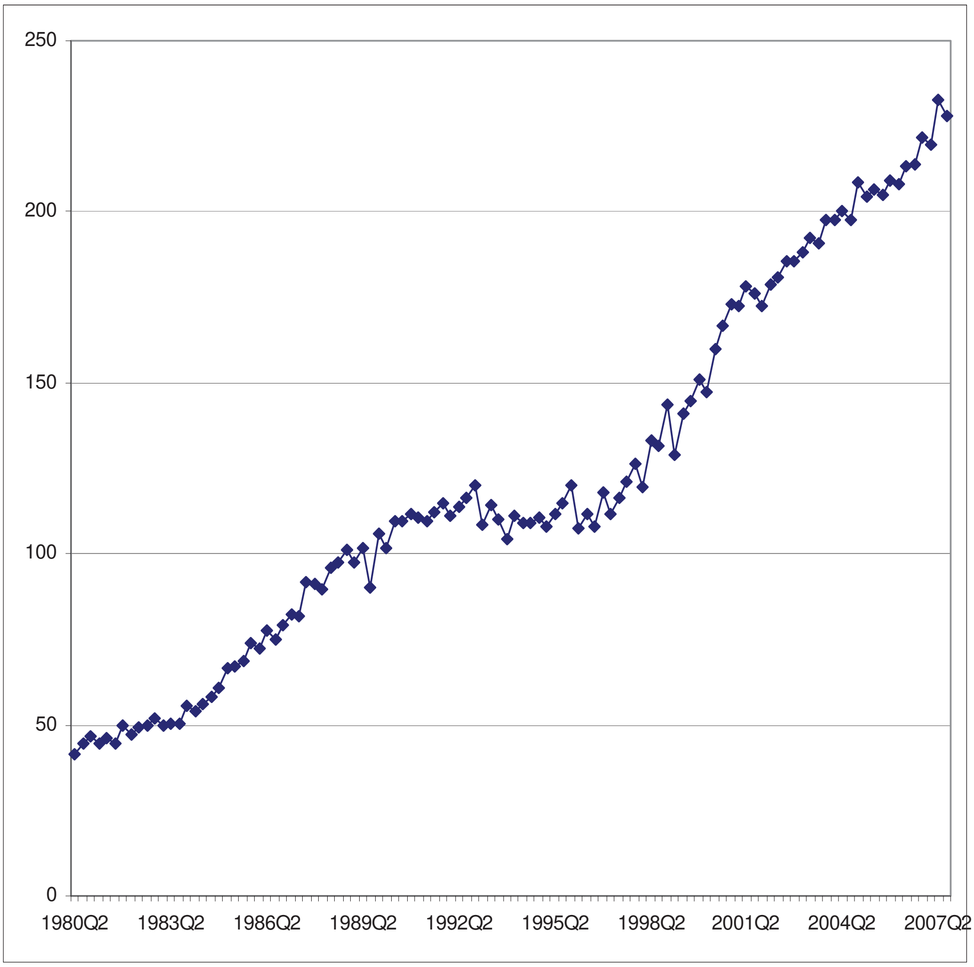
[2] Strictly speaking, the Amihud measure is a measure of illiquidity. This measure has been used in several recent studies on liquidity. Examples are Acharya and Pedersen (2005) and Avramov, Chordia, and Goyal (2006). Amihud (2002) and Hasbrouck (2009) both demonstrate that the Amihud illiquidity measure is highly correlated with the TAQ-based price impact measures.

[3] The illiquidity measure for each stock is calculated each quarter because institutional data is available at a quarterly frequency.

Table 1. Descriptive statistics – illiquidity, number of institutions, and stock characteristics

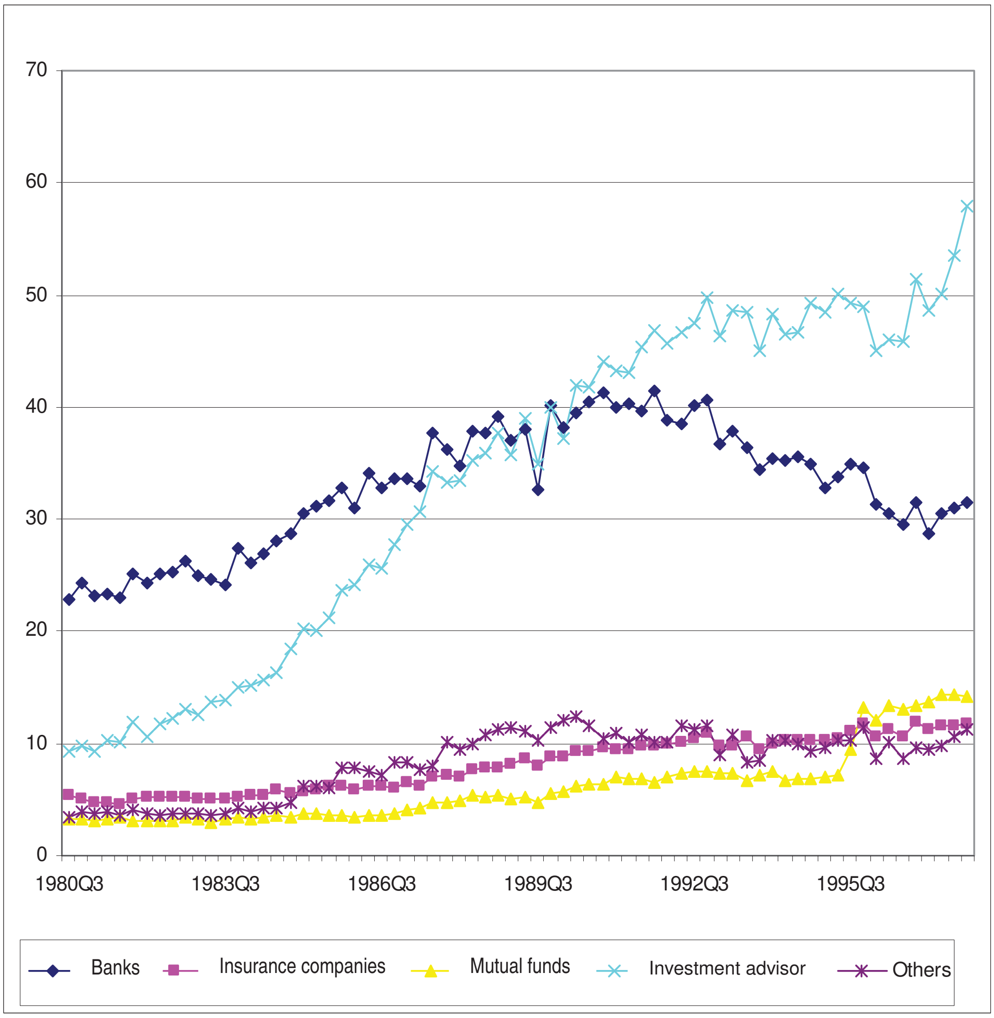
This table shows the time-series average of the quarterly cross-sectional means and standard deviations of the following variables over the sample period. In Panel A, "ILLIQ" is the quarterly Amihud illiquidity measure. "Number" is the number of institutions holding the stock at the end of the quarter. "%Δ*Number*" is the percentage change in the number of institutions holding the stock from the end of the previous quarter to the end of the current quarter. "Size" is quarter-end market capitalization of the firm's equity. "Price" is quarter-end share price. "Return stdv." is the standard deviation of daily returns of individual stocks in the quarter. "Age" is the number of months since the firm's first return appears in the CRSP file. "Dividend yield" is measured as the dollar amount of the cash dividends paid during the fiscal year ended before the most recent June 30, divided by size as of December 31 in that fiscal year. "Momentum return" is the stock's cumulative return in the quarter. "Analysts" is the average number of analysts in the quarter. The sample includes stocks on the NYSE and the AMEX from the first quarter of 1980 to the third quarter of 2007. Panel B report the same set of statistics for "Number" and "%Δ*Number*" by institution type. The sample period is from the first quarter of 1980 to the fourth quarter of 1997.

Panel A										
	ILLIQ	Number	%Δ*Number*	Size ($MM)	Price ($)	Return Stdv.	Age (months)	Dividend yield	Momentum return	Analysts
Mean	0.1415	122	5.38%	2,667	48.62	0.0212	286	0.0279	0.0441	10
Std. dev.	0.3128	114	62.33%	5,508	945.38	0.0084	214	0.0612	0.1628	8
Panel B										
	Number					%Δ*Number*				
	Banks	Insurance companies	Mutual funds	Independent advisors	Others	Banks	Insurance companies	Mutual funds	Independent advisors	Others
Mean	33	8	6	33	8	1.65%	0.39%	0.48%	2.53%	0.40%
Std. dev.	37	8	6	34	9	20.50%	5.50%	5.81%	20.23%	5.67%



Note: This figure shows the cross-sectional average number of institutions holding shares each quarter from the first quarter of 1980 to the third quarter of 2007. The sample includes stocks on the NYSE and the AMEX.

Fig. 1. Average number of institutions holding shares



Note: This figure shows the cross-sectional average number of institutions (by type) holding shares each quarter from the third quarter of 1980 to the fourth quarter of 1997. The sample includes stocks on the NYSE and the AMEX.

Fig. 2. Average number of institutions holding shares – by institutional type

I also compute the percentage change in the number of institutions in each type, $(Number_{ijt} - Number_{ijt\text{-}1})/Number_{it\text{-}1}$, where $Number_{ijt}$ and $Number_{ijt\text{-}1}$ are numbers of type j institutions holding stock i at the end of quarter t-1 and quarter t, respectively. The denominator, $Number_{it\text{-}1}$, is the number of all institutions holding stocks at the end of quarter t-1. Table 1 shows the average of mean $\%\Delta Number_{it}$ for all institutions (Panel A) and by type (Panel B) over the sample period.

To examine whether the percentage changes in the number of institutions increases stock liquidity, I use Fama-MacBeth regressions of the Amihud illiquidity measure on $\%\Delta Number_{it}$. Specifically, at the end of each quarter, I estimate the following cross-sectional regression:

$$ILLIQ_{i,t+1} = \beta_{1,t}\%\Delta Number_{i,t} + \beta_{2,t} ILLIQ_{i,t} + \sum_{j=1}^{7} \gamma_{j,t} X_{i,j,t} + \varepsilon_{i,t}. \quad (1)$$

The dependent variable is the logarithm of the quarterly illiquidity in quarter t + 1 ($ILLIQ_{i,t+1}$). The independent variables include the percentage changes in the number of institutions ($\%\Delta Number_{it}$), the logarithm of illiquidity ($ILLIQ_{i,t}$), and seven stock characteristics ($X_{i,j,t}$) in quarter t. These characteristics are size, price, return standard deviation, age, dividend yield, momentum, and number of analysts. They have been reported to affect the cross-sectional differences in liquidity in previous studies. "Size" is defined as the market capitalization of the firm's equity at the end of quarter t. "Price" is the quarter-end share price. "Return stdv." is estimated as the standard deviation of daily returns in quarter t. "Age" is the number of months from the firm's first return as it appears in the CRSP file till the end of quarter t. "Dividend yield" is measured as the dollar amount of the cash dividends paid during the fiscal year ended before the most recent June 30, divided by size as of December 31 in that fiscal year. "Momentum return" is the cumulative return in quarter *t*. "Analysts" is the number of analysts at the end of quarter *t*. Panel A of Table 1 reports the time-series average of the cross-sectional means and standard deviations of these stock characteristics. Some of these stock characteristic variables have only positive values, therefore, instead of using the original variables, I use their log transformations in the regressions. Table 2 displays the average cross-sectional correlations among ILLIQ, percentage changes in the number of institutions, and stock characteristics (after log transformations) across the sample period.

Table 2. Average cross-sectional correlations

I estimate cross-sectional correlations between the following variables in each quarter. This table presents the time-series averages of these quarterly cross-sectional correlations over the sample period. "ILLIQ" is the natural logarithm of the quarterly Amihud illiquidity measure. "Number" is the natural logarithm of one plus the number of institutions holding the stock at the end of the quarter. "%Δ*Number*" is the percentage change in the number of institutions holding the stock from the end of the previous quarter to the end of the current quarter. "Size" is the natural logarithm of quarter-end market capitalization of the firm's equity. "Price" is the natural logarithm of one plus quarter-end share price. "Return stdv." is the natural logarithm of one plus the standard deviation of daily returns of individual stocks in the quarter. Age is the natural logarithm of the number of months since the firm's first return appears in the CRSP file. "Dividend yield" is measured as the dollar amount of the cash dividends paid during the fiscal year ended before the most recent June 30, divided by size as of December 31 in that fiscal year. I use the natural logarithm of one plus the dividend yield in this table. "Momentum return" is the stock's cumulative return in the quarter. "Analysts" is the natural logarithm of one plus the average number of analysts in the quarter. The sample includes stocks on the NYSE and the AMEX from the first quarter of 1980 to the third quarter of 2007.

	ILLIQ	Number	%Δ*Number*	Size	Price	Return stdv.	Age	Dividend yield	Momentum return	Analysts
ILLIQ	1									
Number	-0.9351	1								
%Δ*Number*	0.0574	-0.0597	1							
Size	-0.9390	0.9357	-0.0553	1						
Price	-0.4180	0.3798	-0.0041	0.4257	1					
Return stdv.	0.2268	-0.2386	0.0514	-0.2806	-0.2554	1				
Age	-0.2869	0.3235	-0.0836	0.2771	0.1597	-0.2700	1			
Dividend yield	-0.0909	0.0963	-0.0314	0.0977	0.0605	-0.2772	0.1822	1		
Momentum return	-0.0186	0.0031	0.2508	0.0559	0.0757	0.0293	-0.0070	0.0065	1	
Analysts	-0.8160	0.8315	-0.0911	0.7992	0.2828	-0.1677	0.1806	0.0749	-0.0246	1

In order to compare coefficients over time and across different types of institutions, I follow the method proposed by Bennett, Sias and Starks (2003) to standardize both the independent and dependent variables. Specifically, for each variable, I first subtract its cross-sectional mean and then divide its standard deviation. Thus, in each quarter, standardized variables have means of zero and standard deviations of one. I estimate quarterly cross-sectional regressions and report the time-series average of the coefficients from these regressions. The *t*-statistics are computed using Newey-West adjusted standard errors[1].

The empirical tests are designed in two steps. First, I examine whether the percentage changes in the number of institutions influence liquidity after controlling for stock characteristics. Second, I conduct two tests to study whether changes in the number of institutions increase liquidity through information competition.

2. Empirical analysis and results

2.1. Liquidity and changes in the number of institutions. In this section, I examine whether the percentage changes in the number of institutions in quarter *t* increase stock liquidity in quarter *t*+1 after controlling for stock characteristics. Table 3 reports the mean coefficients from the quarterly cross-sectional regressions and the *t*-statistics computed using Newey-West adjusted standard errors.

As shown in Table 3, the coefficients on %Δ*Number* are negative and significant in the sample period. Note that because ILLIQ actually measures illiquidity, i.e., the price impact caused by order flows, the negative coefficients on %Δ*Number* indicate that the stock would be more liquid (less illiquid) in quarter *t*+1 if the stock experiences an increase in the number of institutions in quarter *t*. Specifically, the time-series average of the standardized coefficients on %Δ*Number* in the whole sample period is -0.0097, which indicates that, on average, a stock with one standard deviation more %Δ*Number* would be 0.97% standard deviations more liquid (or less illiquid).

Table 3 also reports the mean standardized coefficients on ILLIQ and other stock characteristics in quarter *t*. The results show that apart from $ILLIQ_t$, which has positive coefficients, all other characteristics hold negative coefficients. Since all of the variables are standardized, we can directly compare coefficients to see which variables exert larger impacts on the cross-

[1] See Newey and West (1987).

sectional differences in liquidity. The coefficient on $ILLIQ_t$ is the largest in absolute value and most significant. The fact that the level of liquidity in the current quarter strongly predicts the level of liquidity in the next quarter is consistent with the persistency of liquidity reported in previous studies. Among the seven characteristics, size has the most-negative coefficient; momentum return and the number of analysts also strongly influences liquidity. Brennan and Subrahmanyam (1995) report that institutions influence liquidity by attracting more analysts. The results here show that after controlling for the number of analysts, $\%\Delta Number$ still has strong impacts on stock liquidity.

Table 3. Illiquidity and changes in the number of institutions

I estimate the following cross-sectional regression in each quarter:

$$ILLIQ_{i,t+1} = \beta_{1,t}\%\Delta Number_{i,t} + \beta_{2,t} ILLIQ_{i,t} + \sum_{j=1}^{7} \gamma_{j,t} X_{i,j,t} + \varepsilon_{i,t}.$$

The dependent variable is the natural logarithm of the Amihud illiquidity measure in quarter t+1 ($ILLIQ_{i,t+1}$). The independent variables are the percentage change in the number of institutions holding the stock from the end of quarter t-1 to quarter t ($\%\Delta Number_{i,t}$), the natural logarithm of the Amihud illiquidity measure in quarter t ($ILLIQ_{i,t}$), and seven stock characteristics in quarter t defined in Table 2. I standardized both the independent and dependent variables so that all variables have the same mean (zero) and standard deviation (one) in each quarter. This table presents the mean coefficients from quarterly cross-sectional regressions and t-statistics computed using Newey-West adjusted standard errors. The sample includes stocks on the NYSE and the AMEX from the first quarter of 1980 to the third quarter of 2007.

	%Δ*Number*	ILLIQ	Size	Price	Return stdv.	Age	Dividend yield	Momentum return	Analysts
Mean	-0.0097	0.8328	-0.1265	-0.0068	-0.0208	-0.0082	-0.0049	-0.0422	-0.0314
t-stat.	-9.11	192.87	-33.23	-5.66	-11.53	-9.57	-4.05	-25.05	-19.61

The results in Table 3 indicate that after controlling for current liquidity and other stock characteristics, stocks with larger percentage increases in the number of institutional investors this quarter are more liquid than other stocks in the next quarter. Since institutional investors are generally better informed than other investors, this finding is consistent with the theoretical predictions in the models developed by Admati and Pfleiderer (1988) and Holden and Subrahmanyam (1992) that competition among informed traders increases stock liquidity.

2.2. Liquidity and information competition. In this section, I conduct two empirical tests to examine whether the effect of changes in the number of institutions on stock liquidity is due to information competition among institutional investors. First, I sort stocks into five quintile portfolios based on the values of PIN, which is a measure of private information, and estimate Fama-MacBeth regressions using stocks from each portfolio. If information competition increases stock liquidity, we would expect that the effect of changes in the number of institutional investors on liquidity should be stronger for those stocks with more severe asymmetric information. Second, I examine the effect of changes in the number of institutional investors on liquidity by institutional type. Previous studies have reported that independent investment advisors and mutual funds are more active in trading than bank trust departments, insurance companies, and other institutional investors[1]. Since informed traders are generally active traders, if information competition among institutions increases liquidity, we would expect that changes in the number of active institutions should exert a stronger impact on liquidity than would changes in the number of passive institutions.

2.2.1. PIN portfolios. PIN, a measure of private information, is derived from a microstructure model by Easley, Hvidkjaer and O'Hara (2002, 2010). Stocks with high PIN values indicate that the asymmetric information is severe. PIN data is downloaded from Hvidkjaer's homepage. This data file contains individual stock PIN values at a yearly frequency. I use PIN values in year t-1 to sort stocks into quintiles and form five portfolios in year t. Then, I estimate Fama-MacBeth regressions using stocks from each of these five portfolios. Since PIN data is only available from 1983 to 2001, the whole sample period considered in this test is from the first quarter of 1984 through the fourth quarter of 2002.

Table 4 reports the means and Newey-West adjusted t-statistics of coefficients on $\%\Delta Number$ estimated using stocks in five portfolios respectively. Since the whole sample period in this test is different from the previous one, I also report the regression results using all stocks in the sample. ILLIQ and stock characteristics in quarter t are included in the regressions, but their coefficients are not reported in the table. The last column reports p-values from the Wilcoxon ranked-sum tests of the null hypothesis that the coefficients on $\%\Delta Number$ estimated using stocks in the lowest PIN portfolio (Q1) are not significantly different from those estimated using stocks in the highest PIN portfolio (Q5).

[1] See Binay (2001).

Although the sample period in Table 4 is shorter, the results of using all stocks in the sample period are similar to those in Table 3. The variable *%ΔNumber* has a strong negative coefficient (-0.0117).

The rest of the columns report the results using stocks in different PIN portfolios. As shown in the table, the coefficients are all significantly negative for the five PIN portfolios. In addition, the coefficients on *%ΔNumber* are more negative for portfolios with high PIN values. Among the five quintiles, quintile 1 has the least negative coefficient, and quintile 4 has the most negative one. The coefficient from quintile 5 is also significant and negative. The Wilcoxon ranked-sum test shows that the difference in coefficients between quintile 1 and quintile 5 is significant.

The results in Table 4 suggest that stocks with larger increases in the number of institutions display higher future liquidity compared to other stocks and this effect is stronger for stocks with larger PIN values, that is, stocks with more severe asymmetric information. This finding supports the hypothesis that information competition among institutional investors increases stock liquidity.

Table 4. Illiquidity and changes in the number of institutions – five PIN portfolios

At the beginning of each year, stocks are put into one of the five quintile portfolios according to the value of PIN in the previous year. PIN is a measure of private information. Stocks with high PIN value indicate that the asymmetric information is severe. Quintile 1 portfolio (Q1) has stocks with the lowest PIN values, and quintile 5 portfolio (Q5) has stocks with the highest PINs. Each quarter, I estimate the cross-sectional regression described in Table 3 for all stocks in the whole sample and for stocks in each of the five PIN quintile portfolios. This table presents the mean coefficients on *%ΔNumber* from these quarterly cross-sectional regressions and the *t*-statistics computed using Newey-West adjusted standard errors. The last column reports the p-values from Wilcoxon ranked-sum tests of the null hypothesis that the coefficients on *%ΔNumber* estimated from stocks in quintile 5 and from stocks in quintile 1 are equal. The sample period is from the first quarter of 1984 to the fourth quarter of 2002.

	All stocks	Q1 (Lowest PIN)	Q2	Q3	Q4	Q5 (Highest PIN)	Wilcoxon P
Mean	-0.0117	-0.0100	-0.0167	-0.0230	-0.0235	-0.0191	
t-stat.	-9.51	-4.34	-6.57	-8.12	-7.37	-6.20	0.01

2.2.2. Five types of institutions. This section examines how each type of institutional investor affects stock liquidity differently. As discussed above, if information competition among institutions increases stock liquidity, active institutions such as independent investment advisors and mutual funds are expected to exert stronger influences on liquidity than would passive institutions like banks and insurance companies.

The empirical tests are conducted as follows. At the end of each quarter, I estimate the cross-sectional regressions of stock liquidity in the next quarter on the percentage changes in the number of institutions of each type in the current quarter. The liquidity and stock characteristics in the current quarter are also included in the regressions. In order to distinguish the individual effects and the collective effects of the five types of institutions on stock liquidity, I estimate two sets of regressions. In the first set of regression, *%ΔNumber* of each type of institutional investor is included as an independent variable in the regression separately. In the second set of regression, the percentage changes in the number of institutions (*%ΔNumber*) of all five types are present in the same regression. The sample period considered in this analysis is restricted from the third quarter of 1980 to the fourth quarter of 1997 since the institution classification in CDA Spectrum is not reliable in 1998 and beyond.

Table 5 reports the mean coefficients and *t*-statistics on *%ΔNumber* computed from all institutions and from each type of institution. In the table, the first row in each cell reports the mean of standardized coefficients on *%ΔNumber*. The second row in each cell reports the Newey-West *t*-statistics. The last two rows report the mean and *t* statistics of the coefficients when all five types are included in the regression at the same time. The other rows report the results when each type is added into the regression separately. Since the sample period is different from that for previous tables, results using aggregate institutions are also reported in the first column.

Table 5. Illiquidity and changes in the number of institutions of each type

Each quarter, I estimate the cross-sectional regression described in Table 3. This table presents the mean coefficients on *%ΔNumber* (overall or by type) from quarterly cross-sectional regressions and the *t*-statistics computed using Newey-West adjusted standard errors. The last two rows present the mean coefficients and *t*-statistics when the percentage changes in the number of institutions (*%ΔNumber*) of all five types are included in the regression. The sample period is from the third quarter of 1980 to the fourth quarter of 1997.

Total	Banks	Insurance companies	Mutual funds	Independent advisors	Others
-0.0094					
-7.86					

Table 5 (cont.). Illiquidity and changes in the number of institutions of each type

Total	Banks	Insurance companies	Mutual funds	Independent advisors	Others
	-0.0029				
	-2.74				
		-0.0028			
		-3.28			
			-0.0048		
			-5.03		
				-0.0103	
				-9.68	
					-0.0020
					-2.03
	-0.0040	-0.0016	-0.0028	-0.0117	0.0050
	-1.58	-1.12	-2.87	-6.74	1.43

The results for the aggregate institutions are similar to those reported in previous tables. The coefficients on *%ΔNumber* are negative and significant (-0.0094). When the *%ΔNumber* of each of the five types enters the regression separately, the coefficients for the five types are all significantly negative. When all five types are included in the regression, only the *%ΔNumber* of independent investment advisors and the *%ΔNumber* of mutual funds have significantly negative coefficients.

The results in Table 5 indicate that the percentage changes in the number of independent advisors have a larger effect on stock liquidity than do other types. Compared with bank trust departments and insurance companies, independent advisors and mutual funds are generally considered active traders. They are more aggressive in acquiring information and trading on it. The results that institutions, especially active institutions, play a major role in increasing liquidity are consistent with the prediction that information competition among institutional investors increases stock liquidity[1].

Conclusions

This paper examines whether institutional ownership affects the cross-sectional differences in stock liquidity for a sample of stocks on the NYSE and the AMEX from 1980 to 2007. The main findings in this paper are as follows. First, I document that stocks with higher percentage increases in the number of institutions this quarter are more liquid in the next quarter than are other stocks.

Second, additional analyses on PIN portfolios and different types of institutions show that the evidence that stocks with larger increases in the number of institutions are more liquid than other stocks is consistent with the theoretical prediction that information competition among institutional investors increases stock liquidity.

The empirical evidence in this paper establishes a link to two current research areas: cross-sectional variation in liquidity and institutional investors. On the one hand, this paper contributes to the research on liquidity by demonstrating the important role of institutional investors in affecting liquidity variation across stocks. On the other hand, it adds to the literature on institutional investors by revealing that the effect of the number of institutions is not limited to stock returns as documented in the literature. Changes in the number of institutions also influence the cross-sectional differences in stock liquidity. The current literature in these two areas reports that both liquidity and institutional ownership influence stock returns. The connection between institutional investors and stock liquidity proposed in this paper improves our understanding of the relationships among institutional ownership, liquidity, and returns.

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[1] I also examine the effects of different types of institutions on the five PIN portfolios. The results suggest that the effect of changes in the number of institutions on stock liquidity is mainly from mutual funds and independent advisors and concentrated on high-PIN stocks – stocks with more severe asymmetric information. This finding again is consistent with theoretical prediction that information competition among institutional investors increases stock liquidity.

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