The Neglected Stock Effect on Commonality in Liquidity[1]

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Abstract

In this paper, I examine the relationships among commonality in liquidity, institutional ownership and analyst coverage. I find that institutional ownership has a significant positive relationship with liquidity commonality, and analyst coverage provides a significant determinant of institutional ownership. In particular, neglected stocks (stocks with no single reporting sell-side analyst) have on average 0.34 lower yearly liquidity betas compared to those with at least one covering analyst during 1982 - 2018. This neglected stock effect on commonality in liquidity has been significantly increasing over the sample period. These findings contribute to the understanding of the financial market microstructure underlying the link between institutional ownership and liquidity commonality in the U.S. equity market. Furthermore, institutional investors' tendency of underweighting neglected stocks implies that investors can enjoy better diversifications by investing in neglected stocks.

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1. Introduction

The existing literature on commonality in liquidity show that institutional ownership plays an important role in explaining liquidity commonality, and also that liquidity commonality has been increasing for large capitalization stocks, popular to large institutional investors (Kamara et. al., 2008). It seems that institutional ownership is driving up commonality in liquidity, but it is not fully understood what drives institutional capital flows into certain stocks. This is of great importance because liquidity commonality means that it is harder to diversify away liquidity risks, and especially because liquidity drainage is more likely to occur in distressed markets (See Brunnenmeier & Pedersen, 2008; Naes et. al., 2011). In this paper, I attempt to study the underlying mechanism of liquidity commonality based on investors' attention using analyst coverage as a proxy.

In my paper, I show that there are significant relationships between the sell-side analyst coverage of a stock and its liquidity commonality, and also to its percentage of institutional ownership. This is intuitive because institutional investors may have to rely on external advice in their investment decision-making process. There are several arguments in the literature on what drives institutional owners' investment preferences, and in particular why they would not invest in neglected firms. Arbel & Strebel (1982) argue that institutional investors have demands for certain types of assets, making it more profitable for sell-side analysts to cover these assets, leading to an under-analysis of other types of stocks. Arbel et.al. (1983) list several reasons for why institutional investors avoid neglected firms; liquidity constraints, the five percent insider rule in ownership and prudent investment processes. Merton (1987) further argues that there is a cost for institutional owners of educating their clients before being able to invest in under-analyzed stocks ("neglected stocks") that makes it less likely for institutions to invest in these firms. All these are arguments that make plausible the link between institutional ownership and analyst coverage. Liu (2005) also sees a link between neglected stocks and liquidity: "The reason is that a stock may have little trading because many investors are not aware of a small and less visible stock."

My results support this idea in all aspects. I find that there is a statistically significant positive relation between my analyst coverage measure and liquidity commonality. Using a longer sample period than the existing papers such as Kamara et. al. (2008), I confirm that institutional ownership is an important explanatory factor to liquidity commonality. Further, I find the same pattern when I look at institutional ownership and analyst coverage. Finally, the main finding in this paper is a significant negative effect on liquidity commonality for neglected stocks.

Institutional ownership percentage of the US equity market has been steadily increasing since 1980. In the Kamara et. al. (2008) study, the sample data ended in 2005. In 2005 institutional owners held around 23% of the small firms' market outstanding market capitalization, and they held 43% in 2017. For large firms they held around 71% of outstanding market capitalization in 2005 and 79% in 2017[3] (See Table 1. in appendix). This is a new environment compared to pre-2005 when the Kamara study took place. I find that institutional ownership percentage is indeed a significant explanatory variable to liquidity beta running Fama-MacBeth (1973) regressions over the period 1980 - 2017. Aggregated institutional ownership percentage has a large and statistically significant impact on liquidity beta across size weighted quintile portfolios (see Table 4.).

After concluding that institutional ownership indeed plays a significant role in explaining liquidity commonality this study shows that analyst coverage[4] can also explain part of liquidity beta. There are two sides to this matter: first I show that there is a neglected stock effect to liquidity commonality. Across the period 1982 - 2018, the mean liquidity beta was 0.60 for stocks with at least one covering analyst, and 0.26 for those with zero covering analysts, so-called "neglected stocks", with all liquidity betas being statistically significant (see Table 2. Panel A (appendix), B (appendix) and C).

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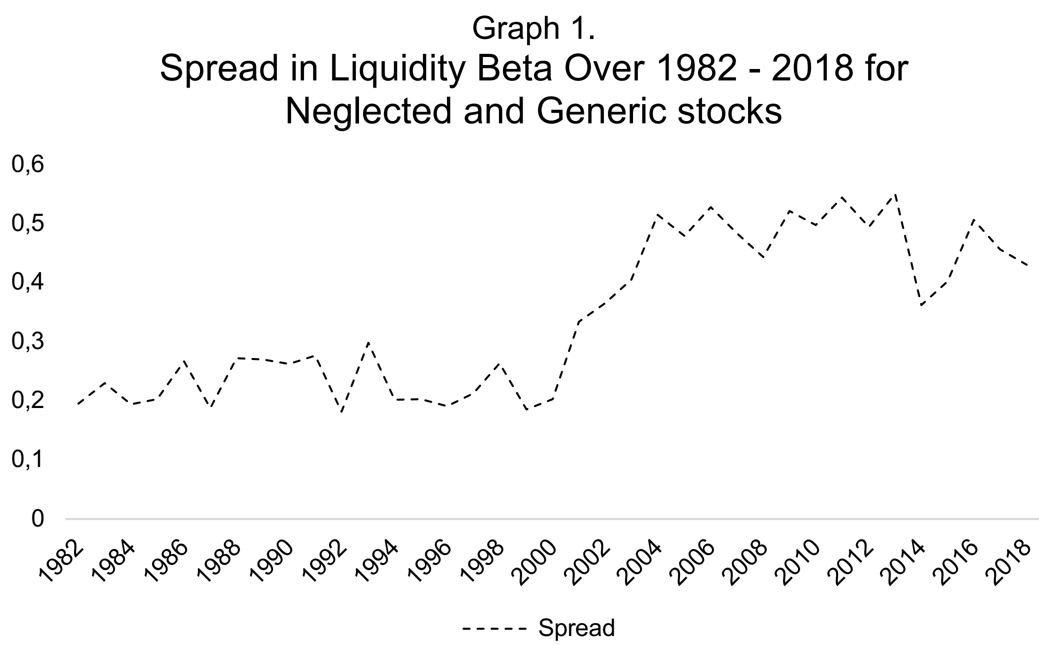
[3] 2018 data on institutional ownership reports 38% and 69% for smallest and largest market capitalized sized quintile portfolios, but that seems unreliable and the observation most likely suffers from underreporting.

[4] By analyst I mean sell-side analyst. For further definition, look into the Definition section of the paper.

Table 2. Panel C	
Mean Statistics Summary	
AC Count	Mean Liquidity Beta
AC > 0	0,60
AC = 1	0,29
AC = 0	0,26

Table 2. Panel C. Summary statistics of the mean liquidity betas from Table 2. Panels A and B. The first column defines the AC count criteria and the second column presents the mean liquidity beta for stocks fulfilling these criteria over the entire sample period 1982 - 2018.

In Graph 1. we see a trend where the spread in liquidity beta is increasing over time for neglected and generic stocks. I argue that because institutional investors are the main liquidity beta drivers, when they are steering away from neglected stocks and channel capital to non-neglected stocks, this is increasing the spread.



Graph 1. This depicts the spread in liquidity beta over sample period 1982 - 2018 between neglected and generic stocks. The liquidity betas are calculated using model (1) and then grouped based on analyst coverage data. For details see Table 3 (appendix).

The second side of analyst coverage explaining liquidity beta is the effect of the number of analysts covering a firm. Fixed effect regressions show that there is a significant relation between liquidity beta and the number of analysts covering a stock, also after adjusting for the size of the firm and the percentage of institutional ownership (see Table 5.). This also links analyst coverage to institutional ownership, and I show that analyst coverage does a good job in explaining institutional ownership (see Table 6. Panel A and B). The number of analysts covering a stock has some explanatory power for the percentage of institutional ownership in general. When it comes to sub-groups of institutional investors the effect looks much weaker after adjusting for size. The only group that the number of analysts does not have a significant effect upon is the "All other" group, meaning institutional owners that are not banks, insurance companies, investment firms or independent investment advisors. The sub-group data, however, has many issues that will be covered in the Data discussion in this paper. To summarize, this study shows that analyst coverage affects liquidity commonality as well as institutional ownership. This analyst coverage effect is the most salient when neglected stocks (without any analyst coverage) and non-neglected stocks (with at least one analyst coverage) are compared.

The implication of this study is that investment managers wishing to manage liquidity risk should hedge liquidity commonality from large cap stocks by investing in small cap stocks, especially neglected small cap stocks. As we see in Table 12 (appendix)., these particular securities have an average yearly liquidity beta of 0.20 during 1982 - 2018. These stocks might not be feasible investments for institutional investors, but there are financial products that may be used to replicate this strategy instead of direct holdings. Institutional investors are already heavily invested into large cap securities. The mean institutional ownership percentage of market capitalization is higher for those US equities with higher market capitalization, and these stocks are also the ones with highest analyst coverage (close to 100 percent in recent years), as is shown in this paper (see Table 1. in appendix). By hedging these liquidity risks associated with liquidity commonality, the equity markets would be less sensitive to negative liquidity shocks that may increase transaction costs and cause harm to market efficiency. Policy makers can also benefit from these results by analyzing how to further reduce transaction costs of trading in smaller cap securities and to facilitate hedging.

These results should be interpreted as follows; institutional investors seem to make investment decisions on other characteristics than simply market capitalization. And the aforementioned effect is naturally stronger the smaller the firm, probably because of the high concentration of neglected stocks in this segment. Analyst coverage seems to guide institutional capital and thus, indirectly, commonality in liquidity. Especially the neglected stock effect is apparent in this study and has practical implications for risk management.

1.1 Related literature

The literature on commonality in liquidity is dominated by two seminal works. Chordia et al (2000) first laid out the idea of commonality in liquidity, measured using the market model of changes in an individual stock's change in liquidity in relation to changes in market liquidity. Their finding that a stock's individual liquidity co-moves with market liquidity is pivotal to my study. Their method of measuring liquidity over size-based portfolios is also adopted by me and others in this field of research. While Chordia et al. (2000) focus on explaining an individual stock's liquidity using liquidity commonality, my interest lies with trying to explain the liquidity commonality itself.

Another seminal work is Kamara et al (2008), which is drawing much of its method from the Chordia et. al. (2000) study. In their study, Kamara et. al. show that over the period 1963 - 2005, the spread in systematic liquidity, measured as an individual stock's sensitivity to changes in market liquidity, has increased for large cap portfolios over small cap portfolios. They explain this trend with increased institutional ownership in, and index-based financial-product inclusion of, large cap securities. Because institutional investors and index-based trading has certain characteristics such as "prudent investment" requirements to investing and basket-trading, the firms that are in demand for index-based financial products and institutional investors are, argues Kamara et. al., showing higher liquidity commonality than other firms. Kamara et. al. (2008) does not argue much about why institutional investors might prefer large cap stocks over small cap stocks, other than the "prudent man" argument. My study further investigates the relationship between institutional ownership and commonality in liquidity by also looking at the possibility of a relation between analyst coverage and institutional ownership. Index inclusion is entirely based on market capitalization and therefore implies that analyst coverage has no explanatory force to the liquidity commonality rising from index-based trading.

In summary, we know that commonality in liquidity is explaining a lot of a firm's individual liquidity from Chordia et. al. (2000), and such liquidity commonality has a significant positive relation with institutional ownership from Kamara et. al. (2008). My study contributes to the literature by taking the next step in explaining what role analyst coverage plays in explaining liquidity commonality.

Finally, my paper is related to the literature on neglected stock effect. While the research on the neglected stock effect has been focused on the pricing of neglected stocks (Arbel & Strebel (1982), Arbel et.al. (1983), Merton (1987), Liu (2005)) there has, to the best of my knowledge, been no study to look at the neglected stock effect on commonality in liquidity. My addition to this literature is by using neglected stocks and analyst coverage as an explanatory factor to liquidity in commonality.

2. Analysis and findings

In this section of the paper I will go through the practical analysis and findings. After an introduction to the data manipulation process the structure will follow the hypotheses. Finally, there will be a conclusion with some further discussion.

2.1 Definitions

In this section I will present the data and methodology, lay out and define certain important concepts that are fundamental to the research analysis and hypotheses of this paper.

Liquidity

Central to this paper is the liquidity measurement. There is much academic debate regarding the best way to estimate a stock's liquidity (Goyenko et. al., 2008). What is most crucial in picking the liquidity measure is to put its potential in relation to the data available. The Amihud illiquidity ratio (Amihud 2002) is based on daily liquidity and is interpreted as the "daily response associated with one dollar of trading volume." Liquidity in this sense is proxied by the pricing impact trading has on the stock. The higher the pricing impact, the higher illiquidity. The Amihud measure has merit because it is using easily available daily data and can thus be calculated over longer time periods without much error. It is also used in the Kamara study, making comparative tests easier.

I will use the Amihud illiquidity measure, defined as:

$$Illiquidity = Average\left(\frac{|r_t|}{Volume_t}\right)$$

where $|r_t|$ is the absolute stock return on day *t* and $Volume_t$ is the dollar volume traded on day *t*. The average is calculated over all positive-volume days, since the ratio is undefined for zero-volume days. Negative volume data points are excluded from the sample in this study.

Analyst coverage measure

For the purpose of this paper, an analyst is a sell-side analyst, defined in the Thomson Reuter's Institutional Brokers' Estimate System (I/B/E/S) a "person at the sell-side institution or contributing analyst who makes [...] forecast[s]." Only analysts that have been reporting to the I/B/E/S database are considered in this study. There may be independent private analysts making forecasts that might drive capital flows in and out of stocks in the US market for equities, and the possibility that these out-of-sample analysts have significant impact on liquidity is probably especially high for neglected stocks (with no I/B/E/S reporting analysts' coverage). The chance of missing any possible explanatory factor is deemed to be so small that using the I/B/E/S narrower scope is found to be suitable.

Neglected stock

A neglected stock is, for the purpose of this paper, defined as any stock with no reported analyst coverage (see above). One important note is that this leads to the assumption that any stock that lacks forecast(s) in the I/B/E/S is considered a neglected stock. The I/B/E/S database does not explicitly state that a stock is neglected, this is instead an *a contrario* conclusion. The research note on the I/B/E/S dataset says:

> "For a company to be available in the I/B/E/S History files there must have been at least one analyst providing estimate forecasts for the company."

This poses the problem that there may indeed be several analysts covering and reporting estimates to the I/B/E/S, but if the database for some reason fail to record the estimate forecasts this would be considered a neglected stock for that period.

This definition is different from the Arbel & Strebel (1982) definition looks at the neglected stock from the other perspective: they use institutional ownership as a proxy for neglection. They did not have access to the I/B/E/S database for their study on 1971-1980 data. I withhold that my measure is more direct and better for the purpose of defining a neglected stock. Firstly, analyst coverage cannot be assumed to have an impact only on institutional investors, meaning that using institutional ownership as a proxy for stock neglection would miss firms that are covered by analysts but for other reasons are not suitable for institutional investors. Secondly, I always prefer the first-hand data to a proxy.

Thirdly, by using institutional ownership as a proxy, we are already assuming the linkage between institutional ownership and analyst coverage. By using the Arbel & Strebel definition we could not test this assumption. This test is however possible with the I/B/E/S dataset.

2.2 Ideal experiment

In this section of the paper I would like to propose an ideal experiment and put the paper's methodology in relation to that ideal setting. This is a way to evaluate the research method and determine how far away from the best possible research it lands.

Determining the effect of institutional ownership investment decisions and their impact on liquidity beta we would ideally like to monitor the exact flows of every institutional investment company as well as a detailed information on what parameters were included in the decision-making process prior to execution of the transaction(s). Every responsible manager at every said company would account for the underlying rationale she executed the trade, if there was a rational at all. In this context, it would be possible to understand the investment styles of managers on the individual level, and on the firm level as well as on the aggregate level. The managers would also report what sources of information on stocks (if any) she based her own forecasts from, down to the level of which person(s), be it analysts or any other individual making judgement on the stock, played a part in the decision.

In this study, I use proxies for all of these measures. Because data on each investment firm's exact capital flows are hard to come by and often proprietary, I look at their reported quarterly holdings from the 13F dataset provided by Thomson Reuter. And instead of running tests on individual firms I aggregate all firms into three groups based on their 13F category: one group contains all bank and insurance companies, one group contains all investment managers and independent investment advisors, one group contains all others. As for sources of information that may guide firms into executing transactions that affect the liquidity in those securities it is impossible to say how managers retrieve this information. With no access to this detailed information, the proxy used it the analyst coverage measures. The underlying assumption is that investment managers to some degree listen to external advice, and the more analysts reported covering a stock, the more likely that the market is efficiently interpreting company information and the more likely that managers are interpreting the guidance in a similar fashion. To summarize, this study is far from ideal for the highest-level purpose - to understand commonality in liquidity and its affinity to institutional ownership. The hypotheses tested in this study are chosen with a realistic approach in mind.

2.3 Data

In this part of the paper I will present the underlying data sources facilitating the study. There are three sources of data: historical stock data, institutional ownership data and analyst coverage data. Each source will be presented separately.

Historical stock data

For calculating the liquidity measure I use the daily recorded stock prices, volume traded, number of shares outstanding and returns from the Center of Research in Security Prices (CRSP). I draw these data points over the period January 2, 1962 to December 31, 2018. Following the methodology in the Kamara study I only include common stocks (CRSP Share Code 10 and 11).

Institutional ownership data

Institutional ownership data is obtained from the Thomson-Reuters Ownership Data. The aggregated institutional ownership data provided by this source goes back to January 1980. But starting in 1997 and fully integrated in 1999 there is also institutional ownership data by type of institution (variable name Type Code). Both these features in the data are utilized in this paper but for obvious reasons they cannot always overlap. The dataset contains institutional ownership information as reported by fiscal quarters for mutual funds (S12 Dataset) as well as calendar quarterly reports by institutional owners via 13F reports.

This data is problematic because it contains many misclassifications[5] in the institutional ownership by type data. Overall the dataset does not seem to be of very high

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[5] See Wharton Research Notes https://wrds-www.wharton.upenn.edu/documents/952/S12_and_S34_Regenerated_Data_2010-2016.pdf#3-13f-ownership-drop

quality. This is however the best reasonable data sample available. It has been hard to estimate the impact of these errors might have on my results. One specific measure taken is to exclude the year 2018 from the ownership data. Looking at Table 1. we see that all portfolios drop 6 to 12 percentage points during the year. This is an extremely unlikely scenario, that aggregated institutional ownership would drop that much in a year. I therefor prefer to leave the observations from 2018 outside. I consider it to be a case of underreporting or other type of data related issue rather than a factual event.

Table 1

Institutional Ownership Percentage by Market Capitalization Weighted Portfolio Decile Over Period 1980 - 2018

Year	Smallest	2nd	3rd	4th	Largest
1980	7%	14%	22%	33%	39%
1981	8%	13%	26%	36%	42%
1982	12%	20%	28%	35%	42%
1983	9%	21%	29%	40%	47%
1984	17%	28%	37%	45%	48%
1985	22%	33%	43%	49%	52%
1986	19%	29%	38%	48%	51%
1987	22%	33%	43%	51%	57%
1988	25%	37%	43%	47%	49%
1989	27%	36%	47%	53%	50%
1990	32%	43%	50%	52%	51%
1991	32%	44%	50%	54%	50%
1992	32%	45%	51%	55%	52%
1993	27%	46%	50%	53%	53%
1994	35%	49%	53%	58%	57%
1995	31%	47%	52%	57%	57%
1996	35%	50%	54%	58%	56%
1997	33%	49%	51%	59%	57%
1998	28%	47%	53%	57%	57%
1999	33%	50%	54%	59%	57%
2000	27%	47%	55%	58%	58%
2001	30%	54%	62%	63%	61%
2002	31%	58%	68%	69%	68%
2003	30%	60%	68%	70%	70%
2004	25%	65%	75%	70%	70%
2005	23%	64%	77%	72%	71%
2006	28%	67%	80%	74%	73%
2007	33%	75%	84%	81%	76%
2008	38%	77%	84%	79%	76%
2009	36%	64%	77%	78%	72%
2010	35%	65%	75%	78%	74%
2011	37%	75%	78%	82%	76%
2012	43%	74%	82%	83%	77%
2013	44%	79%	84%	85%	79%
2014	43%	74%	83%	85%	77%
2015	41%	75%	83%	84%	77%
2016	42%	79%	87%	85%	78%
2017	43%	81%	87%	84%	78%
2018	38%	70%	76%	77%	69%

Table 1. Summary table over the yearly mean of institutional ownership percentage presented by size quintile portfolio from smallest to largest over the period 1980 - 2018. The significant drop in institutional ownership across all portfolios in 2018 has no clear explanation and is an improbable event. This disqualifies the institutional ownership observations of 2018 from the sample.

& https://wrds-www.wharton.upenn.edu/documents/533/Research_Note_-Thomson_S34_Data_Issues.pdf Accessed on 2019-12-06.

Analyst Coverage data

The analyst coverage data is obtained through the Thomson Reuter's Institutional Brokers' Estimate System (I/B/E/S). If is a database that records estimates made by stock analysts and dates back to 1976. The data frequency is quarterly. In the data, analysts can be counted on the individual analyst level or at the level of the sell-side institution. The institution level variable ("estimator") will be used as the identifier of analyst coverage. This is because there may be changes in analysts on the individual level, but that should not be counted as an additional analyst covering the stock.

The period 1980-1981 has data quality issues. As an example, see the percentage of firms in the largest size quintile over 1980-1982 with at least one covering analyst. In 1980 the percentage of generic stocks (that is, stocks with at least one covering analyst) was 20%. In 1981 the figure was 46%. And in 1982 it was 66%. To think that the coverage increased by 330% over three years is unreasonable. After 1982 the percentage is stable at around 66%. Because we cannot rely on the analyst coverage data these first two years they have been excluded.

2.4 Hypotheses development

For the purpose of analysis of the liquidity beta behavior on the US stock market in relation to previous research I am testing the following three hypotheses.

(1) Institutional ownership is significantly impacting commonality in liquidity.

(2) Analyst coverage is significantly impacting commonality in liquidity.

(3) Analyst coverage is significantly impacting institutional ownership.

2.5 Data manipulation

As mentioned in the data presentation the study is based on three datasets. The CRSP dataset for stock prices, volume and returns, the Thomson-Reuters Ownership Data for ownership data and the I/B/E/S for analyst coverage data. Because stocks are identified by CUSIP numbers in all three datasets, merging is done seamlessly whenever needed. The starting point is always the CRSP dataset. If there is no reference in the filtered CRSP data when merging, then the observations are dropped.

Thus, beginning with the CRSP data on daily stock price, volume traded, shares outstanding and return over the period December 31, 1962 to December 31, 2018. This contains 85,251,636 observations. Inspired by the Kamara et. al. (2008) method I calculate the market capitalization as the shares outstanding times the price of the share for the first trading day of each year. This will be the basis for creating market capitalized-sized quintile portfolios. I remove those observations with missing either shares outstanding or price, as well as observations with negative trading volumes as illiquidity cannot be determined for those. For the same reason, observations when the return is exactly equal to zero are dropped.

The Amihud illiquidity ratio ($AIR_{i,d}$) is calculated for each firm *i* and trade day *d*. Next, the log ($AIR_{i,d}$) is calculated. Thus, the change in log ($AIR_{i,d}$), is calculated as:

$$\Delta AIR_{i,d} = \log\left(\frac{\frac{|r_{i,d}|}{Volume_{i,d}}}{\frac{|r_{i,d-1}|}{Volume_{i,d-1}}}\right) \qquad (1)$$

Where $r_{i,d}$ is the absolute return for firm *i* on day *d* and $Volume_{i,d}$ is the daily volume traded for firm *i* on day *d*. $|r_{i,d-1}|$ is the absolute return for firm *i* on the previous trading date *d-1*and $Volume_{i,d-1}$ is the daily volume traded for firm *i* on the previous trading date *d-1*.

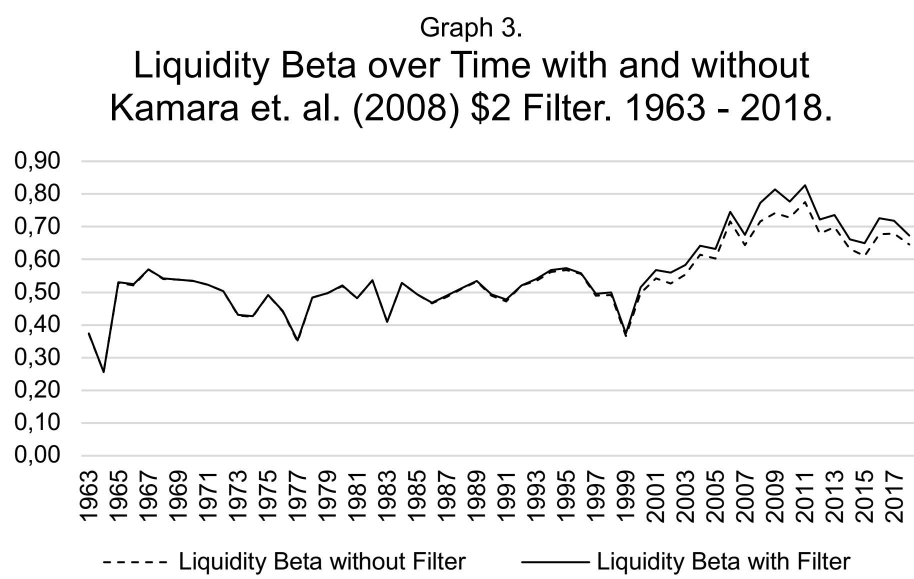
The top and bottom 1 % of $\Delta AIR_{i,d}$ per firm-day are removed from the sample after applying the first two filters as a measure to remove outliers. Filtering away all firms that have less than 100 non-missing observations per year. The remaining firm-year number of observations is 95,984 (see Table 8. in appendix).

To arrive at the liquidity beta per stock and year I use the market model. I run yearly regressions for each firm's $\Delta AIR_{i,d}$ on the value-weighted average market illiquidity changes, $\Delta AIR_{m,d}$:

$$\Delta AIR_{i,d} = a_t + \beta_i \Delta AIR_{m,d} + \varepsilon_{i,t} \qquad (2)$$

Where $\Delta AIR_{i,d}$ is defined in (1) and $\Delta AIR_{m,d}$ is the value-weighted average market change in illiquidity as defined in (1). β_i is the estimate of the sensitivity of firm i's liquidity to the market m liquidity, in other words, the liquidity beta.

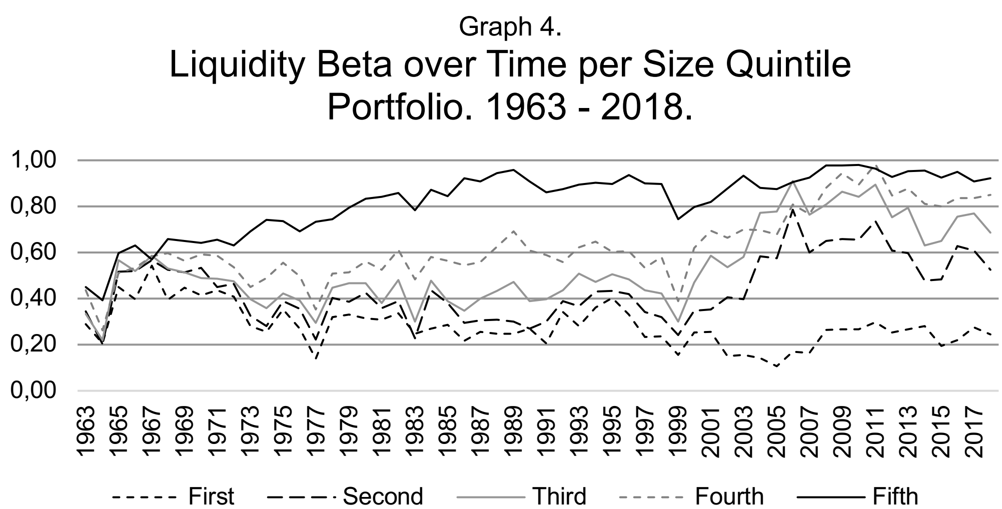
Previous studies have used additional filters on stock price size in order to mitigate liquidity issues caused by tick sizes. Chordia et al. (2000) use no observations for stocks with a trading price less than \$5 the previous day of trading, while Kamara et. al. (2008) use \$2. In this study, no such filter is used. Interestingly, there is a skew towards higher commonality when we apply these filters in recent times data. This is probably because if we remove the stocks with the lowest stock prices, we are likely to trim away more small cap stocks than large cap stocks. And because large cap stocks have a higher commonality in liquidity on average, we are boosting the aggregated commonality in liquidity estimates for the US stock market.



Graph 3. This graph presents the liquidity beta differences with and without the Kamara et.al. (2008) \$2 filter on the sample data. Period 1963 – 2018. For more details, see Table 9 (appendix).

While I see no difference in the period 1963 - 2001, after that there are quite large differences. In April 2001, the U.S. Securities and Exchange Commission (SEC) implemented decimalization on US stock exchanges (Levitt, 2000): “Under the order, all securities must be priced in decimals no later than April 9, 2001 -- shortly after the end of the quarter.” Decimalization has made liquidity in especially stocks with low stock prices more attractive as the trading costs in terms of bid-ask spreads as a portion of the price narrows.[6] This microstructure reform of tick sizes explains the difference between the filtered and unfiltered data sample. This study is using the unfiltered data set with no limit as to how low the previous day’s trading price could be.

The stocks are then assigned to yearly re-balanced quintile portfolios based on the market capitalization of the stock on the first trading day in each year.

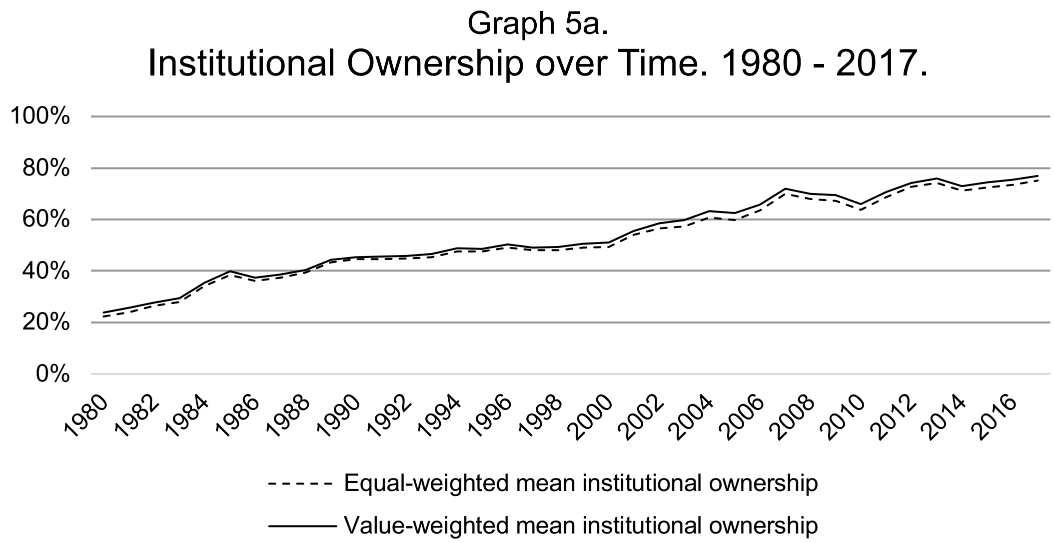


Graph 4. The liquidity betas $\beta_{i,t}$ are sorted into size quintile portfolios based on the market capitalization of firm *i* on the first trading day of year *t*. This graph illustrates the evolution of liquidity betas per size quintile portfolio over the period 1963 – 2018.

[6] In fact, the bid-ask spread as a portion of the price has been used as a proxy for liquidity. See for example Amihud & Mendelson (1986); Loeb (1983).

2.6 Institutional ownership and liquidity beta

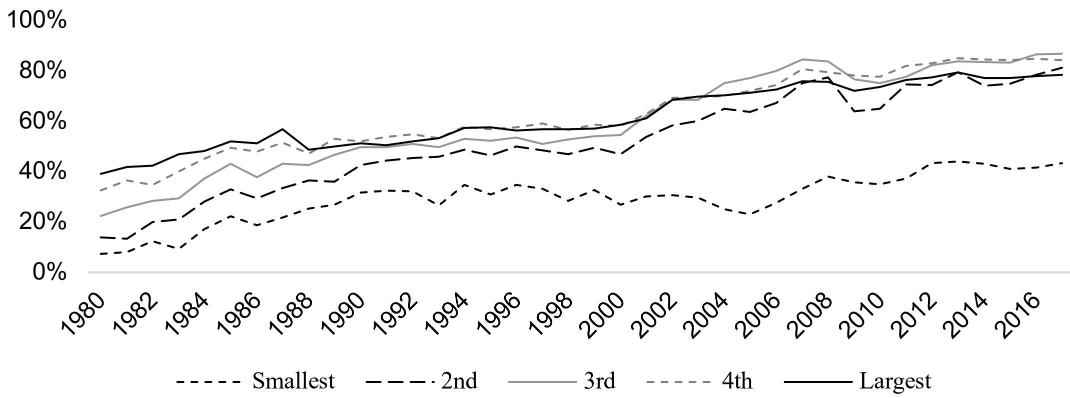
The first hypothesis to test is whether institutional ownership is significantly impacting commonality in liquidity. First, we want to look at the evolution of institutional ownership in the data. Since the data start in 1980 institutional investors in the aggregate have been steadily increasing their investments.



Graph 5a. Institutional ownership over time, using two different measures. The sample period is 1980 – 2017. Institutional ownership is measured as a mean of all firms' reported institutional ownership in the first quarter of year *t* in the sample after applying the filters in section 2.5.

In the data sample institutional investors held as much as 77% of the US stock market in 2017. These figures are in line with previous studies of institutional ownership in the U.S. equity market (Blume & Keim, 2008, 2013). Institutional investors have increased their mean ownership percentage in all the market capitalization weighted portfolios (Graph 5b.)

Graph 5b.
Institutional Ownership Over Time by Size Quintile Portfolio. 1980 - 2017.



Graph 5b. Equal-weighted mean institutional ownership over time. The sample period is 1980 – 2017. Institutional ownership is measured as a mean of all firms' reported institutional ownership in the first quarter of year *t* in the sample after applying the filters in section 2.5, then split up by size quintile portfolio.

It is important to test the impact institutional ownership might have on liquidity beta before establishing a link between analyst coverage and liquidity beta as well as between analyst coverage and institutional ownership.

In order to test the impact institutional ownership might have on liquidity beta I run Fama-MacBeth (1973) regressions with Newey-West (1987) adjusted standard errors on each market capitalized portfolio.

$$\beta_{i,t} = a_t + \lambda_t IO_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t} \qquad (3)$$

Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $IO_{i,t}$ is the institutional ownership percentage of firm *i*'s outstanding market capitalization at the end of the first quarter in year *t*. $IO_{i,t}$ is either the aggregated institutional ownership measurement available from 1980 to 2018, or the sub-group measurement available from 1998 - 2018. $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t.* The Panel A in Table 4 confirms that institutional ownership in general has a significant positive impact on liquidity beta for all sized portfolios also after adjusting for the pure size effect over the period 1980-2018.

The positive size effect on liquidity beta is statistically significant for all portfolios. The results on the positive impact on liquidity data from institutional ownership confirms the previous research done by Kamara et. al. (2008) and Chordia et. al. (2000). In the second and third panel I run the same methodology after dividing the aggregated institutional ownership percentage into three sub-categories: "Bank & Insurance companies", "Investment companies & Independent Advisors" and "All others".

	Table 4. Panel A		**Table 4. Panel B**				**Table 4. Panel C**			
	Estimates from Model (1)									
	1980-2017		**1998-2017**				**2005-2017**			
Portfolio	IO	Size	Group 1	Group 2	Group 3	Size	Group 1	Group 2	Group 3	Size
1	0,26		1,39	0,42	0,18		1,85	0,33	0,21	
	[8,22]		[6,11]	[3,11]	[7,23]		[14,6]	[3,08]	[9,4]	
	0,20	0,03	1,12	0,36	0,12	0,04	1,45	0,26	0,13	0,05
	[7,5]	[4,35]	[6,56]	[2,74]	[5,72]	[5,31]	[13,7]	[2,65]	[6,68]	5,92
2	0,19		0,97	0,52	0,05		1,24	0,32	0,02	
	[11,84]		[6,13]	[4,25]	[1,67]		[7,43]	[3,71]	[0,51]	
	0,17	0,12	0,84	0,43	0,03	0,17	1,07	0,26	0,01	0,16
	[10,47]	[7,61]	[6,04]	[3,72]	[0,93]	[12,05]	[7,13]	[2,96]	[0,21]	[11,07]
3	0,18		1,36	0,26	-0,02		1,74	0,17	-0,08	
	[6,54]		[6,71]	[2,86]	[-0,42]		[15,7]	[1,52]	[-1,82]	
	0,17	0,14	1,34	0,27	-0,02	0,12	1,73	0,15	-0,08	0,14
	[5,88]	[7,63]	[6,54]	[2,64]	[-0,43]	[5,13]	[15,97]	[1,32]	[-2]	[5,01]
4	0,23		1,22	0,78	-0,09		1,59	0,27	-0,14	
	[7,29]		[4,57]	[3,31]	[-2,53]		[5,26]	[4,42]	[-5,29]	
	0,23	0,10	1,18	0,79	-0,09	0,03	1,54	0,28	-0,13	0,02
	[7,25]	[5,82]	[4,5]	[3,31]	[-2,49]	[1,78]	[5,08]	[4,75]	[-4,91]	[1,1]
5	0,23		1,19	0,39	-0,25		1,33	0,20	-0,17	
	[3,22]		[6,38]	[1,32]	[-3,82]		[5,04]	[1,03]	[-3,12]	
	0,33	0,15	1,02	0,43	-0,08	0,09	1,16	0,33	0,00	0,08
	[4,91]	[10,15]	[6,25]	[1,68]	[-1,03]	[8,21]	[5,12]	[1,77]	[0,04]	[5,99]

Table 4. The table presents the mean time-series estimates and t-statistics (in brackets) from Model (3): $\beta_{i,t} = a_t + \lambda_t IO_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t}$. Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $IO_{i,t}$ is the institutional ownership percentage of firm *i*'s outstanding market capitalization at the end of the first quarter in year *t*. $IO_{i,t}$ is either the aggregated institutional ownership measurement (Panel A) available from 1980 to 2018, or the sub-group measurement (Panel B and C) available from 1998 - 2018. $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. The year 2018 has been excluded from the sample due to data issues. The model is estimated using Fama-MacBeth (1973) regressions, with Newey-West (1987) adjusted standard errors. In Panel B and C, the sub-groups of institutional owners are Group 1: "Banks and insurance companies", Group 2: "Investment companies and independent advisors" and Group 3: "All others".

Furthermore, I estimate this model for two different time-periods. One from 1998 - 2018 and one from 2005 - 2018. The reason for this is to make the analysis more robust and spot any deviations across the periods. No such significant deviations were found, the results are robust over both periods. I find that the group "Bank & Insurance companies" has both the strongest and also the most statistically robust impact on liquidity commonality. These results differ from Kamara et. al. (2008) that find the impact of this group to be both the weakest and also insignificant. The "Investment companies & Independent Advisors" group also has strong and statistically significant impact on liquidity beta except for the largest firms. The "All others" group has a weak, or even negative, but for the most part statistically insignificant effect on liquidity commonality. The "All others" category has been reported as erroneous since 1998 with misclassification. I cannot say whether these misclassifications play a role in these results. It is clear that institutional ownership has an impact on liquidity beta. And I will now move on to test the impact analyst coverage has on liquidity beta.

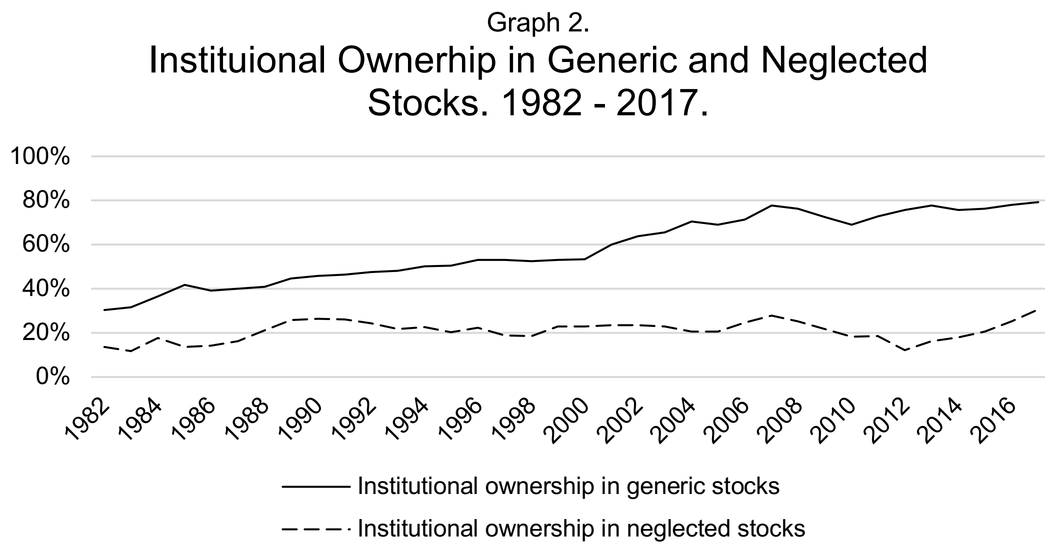
2.7 Analyst coverage and liquidity beta

In the following I will present the results of my study of analyst coverage and liquidity beta. I run two tests. One is to determine whether there is a so-called "neglected stock" effect on liquidity beta. That is, do firms with no analyst coverage have significantly different liquidity commonality on average compared to firms with analyst coverage? The other test focuses on the number of analysts covering a security and if this has an effect.

Neglected stock effect

I find that there are statistically significant differences in liquidity beta for neglected versus not neglected stocks. The period 1980-1981 is excluded because of data quality issues.

In Table 2.A (appendix) I show that the mean liquidity betas are lower for neglected stocks in every year of the sample. The spread also seems to be growing over time. Across 1982 - 2000 the average liquidity beta was 0.23 lower for neglected stocks, while during 2001 - 2018 the liquidity beta spread was twice as high, 0.46, on average. One possible explanation is that there are more and more firms being covered, and with more firms in the informational environment this makes it even harder to pick one that happens to be neglected. These firms are ever harder to come by for institutional investors, and under the assumption that institutional investors are generating a lot of liquidity commonality, it makes intuitive sense that the neglected stock effect on liquidity beta expands if institutional investors are steering away from neglected stocks and into non-neglected stocks. By looking at the mean percentage of institutional ownership in neglected and not neglected stocks we can also see that this is in line with this explanation.

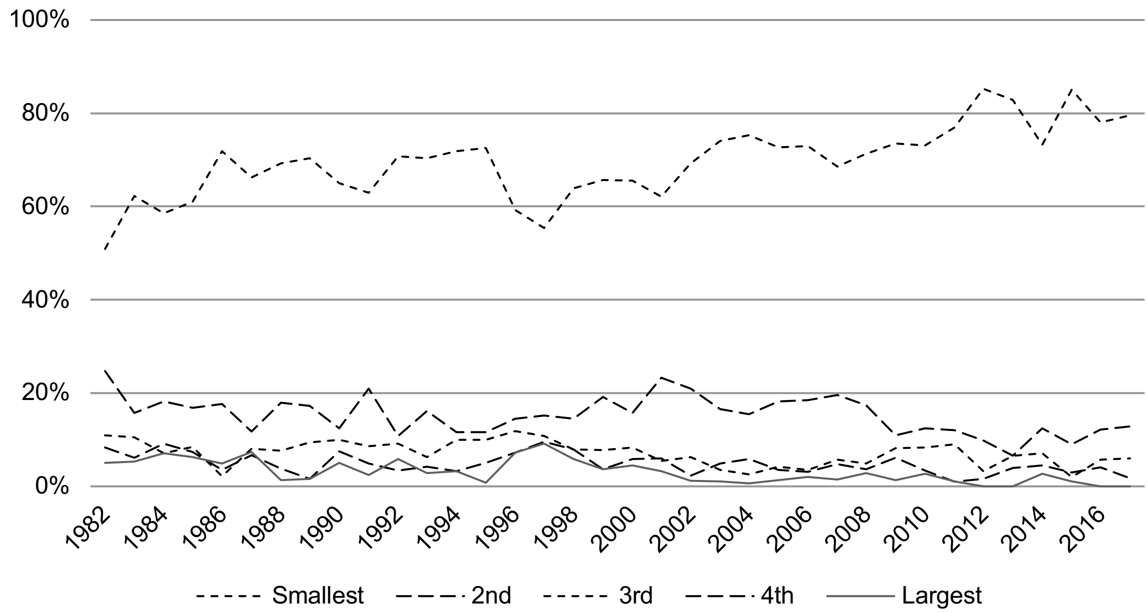


Graph 2. Institutional ownership in generic and neglected stocks over the period 1982 – 2017. Institutional ownership is measured as a mean of all firms' reported institutional ownership in the first quarter of year *t* in the sample after applying the filters in section 2.5. Neglected stocks are firms that had on average zero covering analysts in year *t* and generic stocks are the ones with on average at least one covering analyst in year *t*.

During 1982 - 2017 institutional investors held 21 % of neglected stocks' outstanding market capitalization on average, ranging from 14 % in 1982 to 31 % in 2017, while holding on average 58 % of the generic universe's market cap, ranging from 30 % in 1982 to 79 % in 2017. The spread in mean liquidity beta has increased a lot over the period. Because institutional investors have been investing more and more in the stock market, and selectively picked generic firms, their holdings are clearly skewed away from neglected stocks, following the pattern suggested by Kamara et. al. (2008). By staying away from neglected stocks, institutional investors have increased liquidity betas in generic stocks.

The distribution of neglected and generic stocks in the U.S. equity market has not changed much over the sample period 1982 - 2018. This means that as the percentage level of neglected stocks in the universe stays firm, these stocks are found among the smaller-sized quintiles, see Graph 6. This graph is mapping the evolution of distribution of neglected stocks by market cap-sized portfolios. And we can see that the portfolio containing the smallest market cap-portfolios has gradually been increasing its portion of the total count of neglected stocks in the market. In the period 2008 - 2018, at least 70 % of the neglected stocks in the sample were in the smallest portfolio.

Graph 6.
Distribution of Neglected Stocks by Size Quintile Portfolio. 1982 - 2017.



Graph 6. The distribution of neglected stocks by size quintile portfolio over 1982 – 2017. The measure is the percentage of the sum of neglected stocks in the sample per year *t* as a portion of the total sum of stocks in the sample that year *t*. For example, in the year 2017, the smallest size quintile portfolio contained 79% of the neglected stocks, while the largest size quintile contained 0% of the neglected stocks. For more details, see Table 11 (appendix).

This motivates that size should be adjusted for when estimating the neglected stock effect. To determine the impact of the neglected stock effect on liquidity beta I estimate model (4) using OLS regressions.

$$\beta_{i,t} = a_t + \lambda_t Neglected_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t} \qquad (4)$$

Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $Neglected_{i,t}$ is a dummy variable that takes on the value 1 if the firm *i* in year *t* has a mean analyst coverage of zero and 0 otherwise, $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. For each portfolio there was a significant negative neglected stock effect, after adjusting for size. The effect was particularly large for the three largest size quintile portfolios as we see in Table 13.

Table 13.

Estimates from Model (4)

Portfolio	Neglected	Size
1	-0.10***	
	[-12.53]	
	-0.06***	0.05***
	[-7.67]	[10.53]
2	-0.08***	
	[-6.01]	
	-0.05***	0.17***
	[-3.46]	[29.58]
3	-0.18***	
	[-8.68]	
	-0.13***	.20***
	[-6.51]	[33.56]
4	-0.30***	
	[-12.95]	
	-0.26***	0.14***
	[-11.49]	[23.25]
5	-0.31***	
	[-10.16]	
	-0.27***	0.08***
	[-9.11]	[21.64]

Table 13. The table presents the mean time-series estimates and t-statistics (in brackets) from Model (4): $\beta_{i,t} = a_t + \lambda_t Neglected_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t}$ Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $Neglected_{i,t}$ is a dummy variable that takes on the value 1 if the firm *i* has a mean analyst coverage of zero and 0 otherwise, $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. The year 2018 has been excluded from the sample due to data issues.

In Table 7 (appendix) over analyst coverage we see that analyst coverage for the very largest stocks is in recent years very close to 100% (99.6% in 2017 and 2018). This means that any neglected stock effect would not be observable or very hard to estimate by year per portfolio. What I can conclude is that there is a statistically significant neglected stock effect on liquidity commonality and that it has increased over the sample period.

Mean analyst coverage

After showing that there is an explanation to liquidity beta stemming from neglected stock effects, I also want to understand the relationship between commonality in liquidity and the number of analysts covering a firm. After all, nine tenths of the firms in the sample are not neglected.

I estimate the model:

$$\beta_{i,t} = a_t + \lambda_t AC_{i,t} + \gamma_t Size_{i,t} + \theta_t IO_{i,t} + \varepsilon_{i,t} \quad (4)$$

Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $AC_{i,t}$ is the mean number of sell-side analysts for firm *i* in year *t*. $IO_{i,t}$ is the institutional ownership percentage of firm *i*'s outstanding market capitalization at the end of the first quarter in year *t*. $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. In the data I let the mean number of analysts covering the firm during the year define the number of sell-side analysts and exclude neglected stocks.

This subset of the data consists only of firms that have at least one sell-side analyst covering the firm during the year. The results from the fixed effects panel data regression show a weakly significant positive impact on liquidity beta from the number of analysts covering the firm after adjusting for size and institutional ownership. This effect is indeed very small. One more analyst covering a firm would on average increase the liquidity beta by 0.002 according to the estimate. I have reason to think that this would imply that the relationship is not linear, but using a non-linear model yields similar results. The effect of number of analysts covering was higher before adjusting for size and institutional ownership. One reason might be multicollinearity in the model. Because analyst coverage is correlated both with the size of the firm and the institutional ownership in the firm, I cannot say much about the effect of analyst coverage in isolation.

Table 5

Estimates from Model (4)

	AC	AC + Size	AC + Size + IO
Mean Number of Sell-Side Analysts	0.010***	0.004***	0.002**
	[0.00]	[0.00]	[0.00]
Size		0.088***	0.070***
		[0.00]	[0.00]
Institutional Ownership			0.283***
			[0.02]
Intercept	0.457***	-0.668***	-0.564***
	[0.01]	[0.05]	[0.05]

* p<0.05, ** p<0.01, *** p < 0.001

Table 5. The table presents the estimates and t-statistics (in brackets) from Model (4): $\beta_{i,t} = a_t + \lambda_t AC_{i,t} + \gamma_t Size_{i,t} + \theta_t IO_{i,t} + \varepsilon_{i,t}$. Where $\beta_{i,t}$ is the yearly liquidity beta for firm *i* in year *t*, $AC_{i,t}$ is the mean number of sell-side analysts for firm *i* in year *t*. $IO_{i,t}$ is the institutional ownership percentage of firm *i*'s outstanding market capitalization at the end of the first quarter in year *t*. $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. The year 2018 has been excluded from the sample due to data issues. The model is estimated using fixed effect regressions and robust standard errors. The model is estimated using a subset of the data where only securities with on average at least 1 covering analyst are included. The time period is 1982 - 2018. Institutional ownership data is flawed for 2018 but comparing the results with and without year 2018 in the sample shows no significant difference to the estimates or t-statistics.

Analyst coverage and institutional ownership

In order to test analyst coverage and its relation to institutional ownership I estimate the fixed effect panel data model:

$$IO_{i,t} = a_t + \lambda_t AC_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t} \quad (5)$$

Where $IO_{i,t}$ is either the aggregated institutional ownership percentage of the firm i's outstanding market capitalization or any of the three sub-groups of institutional investors: "Bank & Insurance companies", "Investment companies & Independent Advisors" and "All others" in year t. $AC_{i,t}$ is the mean number of sell-side analysts for firm i in year t. $Size_{i,t}$ is the log of firm i's market capitalization at the first trading date of year t. The results in Table 6. Panels A & B show statistically significant impact on institutional ownership both in the aggregates as well as for sub-groups except for the "All others" group. Because of data issues with this group in particular, I will not put too much effort in trying to explain this exception. The results indicate that, after adjusting for size, institutional ownership increases with 0.34 % with every additional covering analyst. On the sub-group level, I find that, after adjusting for size, the effect on "Bank & Insurance companies" holdings is very weak from increases in analyst coverage. As Kamara et al (2008) point out, banks and insurance companies often have proprietary and long-term relationships with companies that they invest in. This would explain why they are less reliant on sell-side analysts covering the firms they invest in as they have their own in-house financial analysts to rely on.

Table 6. Panel A

Estimates from Model (5)

	AC	AC + Size
Mean Number of Sell-Side Analysts	0.009***	0.003***
	[0.00]	[0.00]
Size		0.074***
		[0.00]
Intercept	0.496***	-0.462***
	[0.01]	[0.03]

* $p < 0.05$, ** $p<0.01$, *** $p < 0.001$

Table 6. Panel A and B. The table presents the estimates and t-statistics (in brackets) from Model (5): $IO_{i,t} = a_t + \lambda_t AC_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t}$. Where $AC_{i,t}$ is the mean number of sell-side analysts for firm i in year t. $IO_{i,t}$ is the institutional ownership percentage of firm i's outstanding market capitalization at the end of the first quarter in year t. $Size_{i,t}$ is the log of firm i's market capitalization at the first trading date of year t. The year 2018 has been excluded from the sample due to data issues. The model is estimated using fixed effect regressions and robust standard errors. The model is estimated using a subset of the data where only securities with on average at least 1 covering analyst are included. For Panel A the sample time period is

1982 - 2018. Institutional ownership data is flawed for 2018 but comparing the results with and without year 2018 in the sample shows no significant difference to the estimates or t-statistics. In Panel B, the sub-groups of institutional owners are Group 1: "Banks and insurance companies", Group 2: "Investment companies and independent advisors" and Group 3: "All others". The sample period for Panel B is 1998 - 2018.

Table 6. Panel B

Estimates from Model (5)

	Banks & Insurance Companies		**Investment Managers & Independent Advisors**		**All others**	
	AC	AC + Size	AC	AC + Size	AC	AC + Size
Mean Number of Sell-Side Analysts	0.001***	0.001***	0.007***	0.005***	0.002***	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size		0.005*		0.025***		0.016***
		(0.00)		(0.00)		(0.00)
Intercept	0.079***	0.013	0.070***	-0.265***	0.429***	0.217***
	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)	(0.03)

* p<0.05, ** p<0.01, *** p < 0.001

Table 6. Panel A and B. The table presents the estimates and t-statistics (in brackets) from Model (5): $IO_{i,t} = a_t + \lambda_t AC_{i,t} + \gamma_t Size_{i,t} + \varepsilon_{i,t}$. Where $AC_{i,t}$ is the mean number of sell-side analysts for firm *i* in year *t*. $IO_{i,t}$ is the institutional ownership percentage of firm *i*'s outstanding market capitalization at the end of the first quarter in year *t*. $Size_{i,t}$ is the log of firm *i*'s market capitalization at the first trading date of year *t*. The year 2018 has been excluded from the sample due to data issues. The model is estimated using fixed effect regressions and robust standard errors. The model is estimated using a subset of the data where only securities with on average at least 1 covering analyst are included. For Panel A the sample time period is 1982 - 2018. Institutional ownership data is flawed for 2018 but comparing the results with and without year 2018 in the sample shows no significant difference to the estimates or t-statistics. In Panel B, the sub-groups of institutional owners are Group 1: "Banks and insurance companies", Group 2: "Investment companies and independent advisors" and Group 3: "All others". The sample period for Panel B is 1998 - 2018.

3. Conclusion and discussion

In the study I have shown how the microstructure of the financial market is important in explaining commonality in liquidity. With new findings regarding the neglected stock effect on liquidity commonality and the importance of analyst coverage we can now understand more of the underlying characteristics of the equities market. What I have first confirmed in my study is that institutional investors are playing a key role in driving up liquidity beta in its holdings, as previously shown by Kamara et. al. (2008). Then I went on and showed how institutional investors are more reluctant to invest in neglected stocks, seeming to cause large differences in liquidity betas for neglected stocks compared to generic stocks. The previous literature argue that neglected stocks suffer from information deficiencies and other associated trading risks such as bad liquidity or preference constraints such as the five percent rule (Arbel et. al., 1983) or lack of visibility (Liu, 2005), causing institutional investors to flinch. This theory of neglected stocks and lack of visibility is further strengthened by the fact that the number of covering analysts has a significant impact on institutional ownership. On average, one additional sell-side analyst covering a security will increase the institutional ownership percentage by 0.34 % in my estimated model (4). My results show that neglected stocks are showing lower commonality in liquidity on average compared to generic stocks (see Table 3.). The spread in liquidity beta has also increased over the sample period and has been steadily high.

There is a case, I argue, for portfolio managers to diversify away liquidity risk stemming from commonality in liquidity by investing more in the small cap universe. The spread in liquidity beta is still around 0.70 between large caps and small caps. This segment of the stock market has much less analyst coverage and has historically captured a majority of the neglected stocks in the market. This means that by investing into small cap stocks an investor is also more likely to expose herself to neglected stocks. The average liquidity beta for neglected small cap stocks in 1980 – 2018 is 0.2 (see Table 12 (appendix)) compared to the mean of 0.25 for the same period of all small cap stocks. Blume & Keim (2012) have shown that hedge funds have been increasing their weights in smaller cap stocks during 1980 to 2010. They have not studied the neglected stock patterns of institutional ownership, however, as I have here. In my study, it is apparent that while institutional investors are locating more capital towards smaller cap stocks, they are still avoiding the neglected securities. This implies that institutional investors are not diversifying away liquidity risks in the most efficient way as even among small cap stocks there is a significant negative neglected stock effect.

The marketing costs that Merton (1987) associates with educating potential investors of the benefits of a financial product investing in neglected stocks might be lower now compared to 1987. In my sample, institutional investors are already holding around 40 % of the outstanding market capitalization of the smallest quintile portfolio. The hurdle of educating the market of the return premium and liquidity risk management potential benefits found in this paper should by now have been significantly reduced. Therefore, there might be good opportunities for marketing and distributing financial products aiming to replicate the "neglected stock" strategy since the need to hedge liquidity commonality among institutional investors has never been larger.

4. References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56. https://doi.org/10.1016/s1386-4181(01)00024-6

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*(2), 223–249. https://doi.org/10.1016/0304-405x(86)90065-6

Arbel, A., Carvell, S., & Strebel, P. (1983). Giraffes, Institutions and Neglected Firms. *Financial Analysts Journal*, *39*(3), 57–63. https://doi.org/10.2469/faj.v39.n3.57

Arbel, A., & Strebel, P. (1982). THE NEGLECTED AND SMALL FIRM EFFECTS. *The Financial Review*, *17*(4), 201–218. https://doi.org/10.1111/j.1540-6288.1982.tb00504.x

Blume, M. E., & Keim, Donald B. (2008). Trends in Institutional Stock Ownership and Some Implications. *Prepared for the Spring 2008 Q-Group Conference*. Retrieved from https://www.researchgate.net/profile/Donald_Keim/publication/255587782_Trends_in_Institutional_Stock_Ownership_and_Some_Implications/links/552511a90cf2caf11bfcff6f.pdf

Blume, M. E., & Keim, D. B. (2012). Institutional Investors and Stock Market Liquidity: Trends and Relationships. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2147757

Brunnermeier, M. K., & Pedersen, L. H. (2008). Market Liquidity and Funding Liquidity. *Review of Financial Studies*, *22*(6), 2201–2238. https://doi.org/10.1093/rfs/hhn098

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, *56*(1), 3–28. https://doi.org/10.1016/s0304-405x(99)00057-4

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Goyenko, R., Holden, C. W., & Trzcinka, C. (2008). Do Measures of Liquidity Measure Liquidity? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1108553

KAMARA, A., LOU, X., & SADKA, R. (2008). The divergence of liquidity commonality in the cross-section of stocks☆. *Journal of Financial Economics*, *89*(3), 444–466. https://doi.org/10.1016/j.jfineco.2007.10.004

Levitt, A. (2000, June 13). SEC Testimony: Decimal Pricing in the Securities and Options Markets (A. Levitt). Retrieved December 6, 2019, from https://www.sec.gov/news/testimony/ts092000.htm

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, *82*(3), 631–671. https://doi.org/10.1016/j.jfineco.2005.10.001

Loeb, T. F. (1983). Trading Cost: The Critical Link Between Investment Information and Results. *Financial Analysts Journal*, *39*(3), 39–44. https://doi.org/10.2469/faj.v39.n3.39

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*(3), 483. https://doi.org/10.2307/2328367

NAES, R., SKJELTORP, J. A., & ØDEGAARD, B. A. (2011). Stock Market Liquidity and the Business Cycle. *The Journal of Finance*, *66*(1), 139–176. https://doi.org/10.1111/j.1540-6261.2010.01628.x

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703. https://doi.org/10.2307/1913610

5. Appendix

Table 1

Institutional Ownership Percentage by Market Capitalization Weighted Portfolio Decile Over Period 1980 - 2018

Year	Smallest	2nd	3rd	4th	Largest
1980	7%	14%	22%	33%	39%
1981	8%	13%	26%	36%	42%
1982	12%	20%	28%	35%	42%
1983	9%	21%	29%	40%	47%
1984	17%	28%	37%	45%	48%
1985	22%	33%	43%	49%	52%
1986	19%	29%	38%	48%	51%
1987	22%	33%	43%	51%	57%
1988	25%	37%	43%	47%	49%
1989	27%	36%	47%	53%	50%
1990	32%	43%	50%	52%	51%
1991	32%	44%	50%	54%	50%
1992	32%	45%	51%	55%	52%
1993	27%	46%	50%	53%	53%
1994	35%	49%	53%	58%	57%
1995	31%	47%	52%	57%	57%
1996	35%	50%	54%	58%	56%
1997	33%	49%	51%	59%	57%
1998	28%	47%	53%	57%	57%
1999	33%	50%	54%	59%	57%
2000	27%	47%	55%	58%	58%
2001	30%	54%	62%	63%	61%
2002	31%	58%	68%	69%	68%
2003	30%	60%	68%	70%	70%
2004	25%	65%	75%	70%	70%
2005	23%	64%	77%	72%	71%
2006	28%	67%	80%	74%	73%
2007	33%	75%	84%	81%	76%
2008	38%	77%	84%	79%	76%
2009	36%	64%	77%	78%	72%
2010	35%	65%	75%	78%	74%
2011	37%	75%	78%	82%	76%
2012	43%	74%	82%	83%	77%
2013	44%	79%	84%	85%	79%
2014	43%	74%	83%	85%	77%
2015	41%	75%	83%	84%	77%
2016	42%	79%	87%	85%	78%
2017	43%	81%	87%	84%	78%
2018	38%	70%	76%	77%	69%

Table 1. Summary table over the yearly mean of institutional ownership percentage presented by size quintile portfolio from smallest to largest over the period 1980 - 2018. The significant drop in institutional ownership across all portfolios in 2018 has no clear explanation and is an improbable event. This disqualifies the institutional ownership observations of 2018 from the sample.

Table 2. Panel A

Mean Neglected and Generic Stock (AC > 0) Liquidity Betas Over Period 1982 - 2018.

Year	AC > 0	t-stat	AC = 0	t-stat	Number of Observations	Spread
1982	0,55	30,50	0,36	16,68	1167	0,20
1983	0,43	17,44	0,20	6,40	1262	0,23
1984	0,54	23,40	0,35	11,86	739	0,19
1985	0,49	19,59	0,29	8,68	785	0,20
1986	0,45	22,67	0,18	6,78	1173	0,27
1987	0,45	30,66	0,26	13,46	1179	0,19
1988	0,49	31,22	0,21	9,78	946	0,27
1989	0,52	28,27	0,25	9,18	875	0,27
1990	0,47	28,81	0,21	10,18	628	0,26
1991	0,44	23,78	0,17	5,96	935	0,28
1992	0,52	19,42	0,34	9,52	1086	0,18
1993	0,52	18,80	0,22	6,50	1234	0,30
1994	0,55	22,38	0,35	10,24	1257	0,20
1995	0,57	21,59	0,37	10,31	1176	0,20
1996	0,56	29,76	0,37	16,64	1227	0,19
1997	0,48	28,21	0,27	13,49	1703	0,21
1998	0,50	24,51	0,24	10,11	1791	0,26
1999	0,36	16,06	0,18	6,34	1699	0,19
2000	0,51	22,28	0,31	10,85	1524	0,20
2001	0,59	31,79	0,26	10,92	1329	0,33
2002	0,59	48,52	0,22	14,48	1452	0,37
2003	0,62	51,92	0,21	13,53	1516	0,41
2004	0,70	45,51	0,18	9,38	1567	0,52
2005	0,69	39,91	0,21	10,20	1601	0,48
2006	0,80	50,16	0,27	14,23	1522	0,53
2007	0,73	62,55	0,25	18,31	1363	0,48
2008	0,77	74,33	0,33	25,09	1494	0,44
2009	0,79	86,21	0,27	22,47	1372	0,52
2010	0,77	91,78	0,27	26,55	1394	0,50
2011	0,82	98,42	0,27	25,40	1344	0,54
2012	0,73	68,81	0,24	15,04	1243	0,49
2013	0,75	58,51	0,20	10,49	1305	0,55
2014	0,66	54,24	0,30	20,07	1420	0,36
2015	0,64	57,45	0,23	16,13	1443	0,40
2016	0,72	54,90	0,22	13,95	1403	0,51
2017	0,72	45,64	0,26	13,85	1369	0,46
2018	0,68	58,47	0,25	18,37	1315	0,43
Mean	0,60		0,26			0,34

Table 2. Panel A. This table presents the yearly mean liquidity betas across the sample securities when the yearly mean analyst coverage (AC) is higher than 0, called "generic stocks", and when AC = 0, called "neglected stocks". The t-stat is the mean t-stat for all firms in the sample fulfilling the criteria per year. The spread is the liquidity beta when AC > 0 less the liquidity beta when AC = 0, calculated per year. The mean liquidity betas are equally weighted per year, but they are value-weighted on market capitalization per firm and year. The sample period is 1982 - 2018.

Table 2. Panel B

Mean Neglected and Generic Stock (AC = 1) Liquidity Betas Over Period 1982 - 2018.

Year	AC = 1	t-stat	AC = 0	t-stat	Number of Observations	Spread
1982	0,31	14,95	0,36	16,68	441	-0,05
1983	0,17	5,73	0,20	6,40	354	-0,03
1984	0,35	12,19	0,35	11,86	173	0,00
1985	0,13	4,40	0,29	8,68	149	-0,16
1986	0,20	7,75	0,18	6,78	232	0,02
1987	0,24	11,66	0,26	13,46	243	-0,03
1988	0,23	9,93	0,21	9,78	131	0,02
1989	0,26	10,41	0,25	9,18	112	0,02
1990	0,26	11,20	0,21	10,18	68	0,06
1991	0,20	8,13	0,17	5,96	131	0,03
1992	0,33	8,98	0,34	9,52	179	0,00
1993	0,18	5,48	0,22	6,50	218	-0,04
1994	0,35	10,68	0,35	10,24	203	-0,01
1995	0,39	11,89	0,37	10,31	194	0,02
1996	0,39	15,94	0,37	16,64	222	0,02
1997	0,26	12,71	0,27	13,49	376	-0,01
1998	0,29	12,44	0,24	10,11	366	0,06
1999	0,21	7,72	0,18	6,34	341	0,04
2000	0,27	9,60	0,31	10,85	314	-0,04
2001	0,25	11,56	0,26	10,92	310	-0,01
2002	0,26	17,93	0,22	14,48	346	0,04
2003	0,26	18,57	0,21	13,53	394	0,05
2004	0,36	21,24	0,18	9,38	425	0,18
2005	0,29	15,47	0,21	10,20	415	0,08
2006	0,36	22,63	0,27	14,23	339	0,10
2007	0,40	32,91	0,25	18,31	278	0,15
2008	0,34	30,76	0,33	25,09	318	0,01
2009	0,31	29,41	0,27	22,47	255	0,05
2010	0,31	33,70	0,27	26,55	246	0,04
2011	0,36	37,89	0,27	25,40	181	0,09
2012	0,35	29,88	0,24	15,04	127	0,12
2013	0,36	25,88	0,20	10,49	142	0,17
2014	0,29	22,16	0,30	20,07	181	-0,01
2015	0,27	21,52	0,23	16,13	171	0,04
2016	0,30	20,97	0,22	13,95	179	0,08
2017	0,34	20,99	0,26	13,85	164	0,08
2018	0,30	23,29	0,25	18,37	174	0,05
Mean	0,29		0,26			0,03

Table 2. Panel B. This table presents the yearly mean liquidity betas across the sample securities when the yearly mean analyst coverage (AC) is exactly 1, a subset of so-called "generic stocks", and when AC = 0, called "neglected stocks". The t-stat is the mean t-stat for all firms in the sample fulfilling the criteria per year. The spread is the liquidity beta when AC = 1 less the liquidity beta when AC = 0, calculated per year. The mean liquidity betas are equally weighted per year, but they are value-weighted on market capitalization per firm and year. The sample period is 1982 – 2018.

Table 3

Liquidity Beta Spread for Neglected Stocks versus Generic Stocks In Different Time Periods

Year	Generic	Neglected	Spread
1982	0,55	0,36	0,20
1983	0,43	0,20	0,23
1984	0,54	0,35	0,19
1985	0,49	0,29	0,20
1986	0,45	0,18	0,27
1987	0,45	0,26	0,19
1988	0,49	0,21	0,27
1989	0,52	0,25	0,27
1990	0,47	0,21	0,26
1991	0,44	0,17	0,28
1992	0,52	0,34	0,18
1993	0,52	0,22	0,30
1994	0,55	0,35	0,20
1995	0,57	0,37	0,20
1996	0,56	0,37	0,19
1997	0,48	0,27	0,21
1998	0,50	0,24	0,26
1999	0,36	0,18	0,19
2000	0,51	0,31	0,20
2001	0,59	0,26	0,33
2002	0,59	0,22	0,37
2003	0,62	0,21	0,41
2004	0,70	0,18	0,52
2005	0,69	0,21	0,48
2006	0,80	0,27	0,53
2007	0,73	0,25	0,48
2008	0,77	0,33	0,44
2009	0,79	0,27	0,52
2010	0,77	0,27	0,50
2011	0,82	0,27	0,54
2012	0,73	0,24	0,49
2013	0,75	0,20	0,55
2014	0,66	0,30	0,36
2015	0,64	0,23	0,40
2016	0,72	0,22	0,51
2017	0,72	0,26	0,46
2018	0,68	0,25	0,43

Period	Mean Spread
1982-2000	0,23
2001-2018	0,46

Table 3. This table presents the equally-weighted yearly liquidity means of all "generic stocks", "neglected stocks" and the spread between these means. In the bottom the table presents the liquidity beta mean spread for two different periods of the sample: 1982 - 2000 (18 years) and 2001-2018 (17 years).

Table 7

Liquidity Beta and Analyst Coverage Percentage over Small and Large Cap Portfolios for Period 1980 - 2018.

Year	Small Cap Liquidity Beta	Small Cap Analyst Coverage	Large Cap Liquidity Beta	Large Cap Analyst Coverage
1980	0,31	1%	0,83	20%
1981	0,30	6%	0,84	46%
1982	0,34	36%	0,86	66%
1983	0,25	35%	0,78	66%
1984	0,27	50%	0,87	66%
1985	0,29	57%	0,84	65%
1986	0,22	52%	0,92	63%
1987	0,26	56%	0,91	64%
1988	0,25	61%	0,95	65%
1989	0,24	60%	0,96	66%
1990	0,27	61%	0,91	64%
1991	0,22	62%	0,86	68%
1992	0,33	55%	0,87	66%
1993	0,27	55%	0,90	69%
1994	0,37	59%	0,90	67%
1995	0,41	52%	0,91	68%
1996	0,34	58%	0,94	69%
1997	0,23	58%	0,90	72%
1998	0,25	60%	0,90	77%
1999	0,16	57%	0,75	80%
2000	0,27	56%	0,81	79%
2001	0,28	50%	0,82	82%
2002	0,21	45%	0,89	86%
2003	0,22	47%	0,94	84%
2004	0,19	43%	0,89	85%
2005	0,19	44%	0,90	84%
2006	0,26	42%	0,91	85%
2007	0,24	47%	0,93	86%
2008	0,42	58%	0,99	85%
2009	0,47	72%	0,98	87%
2010	0,41	69%	0,98	89%
2011	0,46	74%	0,97	90%
2012	0,38	79%	0,93	93%
2013	0,39	78%	0,94	95%
2014	0,34	74%	0,96	95%
2015	0,30	80%	0,94	97%
2016	0,37	74%	0,96	98%
2017	0,41	76%	0,92	100%
2018	0,31	74%	0,94	100%

Table 7. This table presents the yearly evolution of liquidity beta analyst coverage percentage for the smallest and largest firms in the sample. The analyst coverage percentage is defined as the percentage of securities *i* in the portfolio with on average at least one covering analyst during year *t*. The sample period is 1980 - 2018. It is apparent that there are some data issues in the reports from 1980 and 1981.

Table 8

Firm-Year Observations in the Sample

Year	Firm-Year observations (Count)
1963	1267
1964	1357
1965	1518
1966	1649
1967	1860
1968	1999
1969	2075
1970	1954
1971	2047
1972	2078
1973	1894
1974	1520
1975	1549
1976	1636
1977	1560
1978	1768
1979	1748
1980	1816
1981	1785
1982	1681
1983	1886
1984	1662
1985	1594
1986	1624
1987	1650
1988	1375
1989	1353
1990	1350
1991	1424
1992	1531
1993	1719
1994	1762
1995	1809
1996	1890
1997	2110
1998	2214
1999	2076
2000	1970
2001	1906
2002	1853
2003	1841
2004	1884
2005	1905
2006	1863
2007	1850
2008	1749
2009	1599
2010	1602
2011	1571
2012	1543
2013	1517
2014	1562
2015	1572
2016	1505
2017	1458
2018	1444
Sum	95 984

Table 8. This table presents the firm-year observations per year over the sample period, defined as count of firms *i* that were included for observations per year *t* after filtering away daily observations with missing values for price or shares outstanding; with negative trading volumes, with return exactly zero and firms with more than 100 missing values per year. The sum of firm-year observations is presented at the bottom line.

Table 9

Difference in Liquidity Beta With and Without Kamara et. al. (2008) $2 Filter Over Sample Period 1963 - 2018.

	No filter		With $2 Filter	
Year	Liquidity Beta without Filter	t-stat	Liquidity Beta with Filter	t-stat
1963	0,37	15,88	0,37	15,99
1964	0,26	9,04	0,26	8,99
1965	0,53	19,20	0,53	19,21
1966	0,52	24,78	0,52	24,97
1967	0,57	18,11	0,57	18,09
1968	0,54	20,23	0,54	20,25
1969	0,54	20,91	0,54	20,91
1970	0,53	25,01	0,53	25,04
1971	0,52	22,28	0,52	22,28
1972	0,50	16,82	0,50	16,83
1973	0,43	23,03	0,43	23,18
1974	0,42	28,17	0,43	28,45
1975	0,49	25,35	0,49	25,49
1976	0,44	21,42	0,44	21,50
1977	0,35	14,57	0,35	14,63
1978	0,48	25,78	0,48	25,79
1979	0,50	21,66	0,50	21,63
1980	0,52	28,77	0,52	28,84
1981	0,48	19,88	0,48	19,89
1982	0,54	29,75	0,54	29,82
1983	0,41	16,68	0,41	16,70
1984	0,53	22,75	0,53	22,85
1985	0,49	19,70	0,49	19,71
1986	0,47	24,23	0,47	24,32
1987	0,49	33,50	0,49	33,76
1988	0,51	34,01	0,51	34,14
1989	0,53	29,74	0,53	29,82
1990	0,49	30,45	0,49	30,76
1991	0,47	25,59	0,48	25,94
1992	0,52	20,06	0,52	20,17
1993	0,53	19,68	0,54	19,89
1994	0,56	23,16	0,57	23,43
1995	0,57	21,76	0,57	22,03
1996	0,55	29,70	0,56	29,96
1997	0,49	29,07	0,49	29,42
1998	0,49	24,61	0,50	25,05
1999	0,37	16,41	0,37	16,73
2000	0,50	21,95	0,51	22,74
2001	0,54	28,38	0,57	30,07
2002	0,53	43,13	0,56	45,98
2003	0,55	46,07	0,58	48,76
2004	0,61	40,06	0,64	42,04
2005	0,60	35,08	0,63	36,86
2006	0,72	44,79	0,75	46,84
2007	0,64	54,17	0,68	56,92
2008	0,72	68,43	0,77	74,27
2009	0,74	81,07	0,81	88,68
2010	0,73	86,85	0,78	93,39
2011	0,78	93,62	0,83	100,42
2012	0,68	63,46	0,72	68,12
2013	0,70	54,62	0,74	58,20
2014	0,63	51,69	0,66	54,27
2015	0,61	55,06	0,65	58,86
2016	0,68	51,53	0,73	55,59
2017	0,68	43,15	0,72	45,88
2018	0,65	54,91	0,67	57,61

Table 9. Table over mean liquidity betas along with t-stats from running Model (1) with and without applying the Kamara et. al. (2008) $2 filter. Sample period 1963 - 2018.

Table 11

Distribution of Total Neglected Stocks by Size Quintile Portfolio over Period 1980 - 2018.

	Number of Generic Stocks						Number of Neglected Stocks						Distribution of Neglected Stocks by Size Quintile Portfolio				
Year	Smallest	2nd	3rd	4th	Largest	Sum	Smallest	2nd	3rd	4th	Largest	Sum	Smallest	2nd	3rd	4th	Largest
1980	5	7	14	30	61	117	260	277	246	197	152	1132	23%	24%	22%	17%	13%
1981	20	45	80	132	136	413	241	241	167	96	71	816	30%	30%	20%	12%	9%
1982	129	198	201	182	182	892	140	68	30	23	14	275	51%	25%	11%	8%	5%
1983	130	236	243	217	208	1034	142	36	24	14	12	228	62%	16%	11%	6%	5%
1984	113	143	128	126	130	640	58	18	7	9	7	99	59%	18%	7%	9%	7%
1985	131	162	144	133	120	690	58	16	8	7	6	95	61%	17%	8%	7%	6%
1986	188	254	228	200	161	1031	102	25	3	5	7	142	72%	18%	2%	4%	5%
1987	196	262	223	191	171	1043	90	16	11	9	10	136	66%	12%	8%	7%	7%
1988	189	201	181	155	142	868	54	14	6	3	1	78	69%	18%	8%	4%	1%
1989	167	186	171	148	139	811	45	11	6	1	1	64	70%	17%	9%	2%	2%
1990	115	143	123	107	100	588	26	5	4	3	2	40	65%	13%	10%	8%	5%
1991	178	185	183	155	153	854	51	17	7	4	2	81	63%	21%	9%	5%	2%
1992	189	228	200	183	166	966	85	13	11	4	7	120	71%	11%	9%	3%	6%
1993	197	254	237	211	193	1092	100	23	9	6	4	142	70%	16%	6%	4%	3%
1994	210	279	233	223	191	1136	87	14	12	4	4	121	72%	12%	10%	3%	3%
1995	169	245	235	217	190	1056	87	14	12	6	1	120	73%	12%	10%	5%	1%
1996	187	233	224	230	201	1075	90	22	18	11	11	152	59%	14%	12%	7%	7%
1997	284	319	303	287	259	1452	139	38	27	24	23	251	55%	15%	11%	10%	9%
1998	289	341	319	303	298	1550	154	35	19	19	14	241	64%	15%	8%	8%	6%
1999	266	328	310	291	285	1480	144	42	17	8	8	219	66%	19%	8%	4%	4%
2000	220	287	276	275	263	1321	133	32	17	12	9	203	66%	16%	8%	6%	4%
2001	126	224	261	246	253	1110	136	51	12	13	7	219	62%	23%	5%	6%	3%
2002	135	245	263	268	284	1195	178	54	16	6	3	257	69%	21%	6%	2%	1%
2003	140	249	274	281	283	1227	214	48	10	14	3	289	74%	17%	3%	5%	1%
2004	139	254	288	285	297	1263	229	47	8	18	2	304	75%	15%	3%	6%	1%
2005	142	267	288	296	301	1294	223	56	13	11	4	307	73%	18%	4%	4%	1%
2006	135	262	280	294	296	1267	186	47	9	8	5	255	73%	18%	4%	3%	2%
2007	126	224	266	263	274	1153	144	41	12	10	3	210	69%	20%	6%	5%	1%
2008	163	248	281	276	279	1247	176	43	12	9	7	247	71%	17%	5%	4%	3%
2009	189	247	265	258	266	1225	108	16	12	9	2	147	73%	11%	8%	6%	1%
2010	195	246	273	267	268	1249	106	18	12	5	4	145	73%	12%	8%	3%	3%
2011	197	252	261	265	269	1244	77	12	9	1	1	100	77%	12%	9%	1%	1%
2012	178	237	244	257	266	1182	52	6	2	1	0	61	85%	10%	3%	2%	0%
2013	192	258	250	258	271	1229	63	5	5	3	0	76	83%	7%	7%	4%	0%
2014	205	269	277	273	284	1308	82	14	8	5	3	112	73%	13%	7%	4%	3%
2015	210	277	283	283	290	1343	85	9	2	3	1	100	85%	9%	2%	3%	1%
2016	186	271	267	278	278	1280	96	15	7	5	0	123	78%	12%	6%	4%	0%
2017	187	267	265	263	270	1252	93	15	7	2	0	117	79%	13%	6%	2%	0%
2018	181	252	256	249	257	1195	98	16	3	2	1	120	82%	13%	3%	2%	1%

Table 11. This table presents the number count and distribution of generic and neglected stocks over the years 1982 - 2018. Divided by size quintile portfolios.

Table 12

Generic versus Neglected Stock Small Cap Stock Liquidity Beta over Period 1980 - 2018.

	Generic		**Neglected**	
Year	Mean Liquidity Beta	t-stat	Mean Liquidity Beta	t-stat
1980	0,52	28,73	0,32	14,94
1981	0,38	14,61	0,32	10,89
1982	0,34	15,43	0,29	12,57
1983	0,27	9,27	0,21	6,27
1984	0,28	9,04	0,25	7,84
1985	0,29	8,59	0,25	6,70
1986	0,22	8,67	0,18	6,31
1987	0,25	12,85	0,20	9,11
1988	0,26	11,36	0,20	8,19
1989	0,26	10,20	0,18	6,82
1990	0,25	10,46	0,18	7,74
1991	0,20	7,54	0,17	5,24
1992	0,39	10,53	0,26	6,91
1993	0,31	8,62	0,15	4,14
1994	0,36	11,25	0,35	9,57
1995	0,44	12,64	0,42	11,26
1996	0,36	14,56	0,28	11,11
1997	0,25	11,61	0,18	7,21
1998	0,29	11,14	0,14	4,77
1999	0,18	6,27	0,14	3,68
2000	0,30	9,85	0,23	7,38
2001	0,25	10,84	0,21	7,98
2002	0,18	11,78	0,15	8,27
2003	0,17	11,27	0,14	7,49
2004	0,20	10,89	0,12	4,87
2005	0,17	8,06	0,09	3,62
2006	0,16	9,81	0,14	6,47
2007	0,25	17,96	0,14	8,49
2008	0,32	27,52	0,22	14,12
2009	0,31	30,35	0,18	14,14
2010	0,31	34,18	0,16	13,47
2011	0,36	38,59	0,15	12,02
2012	0,31	26,88	0,18	10,67
2013	0,35	25,21	0,11	4,25
2014	0,33	24,52	0,21	12,87
2015	0,22	17,33	0,16	9,91
2016	0,27	18,51	0,13	7,63
2017	0,32	19,17	0,21	10,40
2018	0,28	21,92	0,19	13,31
Mean	0,29		0,20	

Table 12. This table presents the mean liquidity betas estimates per year for the smallest quintile size portfolio along with t-stats generated from Model (2), separated into sub-groups of "generic stocks" and "neglected stocks". We see the mean liquidity betas over the entire sample period 1980 - 2018 in the bottom line.