Style Investing and Commonality in Liquidity*

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Abstract

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JEL classifications: G10, G11, G12

Keywords: Style Investing, Commonality in Liquidity, Systematic Liquidity, Correlated Trading, Transaction Costs

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Abstract

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1 Introduction

Several studies document that the liquidity of different stocks co-moves, a phenomenon known as commonality in liquidity (e.g., Chordia, Roll, and Subrahmanyam 2000). Given the importance of asset liquidity for investors, it is important to understand why such commonality in liquidity arises. To this end, various factors have been shown to affect commonality in liquidity, such as common market making (Coughenour and Saad 2004), program trading (Corwin and Lipson 2011), institutional ownership (Koch, Ruenzi, and Starks 2016; Kamara, Lou, and Sadka 2008) and index tracking (Harford and Kaul 2005). In this paper we draw motivation from behavioural finance to study whether commonality in liquidity arises from correlated trading due to style investing.

Style investing has been proposed by Barberis and Shleifer (2003) who model an economy with boundedly rational agents that classify assets in broad categories based on some characteristic that is unrelated to fundamentals. Style investors trade assets depending on their preferences toward this characteristic at a specific point in time, which results in excess co-variation of stock returns within a specific style.[1]

Although the theory of Barberis and Shleifer (2003) addresses predictability in stock returns, it has also implications for stock liquidity. Since style investing reflects non-fundamental reasons, theories of market microstructure predict that style-level shifts in investors' preferences will influence aggregate style liquidity (e.g., Glosten and Milgrom 1985). Specifically, styles that are in demand, and therefore experience inflows of capital, will become more liquid, whereas styles that are out of favor and experience outflows will become less liquid.[2] Thus, the time-varying preferences of investors toward particular styles, will induce variations in style level liquidity, which imply that a stock's own liquidity will sys-

[1] Several of the predictions made by BS have been tested empirically (see, for example, Teo and Woo 2004 and Wahal and Yavuz 2013).

[2] For empirical evidence that increased noise trading results in liquidity improvements see Greene and Smart (1999),Bloomfield, O'Hara, and Saar (2009) and Peress and Schmidt (2015).

tematically co-move with the liquidity of the other stocks in the same style, a phenomenon we refer to as *style-related commonality in liquidity*.[3]

To test our hypothesis, we have to identify the styles along which investors make their investment decisions. To this end, we rely on previous literature, which demonstrates that style investing along firm size (small vs. large) or growth potential (value vs. growth) dimensions is popular amongst investors (e.g., Teo and Woo 2004, Froot and Teo 2008, Kumar 2009). Furthermore, the fact that mutual funds are routinely selecting names that include a popular style identifier, i.e., the "Vanguard US Growth Portfolio", and that Morningstar, a leading information provider about mutual funds to investors, directly states the extent to which a fund follows specific size or growth potential strategies, provide further evidence that style investing along these dimensions is a wide-spread phenomenon.

Specifically, we examine whether stock liquidity co-moves within the following four investment styles: Small/Large depending on market value (MV), and Value/Growth depending on the book-to-market ratio (B/M). Importantly, these styles are mutually exclusive, which implies that one stock can only belong to one style portfolio at a given point in time. To test our hypothesis, we estimate the market model of liquidity proposed by Chordia, Roll, and Subrahmanyam (2000), by decomposing the market-wide liquidity factor into its style and non-style counterparts. For example, if stock i is classified as a small stock at time t, then we regress changes in the liquidity of stock i at time t on an aggregate liquidity index that reflects the changes in the liquidity of other small stocks, and another aggregate liquidity index that reflects the changes in the liquidity of all remaining non-small stocks. In effect, this procedure decomposes the liquidity beta that is commonly analyzed in the literature in its style and non-style components, which allows us to assess the relative importance of style investing on commonality in liquidity.

[3] In case style investors were informed, the relationship between style flows and style liquidity could be negative. However, in both cases the liquidity of stocks in the same style would co-move, thus giving rise to excess co-movements with liquidity of other stocks in the same style.

Overall, we find strong evidence of systematic liquidity co-movements for stocks that belong to the same style, even after controlling for their liquidity co-movements with remaining stocks in the market. We further show that style-related commonality in liquidity has increased over time and is strongly affected by the extent to which style investors are present for a particular stock. Importantly, systematic liquidity co-movements of stocks in extreme style portfolios dominate their co-movements with the rest of the market, especially in the recent period.

Our sample consists of all common CRSP stocks, traded on NYSE, AMEX and NASDAQ, over 1984-2014. To measure liquidity, we use the Amihud (2002) measure, which can be constructed from daily data, and is commonly used in previous studies on commonality in liquidity (Kamara, Lou, and Sadka 2008, Koch, Ruenzi, and Starks 2016). In our first test, we examine whether an increase in flows into a particular style leads to improvements in its aggregate liquidity. We use flows into mutual funds to capture style-related flows, using the names of mutual funds to classify them into respective styles (small vs large, value vs growth). Our results show that increases in aggregate style flows result in aggregate liquidity improvements for small, value and growth styles, which is consistent with our prediction that style investing is largely driven by uninformed investors. Our findings are also consistent with the evidence in Froot and Teo (2008), Kumar (2009) and Teo and Woo (2004). We do not find a significant relationship between flows into the large style and its liquidity, perhaps because the baseline level of liquidity for these companies is quite high, and therefore remains unaffected by variations in the level of trading due to style investing.

Next, we examine whether liquidity of stocks that belong to the same style exhibits excess co-movements, even beyond its co-movements with aggregate market liquidity. We estimate the market model of liquidity, proposed by Chordia, Roll, and Subrahmanyam (2000), and save the residuals from this model. We then calculate the average excess residual correlations within each size and B/M quintile. Consistent with our expectations, we find a stronger excess correlation for the extreme quintiles (1 and 5), as opposed to the style-neutral quintile 3, which reveals a within-style liquidity co-movement that is orthogonal to its co-movement with aggregate market liquidity.

To more formally establish the notion of style-related commonality in liquidity, we estimate "style liquidity beta" (β_S) as the sensitivity of daily changes in the stock's liquidity to changes in aggregate style liquidity, after controlling for its sensitivity to the aggregate liquidity of the remaining stocks in the market (β_{NS}). To facilitate comparisons, we also estimate standard market liquidity betas (β_M). We find that on average β_M is positive and significant for all styles, confirming the results in Chordia, Roll, and Subrahmanyam (2000). After we decompose the market wide liquidity index into style and non-style components (small/ large, value/growth), we find that both β_S and β_{NS} are positive and significant, but that β_S is significantly larger than β_{NS} for small, value and large stocks. For growth stocks, it is also large and of the same magnitude as β_{NS}. These findings suggest that there exist systematic liquidity co-movements for stocks within the same style that are even dominating co-movements with the rest of the market for most of our style categories.

Importantly, we also find that style liquidity betas display a pronounced U-shape both for size and B/M styles, with the highest values of β_S for stocks in our style portfolios and the lowest values for the corresponding style-neutral stocks (e.g., medium stocks for the size style). The U-shape pattern is consistent with our previous findings of stronger excess correlations in extreme quintiles. Moreover, we find that this relationship holds both for stocks, listed on NYSE/AMEX and NASDAQ, and is stronger in the latter part of the sample, when style investing has become more prominent. Overall, our findings imply that a large proportion of the commonality in liquidity documented in the literature occurs at the style level.

We further examine whether stocks that attract more style investing have higher style liquidity betas. To perform this test, we regress β_S (separately for each style) on a measure of the strength of style investing for stock i (based on the number of funds of a specific style that hold stock i) and additional control variables. This analysis reveals several interesting results. Firstly, β_S increases with our measure of style investing for small, growth and value stocks, which indicates that, for stocks in these categories, the stronger the presence of style investing on the stock level the stronger the co-variation of the stock's own liquidity with the aggregate liquidity of the corresponding style.

Secondly, we find that this positive relationship becomes even stronger during periods, in which style-level outflows are particularly high. Since outflows occur in periods of poor style performance (Teo and Woo 2004), this result shows that style investing impacts commonality in liquidity across good and bad times asymmetrically, perhaps due to the effect of fire sales (Coval and Stafford 2007).

Thirdly, when we estimate models that also include ownership by the opposite style (i.e., a value company owned by growth funds) we find that for small, value and growth stocks ownership by opposite styles *reduces* β_S. This suggests that opposite style ownership, which is driven to some extent by independent forces, actually reduces liquidity co-movements with other stocks in the same style.

Our paper contributes to the literature that studies commonality in liquidity, first documented by Chordia, Roll, and Subrahmanyam (2000) and Huberman and Halka (2001). Several papers have shown that commonality in liquidity is linked to factors such as common market making (Coughenour and Saad 2004), index tracking (Harford and Kaul 2005) and program trading (Corwin and Lipson 2011). The papers that are closest to ours are by Kamara, Lou, and Sadka 2008 and Koch, Ruenzi, and Starks 2016 who show that commonality in liquidity rises with general institutional ownership. However, these papers do not analyze the effects of style investing, which is the focus of our paper. Our models, whilst controlling for the general ownership of the stock by all funds, show that the effects of style investing on commonality in liquidity are large, both economically and statistically.

We also contribute to the literature on style investing pioneered by Barberis and Shleifer (2003). Several empirical studies have highlighted that style investing along firm size or growth potential dimensions is a popular investment strategy amongst investors (Froot and Teo 2008; Kumar 2009), and have have confirmed several of the asset pricing predictions made by BS (Teo and Woo 2004; Wahal and Yavuz 2013). However, the effects of style investing on liquidity and its commonality are less understood. Our paper shows that style investing influences the level of stock liquidity, and contributes significantly to systematic liquidity variations across stocks and over time.

Our paper proceeds as follows. Section 2 provides details of the sample construction. Section 3 examines the relation between style flows and style liquidity. Section 4 establishes the existence of style-related commonality in liquidity and empirically investigates its relation to style investing. Section 5 briefly concludes.

2 Data and Sample Construction

2.1 Sample Construction

We download from CRSP our initial sample that consists of all common stocks with share codes 10 and 11, traded on NYSE, AMEX and NASDAQ. For NYSE and AMEX, our sample period is 1984-2014, and for NASDAQ it is 1986-2014. The NASDAQ sample is shorter, because volume information, needed to calculate our liquidity measure, only becomes available as of 1986 on CRSP. Table 1 provides details of the sample construction.

[Insert Table 1 approximately here]

The initial sample consists of 234,489 firm-years (24,236 firms). We apply two standard data filters.[4] First, we require the stock to be listed at the end of the year and have a

[4]See, for example, Amihud (2002), Acharya and Pedersen (2005), Kamara, Lou, and Sadka (2008) and Ben-Raphael, Kadan, and Wohl (2015).

year-end price higher than \$2. Second, we require the stock to be traded for at least 60 days during the year. Excluding the stocks that do not satisfy the criteria above leaves 194,823 firm-years and 20,709 firms in our final sample.

We further obtain data on mutual fund holdings for all stocks in our final sample from the CDA/Spectrum database provided by Thomson Reuters through WRDS. We use the MFLinks file provided by WRDS to merge CRSP fund data, which is needed to calculate fund flows, with holdings data.

2.2 Measuring Liquidity

Given our long time series, we need a liquidity measure that can be calculated from daily data. To this end we use the liquidity measure proposed by Amihud (2002), which is commonly used in studies that analyze commonality in liquidity (i.e., Kamara, Lou, and Sadka 2008, Koch, Ruenzi, and Starks 2016, Acharya and Pedersen 2005 and Ben-Raphael, Kadan, and Wohl 2015).[5]

Following Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), we adjust the Amihud (2002) measure for aggregate market capitalisation, such that the absolute daily price change per \$1 of volume traded is comparable to the overall size of the stock market. Formally, we calculate $ILLIQ$ for stock i on day d as

$$ILLIQ_{i,d} = \frac{|R_{i,d}|}{DVol_{i,d} \cdot \frac{Mcap_{2014}}{Mcap_{t-1}}},$$

where $Mcap_{t-1}$ is the total market capitalisation of all stocks included in month $t-1$ and $Mcap_{2014}$ is the total market capitalisation of all stocks included in June 2014. All our results remain robust if we adjust by inflation instead. As in Amihud (2002), we censor the upper and lower 1% of the $ILLIQ$ distribution to avoid outliers.

[5] Goyenko, Holden, and Trzcinka (2009) show that the daily Amihud (2002) liquidity measure is highly correlated with Kyle's (1985) lambda, estimated from the intraday data.

2.3 Summary statistics

Table 2 presents time series averages of annual cross-sectional statistics for all stocks in our sample, broken down by the listing exchange. Data on returns, daily stock prices, volume and shares outstanding are from CRSP. Using these data, we calculate market capitalization, *MCap* (in millions of dollars); monthly volume traded, $Volume$ (in thousands of shares); stock turnover, $Turnover$, defined as $Volume$, scaled by the number of shares outstanding; the Amihud measure, $ILLIQ$; stock volatility, *Volat*, calculated as the standard deviation of monthly stock returns over 12-60 months; and the cumulative return over the previous 12 months, $RET12$. $RET12$ is calculated from July of year $t-1$ to June of year t, because we sort stocks into styles as of June of each year. The book-to-market ratio, BM, is calculated as the ratio of the book value of equity with fiscal year-end in calendar year $t-1$ to the market value of equity at the end of December of year $t-1$. Annual data on book values of equity are obtained from Compustat. Appendix A provides a description of variable definitions.

[Insert Table 2 approximately here]

$\#Firms$ indicates the annual average number of firms in our sample. It ranges from 2,981 on NYSE/AMEX to 3,264 on NASDAQ. As expected, stocks listed on NYSE/AMEX are generally larger and more liquid. The average market capitalisation of NYSE/AMEX stocks is $2,221 million, as compared to $639 million for NASDAQ stocks. The adjusted Amihud measure is three times smaller on NYSE/AMEX (0.09), as compared to NASDAQ (0.27). The average monthly volume is also larger on NYSE/AMEX, 9.2 million, as compared to 5.9 million on NASDAQ. However, Atkins and Dyl (1997) document that the volume numbers for NASDAQ stocks are generally inflated and, for this reason, they are not comparable between the two exchanges. The statistics for the remaining variables are generally comparable to those reported in other papers.[6]

[6] See, for example, a recent study on time trends in liquidity premium by Ben-Raphael, Kadan, and Wohl (2015).

3 Style Fund Flows and Style Liquidity

We first test the relation between fund flows into a style and style liquidity levels. To identify styles on the stock level we use NYSE breakpoints from Kenneth French's website to sort stocks into size and B/M styles.[7] Following Teo and Woo (2004), we label stocks below the 30th size (B/M) percentile as "Small" ("Growth"), above the 70th size (B/M) percentile as "Large" ("Value"), and those between the 30th and 70th percentiles as "Medium" ("Blend"). "Medium" ("Blend") stocks do not belong to any style and we therefore use them as a control group. Assigned rankings are valid from July of year t until June of year $t+1$, when we re-sort again. We use the same timing conventions as Fama and French (1993) to ensure that all financial information is available before the sort.

On the fund level, we assign funds into investment styles, based on their name as reported in CRSP, following a procedure similar to Cooper, Gulen, and Rau (2005). Specifically, we label funds as "Small" ("Large") if they have any of the following word combinations in their official name: SMALL, SMALLCAP, SM, SMALLER (LARGE, LARGECAP, LG, LARGER). Similarly, we label funds as "Growth" ("Value") if their name includes any of the following: GROWTH, GR, GRTH (VALUE, VAL).

[Insert Figure 1 approximately here]

Figure 1 shows the development of style investing by mutual funds over time. Prior to 1990s, the Size style was virtually non-existent, with less than 1% of total fund market capitalisation invested into small-cap and large-cap funds. For this reason, our analysis of funds in the Size style start only in 1991. Importantly, this number has increased up to 5% for large-cap funds and up to 7% for small-cap funds as of end 2012, with the total fund market capitalisation of around $8 trillion. The proportions invested in growth and value

[7] We would like to thank Kenneth French for making NYSE size and B/M breakpoints available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

funds constitute 22% and 11% as of end 2012, correspondingly. They have experienced more fluctuations over time, especially around the Dot-Com bubble of 2000-2001, but generally also show an upward trend.

3.1 Style Fund Flows and Aggregate Illiquidity

Table 3 examines the relation between fund flows into a style and its aggregate illiquidity, constructed as the equal-weighted average Amihud measure among all stocks that belong to a given style in month t. Specifically, we estimate the following time series regressions with the style aggregate illiquidity, $SILLIQ$, as the dependent variable:

$$\begin{aligned} SILLIQ_t &= \alpha + \beta_1 SILLIQ_{t-1} + \beta_2 SILLIQ_{t-2} + \beta_3 SFlow_t \\ &+ \beta_4 Size_t + \beta_5 Volat_t + \beta_6 Turnover_t + \sum YearFE + \varepsilon_t. \end{aligned}$$

We calculate the fund flows into a style, $SFlow_t$, as the sum of flows for all mutual funds that belong to a given style in month t, as a percentage of total net assets in a style in month $t-1$. We use the CRSP Mutual Fund Database to calculate flows on the fund level for all domestic equity funds between 1991 and 2014.[8] Following the standard procedure in the literature (Frazzini and Lamont 2008, Sapp and Tiwari 2004), we infer flows for fund i, $Flow_{i,t}$, from fund returns,$R_{i,t}$, and total net assets, $TNA_{i,t}$:

$$Flow_{i,t} = TNA_{i,t} - (1 + R_{i,t})TNA_{i,t-1} - MGN_{i,t},$$

where $MGN_{i,t}$ denotes the increase in total net assets due to mergers. We implicitly assume that existing investors reinvest dividends and other distributions in the fund and that investors in the merged funds invest their money into the surviving fund. Initial fund inflows equal their initial TNA and the final fund outflows equal their terminal TNA.

[8] We start in 1991, because fund flows on a monthly level can only be calculated as of this year.

The vector of control variables consists of two lags of the dependent variable; average market capitalisation, $Size$; average stock return volatility, $Volatility$ and average turnover, $Turnover$ across all stocks in a style. We also include year-fixed effects and use Newey-West standard errors with one lag to account for potential serial correlation in error terms.

[Insert Table 3 approximately here]

Models (1) to (3) report results for the size style. Models (4) to (6) refer to the B/M style. In line with our hypothesis, we find that larger style inflows significantly improve aggregate style liquidity for small stocks (Model 1), growth stocks (Model 4) and value stocks (Model 6). We also find similar, but insignificant effects for medium and blend stocks. This finding can be explained by the fact that medium and blend are not well defined styles, which is a basic prerequisite for style investing. The effect of style level inflows on large stocks is also insignificant and close to zero, most likely because these stocks are already very liquid.

Overall, these findings show that inflows in the small, value and growth styles increase style-level liquidity. In the context of the theory of Glosten and Milgrom (1985), this positive relationship between inflows and liquidity suggests that style investing along these dimensions can be classed as uninformed, consistent with the evidence in Froot and Teo (2008), Kumar (2009) and Teo and Woo (2004), and complements earlier results that increases in noise trading improve liquidity (Greene and Smart 1999, Bloomfield, O'Hara, and Saar 2009).

4 Style Investing and Commonality in Liquidity

To set the stage for our style-related commonality in liquidity tests we first conduct analysis using the model of Chordia, Roll, and Subrahmanyam (2000), with the market-wide liquidity index as the only regressor. This model assumes that commonality in liquidity across stocks is solely related to variations in aggregate market wide liquidity. However, according to our hypothesis, commonality in liquidity is driven independently by both the style and non-style related components of the market wide liquidity index. In effect, this means that the market-only model, which does not capture the effects of style investing, is “misspecified”, and the residuals from that model should exhibit a correlation structure that reflects unexplained variation in liquidity due to style investing. Specifically, we should observe that residuals from the model are more strongly correlated for stocks belonging in style portfolios (Small, Large, Value and Growth) where style investing is more prominent, and weakly correlated for stocks in the medium and blend groups, where style investing is not as strong.

We estimate the market model of liquidity, employed by Chordia, Roll, and Subrahmanyam (2000), and examine average pairwise residual correlations following the procedure in Lou and Polk (2012), separately for size and B/M quintiles.[9] Specifically, at the end of June of each year, we run the following time series regression for each firm i:

$$\Delta ILLIQ_{i,d}, = \alpha + \beta_{i,M} \Delta ILLIQ_{m,d} + \varepsilon_{i,d}, \tag{1}$$

where $\Delta ILLIQ_{i,d}$ captures changes in daily illiquidity of stock i. Following Kamara, Lou, and Sadka (2008), we use changes in the Amihud measures (in logs) to resolve issues with nonstationarity of liquidity levels. We follow Amihud (2002), Chordia, Roll, and Subrahmanyam (2000), Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) and define the market's change in illiquidity, $\Delta ILLIQ_{m,d}$, as the daily cross-sectional equally-weighted average of $\Delta ILLIQ_{j,d}$ for all NYSE/AMEX stocks with $j \neq i$.[10] We exclude NASDAQ stocks from market portfolio, because of the well-known problem of double counting of volume in NASDAQ. Other studies, e.g., Pástor and Stambaugh (2003) and Ben-Raphael, Kadan, and Wohl (2015) follow the same procedure. Figure 2 shows excess residual correlations separately within quintiles of size (Panel A) and B/M (Panel B).

[9] We use quintiles in this part of the analysis for illustrative purposes. In the remaining part, we use our benchmark 30%-40%-30% split to sort stocks into styles.

[10] In our setup, using equal-weighted averages also makes sense, because we will later analyze liquidity on the style level. Value-weighting within style would bias changes in style liquidity to those of larger and more liquid stocks. We discuss our findings with value-weighted liquidity later in this section.

[Insert Figure 2 approximately here]

Excess correlations within both size and B/M styles display a striking U-shaped pattern, with the highest excess correlations in the extreme quintiles 1 and 5 that correspond to a clearly defined style (small/large and growth/value, correspondingly). Importantly, we observe the lowest excess correlations in quintile 3, which is "style-neutral". Overall, our analysis of residual correlations from the market-only model provides first evidence that changes in liquidity of individual stocks indeed co-move with the liquidity of the other stocks in the same style.

4.1 Commonality in Style Liquidity

We continue to test more formally whether the liquidity of stocks in a specific style systematically co-varies with the aggregate style liquidity. To achieve this, we decompose the market wide illiquidity index into its style and non-style components defining two indices: $\Delta ILLIQ_{S,d}$ the daily equally-weighted average of $\Delta ILLIQ_{j,d}$ across all NYSE/AMEX stocks in the particular style (excluding stock i), and $\Delta ILLIQ_{NS,d}$, the daily equally-weighted average of $\Delta ILLIQ_{j,d}$ for all remaining NYSE/AMEX stocks and run the following regression:

$$\Delta ILLIQ_{i,d}, = \alpha + \beta_{i,NS}\Delta ILLIQ_{NS,d} + \beta_{i,S}\Delta ILLIQ_{S,d} + \varepsilon_{i,d}. \tag{2}$$

We estimate the regression above for each stock i and year t. We sort stocks into styles, using our benchmark 30%-40%-30% split, based on the stock's ranking as of year $t-1$. However, all our main results hold if we sort in quintiles instead. Therefore, $\beta_{i,S}$ captures the sensitivity of the stock's liquidity to the aggregate style liquidity and $\beta_{i,NS}$ captures sensitivity of the stock's liquidity which is not style related. In the following, we refer to $\beta_{i,S}$ as style liquidity beta. This procedure allows us to clearly decompose liquidity co-variation of an individual stock with other stocks in the same style from its co-variation with the rest of the market. After obtaining $\beta_{i,S}$ and $\beta_{i,NS}$ for each firm-year, we calculate equal-weighted averages in each of style categories.

[Insert Table 4 approximately here]

Panel A of Table 4 reports the cross-sectional averages of $\beta_{i,S}$ and $\beta_{i,NS}$ for stocks sorted in three categories of the Size style and Panel B for the corresponding three categories of the B/M style. For comparison purposes, we also estimate the standard market model of liquidity and report average market liquidity betas, $\beta_{i.M}$, in the first column. The last column shows the t-statistics of the equality-of-means test for $\beta_{i,S}$ and $\beta_{i,NS}$ in each of our style categories. We also test whether average liquidity betas of stocks that belong in style portfolios differ significantly from those in the corresponding "style-neutral" portfolio (i.e., Medium or Blend stocks) and report the t-statistics in the last two rows of each panel.

Consistent with previous findings of Chordia, Roll, and Subrahmanyam (2000), Panel A shows that the sensitivity of the stock's liquidity to market liquidity increases with the firm's size. Average β_M is 0.43 for small stocks, 0.88 for medium stocks and 1.04 for large stocks. T-tests in the last two rows show that the differences in means of market liquidity betas across three groups are all statistically significant at the 1% level. Column (2) summarizes average liquidity co-movements with the market, obtained after controlling for co-movements with other stocks in the same style (β_{NS}). Importantly, with the aggregate style illiquidity in the model, liquidity co-variations with the rest of the market drop for every size category, but especially so for small and large stocks. By contrast, style liquidity betas (β_S) are high and display a U-shape pattern, with the highest values of 0.63 and 0.79 for small and large stocks and the lowest value of 0.55 for medium stocks. Results of the t-tests also confirm that average style liquidity betas of small and large stocks are significantly higher than those of medium stocks. Further, we find that style liquidity betas are significantly higher than the corresponding non-style betas for all three size categories, but especially so for stocks in extreme style portfolios.

Panel B reports similar findings for the B/M style. Interestingly, market liquidity betas from the standard market model of liquidity are highest for growth stocks, 0.81, and lowest for value stocks, 0.55. Consistent with findings for the size style, liquidity co-variations with the rest of the market drop substantially after we include aggregate style illiquidity in the model. Importantly, B/M style liquidity betas also display a U-shape pattern, with higher betas of 0.42 and 0.44 for growth and value stocks, correspondingly. Their differences with the average style liquidity beta of blend stocks, equal to 0.28, are statistically significant at the 1% level. Further, $\beta_{i,S}$ dominates $\beta_{i,NS}$ for value stocks, but they are approximately of the same magnitude for growth stocks. By contrast, $\beta_{i,NS}$ is significantly larger than $\beta_{i,S}$ for blend stocks, suggesting that their liquidity co-movements with the rest of the market are stronger than with other blend stocks. This finding is consistent with our expectations, because blend stocks are style-neutral, and should therefore exhibit weaker liquidity co-movements within their group.

The U-shape pattern of style liquidity betas is consistent with our previous evidence of stronger excess correlations in extreme quintiles from the last section. Overall, our findings suggest that liquidity of individual stocks in style portfolios systematically co-varies with the aggregate style liquidity, even after controlling for its co-variation with the aggregate liquidity of the rest of the market. Importantly, liquidity co-variations with other stocks in the same style dominate co-variations with remaining stocks in the market for most of our style categories.

We also conduct robustness checks of our main results, by including standard control variables from Chordia, Roll, and Subrahmanyam (2000). Specifically, we include one lead and one lag of the aggregate market and style illiquidity variations as well as the current, leading and lagged market return and the current change in the stock's squared return as a proxy for volatility. The results with control variables are qualitatively similar to our benchmark results.

We further replicate our results with value-weighted market and style liquidity. However, value-weighting biases liquidity changes towards those of larger stocks, which introduces some distortions in our analysis, especially for size style. We still find significant style liquidity betas for all style categories, but we no longer find U-shape for size style. Small stocks and medium stocks essentially co-vary only within their groups, because the rest of the market is biased towards large stocks. Consequently, their β_{NS} is close to zero. For large stocks, style liquidity beta is lower than for medium stocks, because they co-vary substantially with the rest of the market, which is biased towards other relatively large stocks. For brevity, we do not tabulate results from these robustness checks, but they are available from authors upon request.

4.2 Style Liquidity Betas and Style Holdings

Our results so far suggest that there exist systematic co-movements with the aggregate style liquidity for stocks in extreme style portfolios. We continue to test for cross sectional effects in the sensitivity to style liquidity by examining whether $\beta_{i,S}$ is higher for stocks with more pronounced style investing. The rationale is that, if style investing is more pronounced for a specific stock, then the style liquidity beta of that stock should be higher. To test this hypothesis, we form the following index for style investing in company i at year t.

$$Style_{i,t-1} = w_{i,t-1} \times Log\left(1 + N_{i,,t-1}\right)$$

where $N_{i,t-1}$ is the number of style funds that hold shares in company i as of June t-1. $w_{i,t-1}$ is a weight, equal to the ratio of total shares held by funds that are in the same style as company i, divided by the total shares held in company i by all funds, regardless of their style (e.g., Small, Medium, Large or Value, Blend, Growth).[11] The intuition of our measure

[11]We set $N_{i,t-1}$ and $w_{i,t-1}$ to zero if the stock is not held by any style funds.

is that style investing in company i increases when a larger number of same style funds are invested in the company holding a larger fraction of shares held by all mutual funds. Using this measure, we estimate the cross-sectional effect of style investing on style liquidity betas from the following model:

$$\beta_{S,i,t} = \alpha_{i,t} + \gamma_1 \cdot Style_{i,t-1} + \gamma_2 \cdot Log(Mcap)_{i,t-1} + \gamma_3 \cdot Prop_{i,t-1} + YearFE + \varepsilon_{i,t.},$$

where $Log(MCap_{t-1})$ is the natural logarithm of firm i's market capitalization, and $Prop_{t-1}$ is the amount of shares held in stock i by all mutual funds as a proportion of total shares outstanding, measured as of June $t-1$. $MCap_{t-1}$ captures systematic variation in commonality in liquidity across companies of different size (Kamara, Lou, and Sadka 2008), and $Prop_{t-1}$ across companies with different levels of institutional ownership (Kamara, Lou, and Sadka 2008, Koch, Ruenzi, and Starks 2016). We additionally include year fixed effects in our models to capture temporal variations in style liquidity betas, and cluster standard errors on the firm level.

We identify fund styles based on fund names (Small, Large, Value, Growth), sort all stocks into their corresponding styles (top/bottom 30% according to market value and B/M ratio), and run the regression separately within each style category.

[Insert Tables 5 and 6 approximately here]

In Table 5 we present results for the size style and in Table 6 for the B/M style. From column (1) in Table 5 we observe that increases in style investing index for small stocks held by small-cap funds, labeled as *Small Own*, are associated with significant increases in their style-related commonality in liquidity. The effect is economically substantial, as a 1% increase in $Style_{i,t-1}$ results in a 0.148 increase in $\beta_{i,S}$. In column (2), we observe that the same is not true for large companies, as $Style_{i,t-1}$, labeled as *Large Own*, is statistically insignificant. This shows that for large companies variations in style investing are not associated with variations in style-related commonality in liquidity, perhaps because these companies are already very liquid and therefore unaffected by the actions of style investors.[12]

Although mutual funds do not want to deviate much from their benchmark, they do on occasion invest in different styles, as documented by the literature on "style dispersion" (e.g., Amihud and Goyenko 2013, Wermers 2012, Luo and Qiao 2012). In columns (3) and (4) of Table 5, we estimate the same model, but also include ownership by the opposite style as an additional regressor to capture any effects of style dispersion on style-related commonality in liquidity. For example, if a small stock is held by large funds, whose flows are to some extent independent from the flows into small funds, then the co-variation of the liquidity of this small stock with its corresponding style may actually decrease. Column (3) shows that for small stocks this is indeed the case, as $\beta_{i,S}$ decreases with ownership by large-cap funds. Column (4) shows no significant cross-ownership effects for large companies.[13]

In columns (5) and (6) we interact $Style_{i,t-1}$ with a dummy $Neg\,Flow_{i,t-1}$, which takes the value of 1 if the aggregate style related flow during the prior year (i.e., flow into small funds) is in the bottom quartile of all years in our sample and 0 otherwise.[14] The rationale of this test is to examine whether there exist any asymmetries in style-related commonality in liquidity during periods with high fund inflows or outflows. A priori we may expect that $\beta_{i,S}$ is higher in periods with larger outflows because the effect of flow-motivated sales on asset prices is stronger than the effect of flow-motivated purchases (Coval and Stafford 2007). The results in column (5) show that for small companies the coefficient on $Style_{i,t-1}$ increases by roughly 50%, from 0.131 to 0.195 (0.131 + 0.064), when aggregate flows into small funds are in the bottom quartile. Similar to previous results, we find no significant relationship for large companies, as shown in column (6).

[12]We get a much smaller number of observations for the large group , because we classify firms into size groups using NYSE breakpoints, which results in the majority of NASDAQ firms being classified as small.

[13]The number of observations in column (3) drops, as compared to column (1), because sorting funds into "large" style only becomes possible as of June 1994. Sorting funds into "small" style is possible earlier, as of 1991.

[14]We do not include $Neg\,Flow_{i,t-1}$ as a separate regressor, because we use year-fixed effects

In terms of control variables we find that style-related commonality in liquidity significantly increases with $Log(MCap_{t-1})$ for both small and large stocks, and significantly decreases with $Prop_{t-1}$ for large companies. These results are consistent with the findings of Koch, Ruenzi, and Starks (2016) and Kamara, Lou, and Sadka (2008) and suggest that liquidity co-movements of large stocks can be rather explained by higher total institutional investor ownership than style investing.

We continue with the corresponding analysis for growth and value firms in Table 6. From columns (1) and (2) we observe that $\beta_{i,S}$ increases with $Style_{i,t-1}$ both for value and growth companies, and that the effect is larger for the former. From columns (3) and (4), we further observe that cross-ownership effects are negative and significant for both categories, and again the effects are more significant for value stocks. Finally, in the last two models we find that $\beta_{i,S}$ for growth stocks is 78% higher when aggregate flows into growth funds are in the bottom quartile.[15] In terms of control variables we find that style-related commonality in liquidity increases with $MCap_{t-1}$ for both value and and growth stocks, and increases with $Prop_{t-1}$ for growth companies.

To summarize, our results show that style-related commonality in liquidity increases with stronger style investing for small, growth and value stocks. For large stocks, liquidity co-movements are not significantly related to ownership by large-cap funds, but rather to total mutual fund ownership, consistent with findings of Koch, Ruenzi, and Starks (2016) and Kamara, Lou, and Sadka (2008). As expected, stock's liquidity co-movements with its style significantly decrease with larger ownership by funds of the opposite style. In addition, we find that style-related commonality in liquidity is stronger in periods with high aggregate style fund outflows for small and growth stocks. Overall, our findings are consistent with the notion that the sensitivity of the stock's liquidity to the aggregate style liquidity is strongly affected by the extent to which style investors are present for this particular stock.

[15] The number of observations in columns (5) and (6) is lower, because fund flows on the monthly level only become available as of 1991 from CRSP Mutual Fund Database.

4.3 Sub-period Analysis and Partitions by Exchange

To investigate whether style-related commonality in liquidity is potentially different for stocks listed on NYSE/AMEX from those listed on NASDAQ, we replicate our analysis from Table 4, breaking down our sample by the listing exchange. The upper panel of Table 7 reports our results for the size style. Columns (1) to (4) display our findings for stocks, listed on NYSE and AMEX, and columns (5) to (8) for those listed on NASDAQ.

[Insert Table 7 approximately here]

Importantly, all our previous results hold for both exchanges. We observe the U-shape pattern in style liquidity betas, both on NYSE/AMEX and NASDAQ. Style liquidity betas for small stocks are approximately of the same magnitude for NYSE/AMEX and NASDAQ, 0.61 and 0.64, correspondingly. However, their difference with β_{NS} is more pronounced for NASDAQ stocks, suggesting that style-related commonality in liquidity is the most important factor in explaining liquidity co-movements of small stocks on NASDAQ. By contrast, style liquidity betas of large stocks are higher on NYSE/AMEX, as compared to NASDAQ: 0.80 vs 0.67, correspondingly. This finding can be explained by the fact that NYSE stocks are generally larger and more liquid, which probably induces stronger co-movements within their group. Further, style liquidity betas are significantly larger than their non-style related counterparts on both exchanges.

We further split our total sample into two subperiods of around 15 years each, 1984-1999 and 2000-2014.[16] For NYSE/AMEX, we observe a considerable increase in style liquidity betas over time, especially for small stocks. They increase by 0.21, from 0.51 in the first half of our sample to 0.72 in the last years. In contrast, liquidity co-movements with the rest of the market drop substantially and are as low as 0.14 both for small and large stocks in the recent period. For NASDAQ, we observe considerable increases in style liquidity betas both

[16]As noted previously, NASDAQ data only start as of 1986.

for small and large stocks. The co-movements with the rest of the market also drop, and are even close to zero for small stocks.

Importantly, the U-shape pattern on both exchanges is more pronounced in the last period. Over 2000-2014, the differences of style liquidity betas for small and large stocks with betas of style-neutral medium stocks are significant at the 1% level, both for NYSE/AMEX and NASDAQ. By contrast, they are not significantly larger than betas of medium stocks in the first half of our sample. This finding is consistent with a substantial increase in size-based style investing in the recent period. From Figure 1, the proportion of total fund market capitalisation invested in small-cap and large-cap funds has steadily increased, from virtually zero in 1991 and up to 12% in 2012.

[Insert Table 8 approximately here]

Table 8 presents corresponding sample splits for the B/M style. Style liquidity betas are overall larger for NYSE/AMEX stocks, with beta of 0.55 for growth stocks and 0.49 for value stocks. The corresponding betas on NASDAQ are 0.32 and 0.39. Still, we observe the U-shape pattern in style liquidity betas on both exchanges, with betas of blend stocks significantly lower than betas of stocks in style portfolios. Subperiod analysis again shows an increase in style liquidity betas in the recent period. For NYSE/AMEX, they rise from 0.47 over 1984-1999 to 0.65 over 2000-2014 for growth stocks, and from 0.39 to 0.61 for value stocks. For NASDAQ, they also increase, but to a lesser extent, from 0.25 to 0.39 for growth stocks and from 0.36 to 0.42 for value stocks.

Consistent with prior findings for the size style, the U-shape pattern is more pronounced in the last fifteen years, especially for value stocks. Figure 1 shows that the proportion of total fund market capitalisation invested in growth funds is already around 15% at the beginning of 1990s, whereas it is only 5% for value funds. Therefore, we expect liquidity co-movements of growth stocks with their style to be already significant in the first period, whereas they should be weaker for value stocks in the first half of our sample. These predictions are consistent with our findings in Table 8.

Style liquidity betas start dominating the non-style betas for growth stocks on NYSE/AMEX only in the recent period. For NASDAQ, they are significantly lower than non-style betas over 1984-1999, but increase to the same magnitude in the last fifteen years. Style liquidity betas of value stocks also start dominating non-style betas on both exchanges only in the second half of our sample.

Overall, our findings for exchange splits are consistent with our prior findings for the total sample, suggesting that liquidity of style stocks systematically co-varies with the aggregate style liquidity, both for NYSE/AMEX and NASDAQ stocks. Further, with a substantial increase in style investing, liquidity co-variations with other stocks in the same style have become stronger in the last fifteen years, and are now dominating liquidity co-variations with the rest of the market for all styles.

5 Conclusions

In this paper, we examine implications of style investing for systematic co-movements of the stock's liquidity with its aggregate style liquidity, which we refer to as *style-related commonality in liquidity.* We show that style-related liquidity co-movements are significant, even after controlling for liquidity co-movements with the remaining stocks in the market. By contrast, style-related co-movements are lower and less significant for stocks that do not belong to any well-defined style, or style-neutral stocks. For stocks in extreme style portfolios, systematic co-movements with style liquidity even dominate liquidity co-movements with the rest of the market in the recent period.

We explain our findings by a pronounced increase in style investing since 1990s and show that style-related commonality in liquidity is indeed significantly stronger for stocks with larger exposure to style investing. Further, this relation is especially pronounced during periods, in which style-level fund outflows are the highest, which implies that the impact of style investing on liquidity co-movements is the strongest at the time when the aggregate style liquidity is already low. Thus, it becomes costlier for style funds to liquidate their holdings exactly at the time when the liquidation is needed most.

Importantly, our data in this paper comes from US public equity markets, which arguably represent the most liquid markets in the world. Liquidity risks, associated with style investing, are potentially even more pronounced in other countries with less liquid stock markets or in less liquid asset classes, such as, for example, fixed income. Notably, Morningstar also provides its style classification for fixed income along credit quality and interest-rate sensitivity dimensions. Recently, with extremely low interest rates, investors started actively investing in commodities and real estate, which also represents a shift in their preferences towards these asset classes, as opposed to equity and fixed income. It would be hard to impossible to analyze the implications of investors' preference shifts for these very illiquid assets, but the existence of liquidity risks, associated with style investing, should be a warning signal to investors and asset managers alike.

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Appendix A

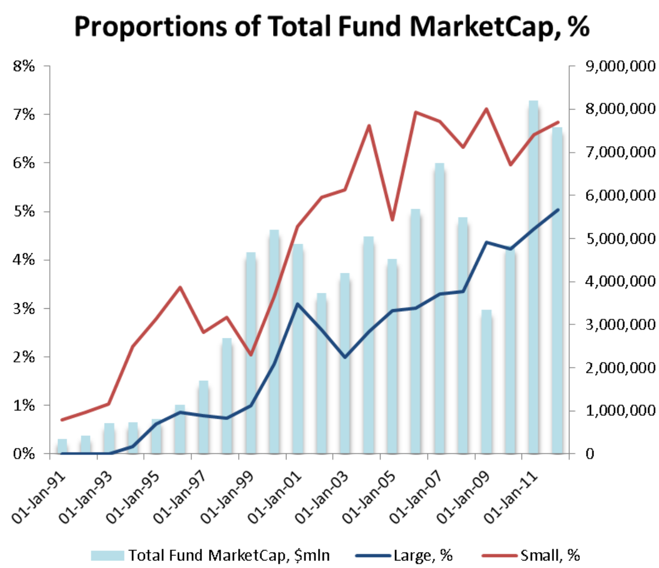
Variable Definitions

Variable	Description	Source
BM	The book-to-market ratio, calculated as the ratio of the book value of equity with fiscal year-end in calendar year $t-1$ to the market value of equity at the end of December of year $t-1$	Compustat
$ILLIQ$	The Amihud (2002) measure, calculated as the ratio of the absolute daily price change to the daily dollar volume traded, adjusted for aggregate market capitalisation as of June 2014. We calculate $ILLIQ$ for stock i on day d as $$ILLIQ_{i,d} = \frac{\lvert R_{i,d}\rvert}{DVol_{i,d} \cdot \frac{Mcap_{2014}}{Mcap_{t-1}}},$$ where $Mcap_{t-1}$ is the total market capitalisation of all stocks included in month $t-1$ and $Mcap_{2014}$ is the total market capitalisation of all stocks included in June 2014.	CRSP
$RET12$	The cumulative return from July of year $t-1$ to June of year t	CRSP
$Mcap$	Market capitalization (in millions of dollars), calculated at the end of June of year t	CRSP
Neg Flow	A dummy variable, which takes the value of 1 if the aggregate style-related flow in year $t-1$ is in the bottom quartile of all years in our sample, and 0 otherwise	CRSP MF Database

Variable	Description	Source
Prop	The amount of shares held in stock i by all mutual funds as a proportion of total shares outstanding as of June $t-1$	Thomson Financial (S12)
Style	Style investing index, calculated as $Style_{i,t-1} = w_{i,t-1} \cdot Log(1+N_{i,t-1})$, where $N_{i,t-1}$ is the number of style funds that hold shares in company i as of June $t-1$, and $w_{i,t-1}$ is a weight, equal to the ratio of total shares held by funds that are in the same style as company i, divided by the total shares held in company i by all funds	Thomson Financial (S12)
$SILLIQ$	Aggregate style illiquidity, calculated as the equally-weighted average of $ILLIQ$ across all stocks that belong to a specific style in month t	CRSP
Small Own	Equals to *Style* for stocks held by small-cap style funds. We define *Large Own, Growth Own* and *Value Own* in a similar way for large-cap, growth and value funds, correspondingly.	Thomson Financial (S12)
$SFlow$	Aggregate flow into funds that are classified into a specific style as of month t	CRSP MF Database
$Turnover$	Stock turnover, defined as the monthly volume traded, scaled by the number of shares outstanding	CRSP
$Volume$	Monthly volume traded (in thousands of shares)	CRSP
$Volat$	Stock volatility, calculated as the standard deviation of monthly stock returns over 12-60 months	CRSP

Figure 1: **Development of Style Investing over Time.** Panel A of the figure illustrates development of Size style over 1991-2012. The red line shows the proportion of small-cap funds in the total fund market market capitalisation. The blue line shows the proportion of large-cap funds in the total fund market capitalisation. Values of total fund market capitalisation for each year, depicted as light-blue bars, are shown on the right hand axis. Panel B shows the corresponding values for B/M style.

A. Size Style.



B. B/M Style.

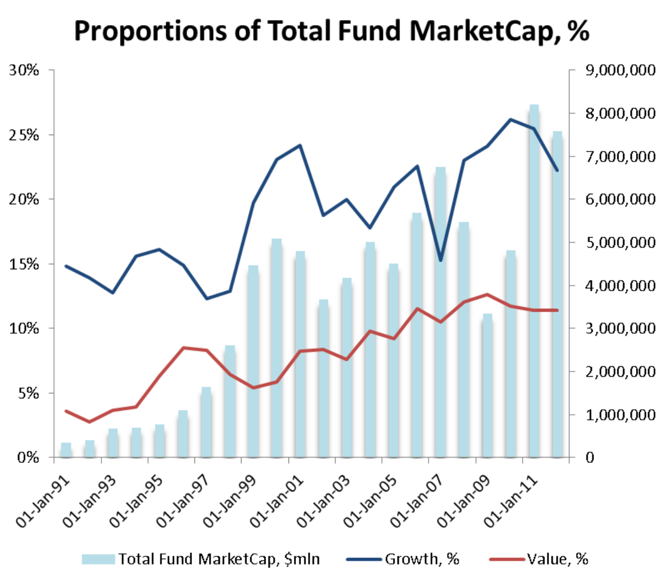


Figure 2: **Excess Liquidity Co-Movements within Styles.** This figure depicts excess residual correlations from the market model of liquidity within each quintile of size and B/M. For each stock and each year ending in June, we estimate the following regression: $\Delta ILLIQ_{i,d}, = \alpha + \beta_{i,M} \Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where $\Delta ILLIQ_{i,d}$ is the log-change of the daily Amihud (2002) measure of firm i on day d, and $\Delta ILLIQ_{m,d}$ is the equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks with $j \neq i$. We then compute the average pairwise correlation of the residual of every stock in a given quintile with the quintile in question (excluding stock i). Panel A of the figure shows excess residual correlations within size quintiles and Panel B within B/M quintiles.

A. Size Style.

B. B/M Style.

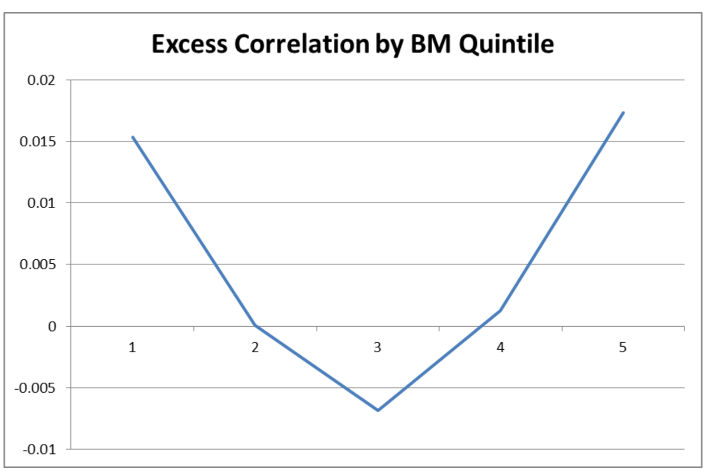


Table 1: **Sample Construction.** Our initial sample consists of all common stocks downloaded from CRSP with share codes 10 and 11. For NYSE and AMEX, our sample period is 1984-2014. For NASDAQ, our sample period is 1986-2014.

Criteria	**Firm-years**	**Firms**
Initial sample	234,489	24,236
Stock is listed at the end of the year and its end-of-year price is greater than $2	196,340	21,255
Stock is traded for at least 60 days during the year	194,823	20,709

Table 2: **Summary statistics.** This table presents the time-series averages of annual (end-of-June) cross-sectional statistics for all stocks in our sample, traded on NYSE, NASDAQ and AMEX. The sample period for stocks, traded on NYSE and AMEX, is 1984-2014. The sample period for stocks, traded on NASDAQ, is 1986-2014. *#Firms* represents the number of firms in our sample. *Size* is the market capitalisation (in millions of dollars), *Volume* is monthly volume traded (in thousands of shares), and *Turnover* is monthly volume, scaled by the number of shares outstanding. *ILLIQ* is the Amihud (2002) illiquidity measure, adjusted for total market capitalisation as of June 2014. *Volat* is volatility of stock returns, calculated as the standard deviation of monthly stock returns over 12-60 months. *BM* is the book-to-market ratio, calculated as the ratio of the book value of equity with fiscal year-end in calendar year *t-1* to the market value of equity at the end of December of year *t-1*. *RET12* is the cumulative return over the previous 12 months, from July of year $t-1$ to June of year t. Data on book values of equity are from Compustat. Data for all remaining variables are taken from CRSP. See Appendix A for a detailed description of variable definitions.

	Total			NYSE/AMEX			NASDAQ		
	Mean	50%	SD	Mean	50%	SD	Mean	50%	SD
#Firms	3,118	2,985	705	2,981	2,872	460	3,264	3,108	881
MCap	1,455	305	3,393	2,221	458	4,736	639	142	1,960
Volume	7,581	1,919	15,248	9,175	2,456	16,627	5,880	1,346	13,777
Turnover	1.19	0.77	1.35	1.03	0.70	1.14	1.36	0.84	1.58
ILLIQ	0.18	0.03	0.35	0.09	0.01	0.25	0.27	0.06	0.44
Volat	0.13	0.12	0.06	0.10	0.09	0.05	0.15	0.14	0.07
BM	0.74	0.62	0.58	0.78	0.66	0.58	0.71	0.58	0.57
RET12	0.14	0.07	0.50	0.13	0.08	0.43	0.15	0.05	0.57

Table 3: **Style fund flows and style liquidity.** This table reports results of monthly time series regressions with the aggregate style illiquidity, $SILLIQ_t$, as the dependent variable. The sample period is 1991-2014, because fund flows on a monthly level are only available as of the beginning of 1990s in CRSP Mutual Fund Database. We calculate $SILLIQ_t$ as the equally-weighted average Amihud measure, adjusted for total market capitalisation as of June 2014, among all stocks that belong to a given style in month t. We calculate the fund flows into a style, $SFlow_t$, as the sum of flows for all mutual funds that are classified into a given style as of month t. Additional controls include two lags of the dependent variable; average market capitalisation, $Mcap$; average stock return volatility, $Volat$; and average stock turnover, $Turnover$ in each style. See Appendix A for a detailed description of variable definitions. We also include year-fixed effects and use Newey-West standard errors with one lag to account for serial correlation in error terms. Models (1) -(3) report results for the size style. Models (4)-(6) report results for the BM style. P-values of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, *** denotes statistical significance at the 1% level.

	Small (1)	Medium (2)	Large (3)	Growth (4)	Blend (5)	Value (6)
L.SILLIQ	0.420 ***	0.609 ***	0.558 ***	0.612 ***	0.602 ***	0.395 ***
L2.SILLIQ	-0.054	-0.021	0.062	-0.098	0.014	-0.070
SFlow	-1.188 **	-0.411	-0.001	-0.271 **	-0.269	-0.303 *
Mcap	-4.969 ***	-0.135 ***	-0.000 ***	-0.004 ***	-0.015 ***	-0.043 ***
Volat	-0.950	-0.231	-0.028 **	0.194 **	-0.823 ***	-0.458 *
Turnover	-0.065 ***	-0.015 ***	-0.000	-0.005 *	-0.006	-0.026 ***
N	280	280	280	280	280	280
F-stat	195.18	341.56	268.30	209.00	195.78	170.57
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: **Commonality in style liquidity.** For each stock and each year ending in June, we first estimate the following regression: $\Delta ILLIQ_{i,d} = \alpha + \beta_{i,M}\Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where $\Delta ILLIQ_{i,d}$ is the log-change of the daily Amihud (2002) measure of firm i on day d, and $\Delta ILLIQ_{m,d}$ is the equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks with $j \neq i$. Each year t, at the end of June, firms are sorted into three size groups: Small (lower 30%), Medium (30%-70%) and Large (upper 30%), based on their market capitalisation as of June of year $t-1$. Column (1) of this table reports the cross-sectional average of $\beta_{i,M}$, market liquidity beta, for each of size groups. Columns (2) and (3) report the cross-sectional averages of non-style related betas, $\beta_{i,NS}$, and style liquidity betas, $\beta_{i,S}$, estimated from the following regression: $\Delta ILLIQ_{i,d} = \alpha + \beta_{i,NS}\Delta ILLIQ_{NS,d} + \beta_{i,S}\Delta ILLIQ_{S,d} + \varepsilon_{i,d}$. $\Delta ILLIQ_{S,d}$ is the daily equally-weighted average of $\Delta ILLIQ_{j,d}$ for all NYSE/AMEX stocks in the particular style (excluding stock i), and $\Delta ILLIQ_{NS,d}$ is the daily equally-weighted average of $\Delta ILLIQ_{j,d}$ for all remaining NYSE/AMEX stocks. Column (4) reports the t-statistics of the equality-of-means test for $\beta_{i,S}$ and $\beta_{i,NS}$ in each of style categories. Panel A displays the results for Size style and Panel B for B/M style. The last two rows in each panel show the t-statistics of the equality-of-means test for liquidity betas of stocks in extreme style portfolios and stocks in the corresponding "style-neutral" portfolio.

Panel A: Size style

		Market Only	Market and Size		t-test
		β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$
		(1)	(2)	(3)	(4)
Total	Small	0.43	0.09	0.63	67.10
	Medium	0.88	0.35	0.55	14.19
	Large	1.04	0.20	0.79	44.06
t-test	Small-Medium	-85.37	-33.40	9.24	
	Large-Medium	26.24	-13.35	22.93	

Panel B: B/M style

		Market Only	Market and BM		t-test
		β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$
		(1)	(2)	(3)	(4)
Total	Growth	0.81	0.40	0.42	1.48
	Blend	0.75	0.48	0.28	-12.07
	Value	0.55	0.20	0.44	15.43
t-test	Growth-Blend	11.01	-7.05	13.14	
	Value-Blend	-32.30	-23.11	13.87	

Table 5: **Size liquidity betas and style holdings.** This table reports results of panel data OLS regressions with the style liquidity beta, $\beta_{i,S}$, as the dependent variable. We sort all stocks into size categories, according to the 30%-40%-30% split, and run regressions separately within each category. We calculate style investing index, $Style_{i,t-1}$, as $w_{i,t-1} \cdot Log(1 + N_{i,t-1})$ where $N_{i,t-1}$ is the number of style funds that hold shares in company i as of June $t-1$, and $w_{i,t-1}$ is a weight, equal to the ratio of total shares held by funds that are in the same style as company i, divided by the total shares held in company i by all funds. *Small Own* denotes style investing index, $Style_{i,t-1}$, for stocks held by small-cap funds and *Large Own* by large-cap funds, correspondingly. *Neg Flow* is a dummy variable, equal to 1 if the aggregate flow into the funds of a given style in the previous year is in the bottom quartile of all years in our sample, and 0 otherwise. Additional controls include the natural logarithm of firm i's market capitalization as of June $t-1$, $Log(Mcap_{t-1})$ and the amount of shares held in stock i by all mutual funds as a proportion of total shares outstanding as of June $t-1$, $Prop_{t-1}$. See Appendix A for a detailed description of variable definitions. Observations are on the firm-year level. All regressions include year-fixed effects and allow for clustering of standard errors at the firm level. P-values of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Small (1)	Large (2)	Small (3)	Large (4)	Small (5)	Large (6)
Constant	-1.416 ***	-3.051 ***	-1.550 ***	-3.025 ***	-1.408 ***	-3.050 ***
Small Own	0.148 ***		0.141 ***	-0.033	0.131 ***	
Large Own		-0.045	-2.623 ***	-0.057		-0.037
Small Own · Neg Flow					0.064 ***	
Large Own · Neg Flow						-0.018
Prop	0.107	-0.588 ***	0.096	-0.585 ***	0.072	-0.588 ***
Log(MCap)	0.112 ***	0.176 ***	0.122 ***	0.175 ***	0.112 ***	0.176 ***
N	52,925	9,875	46,863	9,875	52,925	9,875
R2	0.026	0.073	0.029	0.073	0.026	0.073
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **B/M liquidity betas and style holdings.** This table reports results of panel data OLS regressions with the style liquidity beta, $\beta_{i,S}$, as the dependent variable. We sort all stocks into B/M categories, according to the 30%-40%-30% split, and run regressions separately within each category. We calculate style investing index, $Style_{i,t-1}$, as $w_{i,t-1} \cdot Log(1 + N_{i,t-1})$ where $N_{i,t-1}$ is the number of style funds that hold shares in company i as of June $t-1$, and $w_{i,t-1}$ is a weight, equal to the ratio of total shares held by funds that are in the same style as company i, divided by the total shares held in company i by all funds. *Growth Own* denotes style investing index, $Style_{i,t-1}$, for stocks held by growth funds and *Value Own* by value funds, correspondingly. *Neg Flow* is a dummy variable, equal to 1 if the aggregate flow into the funds of a given style in the previous year is in the bottom quartile of all years in our sample, and 0 otherwise. Additional controls include the natural logarithm of firm i's market capitalization as of June $t-1$, $Log(Mcap_{t-1})$ and the amount of shares held in stock i by all mutual funds as a proportion of total shares outstanding as of June $t-1$, $Prop_{t-1}$. See Appendix A for a detailed description of variable definitions. Observations are on the firm-year level. All regressions include year-fixed effects and allow for clustering of standard errors at the firm level. P-values of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Growth (1)	Value (2)	Growth (3)	Value (4)	Growth (5)	Value (6)
Constant	-0.333 **	-2.756 ***	-0.386 **	-2.785 ***	-0.275 *	-2.659 ***
Value Own	0.223 ***		0.209 ***	-0.060 *	0.205 ***	
Growth Own		0.120 ***	-0.087 **	0.109 ***		0.101 ***
Value Own · Neg Flow					0.067	
Growth Own · Neg Flow						0.078 ***
Prop	0.118	0.284 **	0.206	0.326 ***	0.002	0.327 ***
Log(MCap)	0.036 ***	0.163 ***	0.039 ***	0.165 ***	0.044 ***	0.157 ***
N	30,492	34,540	30,492	34,540	25,295	28,302
R2	0.010	0.073	0.011	0.073	0.011	0.075
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Subsample splits: Size style.** For each stock and each year ending in June, we first estimate the following regression: $\Delta ILLIQ_{i,d} = \alpha + \beta_{i,M}\Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where $\Delta ILLIQ_{i,d}$ is the log-change of the daily Amihud (2002) measure of firm i on day d, and $\Delta ILLIQ_{m,d}$ is the equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks with $j \neq i$. Each year t, at the end of June, firms are sorted into three size groups: Small (lower 30%), Medium (30%-70%) and Large (upper 30%), based on their market capitalisation as of June of year $t-1$. Column (1) of this table reports the cross-sectional average of $\beta_{i,M}$, market liquidity beta, for each of size groups for NYSE/AMEX stocks. Columns (2) and (3) report the cross-sectional averages of $\beta_{i,NS}$ and $\beta_{i,S}$, estimated from the following regression: $\Delta ILLIQ_{i,d} = \alpha+\beta_{i,M}\Delta ILLIQ_{m,d}+\beta_{i,S}\Delta ILLIQ_{S,d}+\varepsilon_{i,d}$. $\Delta ILLIQ_{S,d}$ is the daily equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks in the particular style (excluding stock i). Column (4) reports the t-statistics of the equality-of-means test for $\beta_{i,S}$ and $\beta_{i,NS}$ in each of style categories. Columns (5) to (8) present the corresponding results for NASDAQ stocks. The last two rows show the t-statistics of the equality-of-means test for liquidity betas of stocks in extreme style portfolios and betas of style-neutral medium stocks. The upper part of the table reports results for the total sample, the middle part for years 1984-1999 and the lower part for years 2000-2014. NASDAQ data start as of 1986.

		NYSE/AMEX				NASDAQ			
		Market Only	Market and Size		t-test	Market Only	Market and Size		t-test
		β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$	β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	Small	0.59	0.20	0.61	25.81	0.38	0.06	0.64	62.12
	Medium	0.84	0.35	0.54	10.01	0.93	0.34	0.57	10.30
	Large	1.03	0.18	0.80	42.90	1.14	0.37	0.67	10.32
t-test	Small-Medium	-30.77	-12.17	5.13		-70.80	-25.34	5.19	
	Large-Medium	25.77	-13.67	21.82		13.48	1.08	4.00	
1984-1999	Small	0.55	0.25	0.51	11.31	0.39	0.10	0.60	32.40
	Medium	0.73	0.35	0.48	5.12	0.75	0.26	0.56	8.47
	Large	1.06	0.21	0.78	27.47	1.09	0.45	0.54	1.53
t-test	Small-Medium	-16.09	-5.93	1.39		-27.67	-8.66	1.79	
	Large-Medium	31.82	-7.94	17.27		10.96	3.57	-0.34	
2000-2014	Small	0.65	0.14	0.72	28.91	0.37	0.01	0.69	60.72
	Medium	0.97	0.35	0.60	9.56	1.10	0.42	0.58	5.93
	Large	0.99	0.14	0.83	34.57	1.16	0.34	0.72	11.59
t-test	Small-Medium	-30.47	-12.12	6.59		-84.93	-31.43	6.21	
	Large-Medium	1.40	-11.98	13.35		3.63	-2.58	5.56	

Table 8: **Subsample splits: B/M style.** For each stock and each year ending in June, we first estimate the following regression: $\Delta ILLIQ_{i,d} = \alpha + \beta_{i,M}\Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where $\Delta ILLIQ_{i,d}$ is the log-change of the daily Amihud (2002) measure of firm i on day d, and $\Delta ILLIQ_{m,d}$ is the equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks with $j \neq i$. Each year t, at the end of June, firms are sorted into three B/M groups: Growth (lower 30%), Blend (30%-70%) and Value (upper 30%), based on their B/M ratio as of June of year $t-1$. Column (1) of this table reports the cross-sectional average of $\beta_{i,M}$, market liquidity beta, for each of B/M groups for NYSE/AMEX stocks. Columns (2) and (3) report the cross-sectional averages of $\beta_{i,NS}$ and $\beta_{i,S}$, estimated from the following regression: $\Delta ILLIQ_{i,d} = \alpha + \beta_{i,M}\Delta ILLIQ_{m,d} + \beta_{i,S}\Delta ILLIQ_{S,d} + \varepsilon_{i,d}$. $\Delta ILLIQ_{S,d}$ is the daily equally-weighted average of $\Delta ILLIQ_{i,d}$ for all NYSE/AMEX stocks in the particular style (excluding stock i). Column (4) reports the t-statistics of the equality-of-means test for $\beta_{i,S}$ and $\beta_{i,NS}$ in each of style categories. Columns (5) to (8) present the corresponding results for NASDAQ stocks. The last two rows show the t-statistics of the equality-of-means test for liquidity betas of stocks in extreme style portfolios and betas of style-neutral blend stocks. The upper part of the table reports results for the total sample, the middle part for years 1984-1999 and the lower part for years 2000-2014. NASDAQ data start as of 1986.

		NYSE/AMEX				NASDAQ			
		Market Only	Market and BM		t-test	Market Only	Market and BM		t-test
		β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$	β_M	β_{NS}	β_S	$\beta_S - \beta_{NS}$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	Growth	0.96	0.40	0.55	8.01	0.71	0.39	0.32	-3.95
	Blend	0.90	0.52	0.40	-5.38	0.62	0.44	0.18	-11.03
	Value	0.73	0.33	0.49	7.82	0.38	0.07	0.39	13.49
t-test	Growth-Blend	6.96	-7.61	10.49		11.44	-3.01	9.81	
	Value-Blend	-21.96	-11.81	5.95		-26.89	-20.67	12.31	
1984-1999	Growth	0.96	0.47	0.47	0.15	0.68	0.43	0.25	-6.02
	Blend	0.84	0.52	0.35	-5.59	0.57	0.45	0.14	-7.83
	Value	0.70	0.39	0.39	-0.11	0.41	0.13	0.36	5.62
t-test	Growth-Blend	10.50	-2.29	5.91		9.11	-0.59	4.99	
	Value-Blend	-12.35	-5.83	1.75		-10.45	-10.49	7.55	
2000-2014	Growth	0.95	0.30	0.65	13.18	0.74	0.36	0.39	1.66
	Blend	0.98	0.51	0.45	-1.72	0.67	0.44	0.21	-7.84
	Value	0.76	0.25	0.61	13.15	0.36	0.02	0.42	14.76
t-test	Growth-Blend	-2.57	-9.43	9.46		7.64	-4.34	10.10	
	Value-Blend	-20.26	-11.65	7.42		-30.62	-19.87	10.17	