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COMOVEMENT, LIQUIDITY AND ASYMMETRIES

James X. Xiong, PhD, CFA[a]

Substantially increased institutional investing and index trading in the US stock market have a meaningful impact on the mechanical relationship between return comovement and liquidity, which can be quantified by a power-law function and explained by a liquidity supply model. Three well-documented asymmetries (asymmetric volume, asymmetry in non-market volatility, and positive skewness for individual stocks) are disappearing with increased basket trading, however, asymmetric correlation survives.

1 Introduction

One of the key changes in the US stock market over the last half-century is the substantial increase in institutional investing and index investing (e.g. Kamara *et al.*, 2008). Both types of investing are associated with basket trading.[1] The estimated percent of US equity shares held by institutional investors rose from 21% in 1965 to 35% in 1980 and to 80% in 2017 (source: NYSE, Pension & Investments). The estimated dollar amount of US equity shares held by passive investing (combining US passive equity mutual funds and US equity exchange-traded funds (ETFs)) grew from $365 billion in 2000 to $3.57 trillion in 2018 (source: Morningstar Direct).

The substantially increased basket trading has played an important role in the increases of trading volumes and liquidity levels of US equity markets, however, it has also introduced increased comovement—many stocks are trading and comoving at the same time. It has implications for the liquidity of individual stocks and the overall market. Chordia *et al.* (2000) document that liquidity strongly covaries across stocks, i.e. commonality in liquidity. Kamara *et al.* (2008) demonstrate that the cross-sectional variation in liquidity commonality has increased over the period 1963–2005, and the increased systematic liquidity risk in large stocks can be explained by the increased institutional investing.

Koch *et al.* (2016) hypothesize that one source of commonality in a stock's liquidity arises from correlated trading among the stock's investors. Focusing on correlated trading of mutual funds, they found that stocks with high mutual fund

[a]Morningstar Investment Management LLC, 22 West Washington Street, Chicago, IL, 60602, USA. Phone: (630) 890-8334, Email: james.xiong@morningstar.com

ownership have a commonality in liquidity that is, about twice as large as those for stocks with low mutual fund ownership. They also found that stocks owned by mutual funds with higher turnover and those owned by mutual funds that experience liquidity shocks themselves have a higher commonality in liquidity. These results suggest an important role for the demand side of liquidity in explaining commonality.

On the liquidity supply side, market makers face funding constraints and obtain financing by posting margins and pledging the securities they hold as collateral. Thus, when stock prices decline considerably, the intermediaries hit their margin constraints and are forced to liquidate. They become liquidity demanders as they liquidate their positions in risky assets. In the coordination failure models of Bernardo and Welch (2003), traders face different trading limits that cause them to sell. Since one trader hitting his limit may push down the price and make other traders' limits be hit, early liquidation gives a better price than late liquidation. Traders rush to liquidate following negative shocks, and when prices fall enough, liquidity black holes emerge (Morris and Shin, 2004). These studies highlight that liquidity is more relevant in downturned markets.

A relatively new source for comoved stocks is index investing. While index investing, such as index funds and exchange-traded funds (ETFs), has enjoyed spectacular growth since the late 1990s, a few recent academic studies have highlighted certain unintended consequences the ETFs have on the underlying securities. For example, ETFs distort stock prices and risk–return tradeoffs (Wurgler, 2010) increase the comovement in returns (Da and Shive, 2017) and increase the volatility of the underlying securities (Ben-David *et al.*, 2018). Sullivan and Xiong (2012) document that the observed increase in trading commonality since 1997 has led to lower cross-sectional dispersion in trading volume changes. They attributed this increased trading commonality to the increased basket and index trading. Bolla *et al.* (2016) confirm the increased trading commonality in global stock markets. Agarwal *et al.* (2019) document that ETF ownership exacerbates the comovement in the liquidity of constituent stocks.

Previous researches mainly relied on liquidity beta to measure the commonality in liquidity. Through appropriately normalized returns and trading volumes, we provide a better way to directly measure the mechanical relationship between return comovement and liquidity across stocks over time. We find that the impact of return comovement on liquidity has gradually increased over the last half-century with increased basket trading. More importantly, the relationship between return comovement and liquidity can be quantified by a power-law function and explained by a liquidity supply model. Finally, we show that the disappearances of three well-documented asymmetries (asymmetric volume, asymmetry in non-market volatility, and positive skewness for individual stocks, see Duffee, 2001) are all associated with increased basket trading.

2 Description of data

Our stock universe consists of all the US stocks on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and the Nasdaq Stock Market (NASDAQ) over the 56-year period from January 1963 through December 2018. Daily prices, returns (including dividends), trading volumes, and shares outstanding are collected from the University of Chicago's Center for Research in Security Prices (CRSP) from 1963 to 2011 and Morningstar Direct from 2012 to 2018. Common stocks with an initial price greater than \$5 and less than \$1000 in each calendar year are included, while derivative securities of foreign stocks like ADRs are excluded.

The stock universe is broken into large and small stocks by the median market cap at the beginning of each calendar year. More attention is paid to large stocks because they are impacted by comovement to a larger degree than small stocks. Also, more focus is put on negative returns because liquidity can be more relevant in downturned markets.

Since trading volumes are not stationary over time, it is important that they are normalized for each calendar year. Returns are normalized for most of the study as well. The normalization methodology for trading volumes and returns is shown in Appendix.

3 Measuring return comovement

Comovement refers to the positive correlation of returns. Barberis *et al.* (2005) identify that comovement can be induced by both fundamental news and trading (such as basket or index trading). In this paper, the return comovement is measured as the percentage (in decimal) of stocks that have returns exceeding a given threshold (negative or positive) in a trading day. This daily measurement for comovement is important because it allows its mechanical relationship with average daily liquidity for comoved stocks to be quantified. For most of this study, the threshold is chosen as -1 for negative return comovement and $+1$ for positive comovement for normalized returns.[2] By construction, return comovement varies between 0 and 1 for both negative and positive returns.[3] For convenience, we use *comovement* and *return comovement* interchangeably.

Figure 1 shows the probability of comovement with a value greater than 0.5 for large stocks from 1963 to 2018. The probability is calculated as the number of trading days, in which more than 50% of the stocks have losses exceeding -1 for negative comovement or gains exceeding 1 for positive comovement, divided by the total number of trading days in each year. For negative returns, the comovement with a value greater than 0.5 ($C > 0.5$) is much more likely to happen after 2000, and it remains relatively high in 2018. More specifically, the average probability of having negative comovement greater than 0.5 is 1.0% during 1963–1970, and it increases to 4.3% during 2011–2018. Positive returns also show an increased comovement after 2000 but to a less degree. It indicates an increased downside comovement risk for investors since 2000.

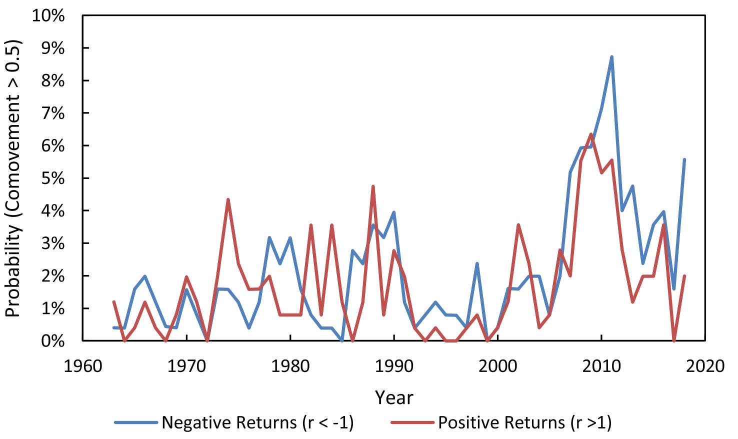


Figure 1 The probability of (comovement $>$ 0.5) for large stocks from 1963 to 2018 (returns are normalized in each year).

4 Liquidity and comovement

Amihud (2002) defines the liquidity (or illiquidity) as absolute return divided by dollar volume (dollar volume = price * trading volume). Since we normalize the trading volume, we define the liquidity in a simpler way in this paper: absolute normalized return divided by normalized volume.[4]

Previous researches have studied commonality in liquidity via liquidity beta (e.g. Kamara *et al.*, 2008; Koch *et al.*, 2016; Agarwal *et al.*, 2019). The liquidity beta measures the sensitivity of changes in individual stock's liquidity to changes in aggregated market liquidity. It does not directly measure the mechanical relationship between return comovement and liquidity. In contrast, we study how comovement impacts liquidity by using a different and more straightforward method. We measure return comovement and quantify its mechanical relationship with the average liquidity of comoved stocks, and then develop a liquidity supply model to explain it.

To investigate how the average liquidity of comoved stocks is related to the comovement over time, we run a regression of average daily liquidity on the daily comovement for each year from 1963 to 2018 by combining negative and positive comovements (they are separated later)[5]:

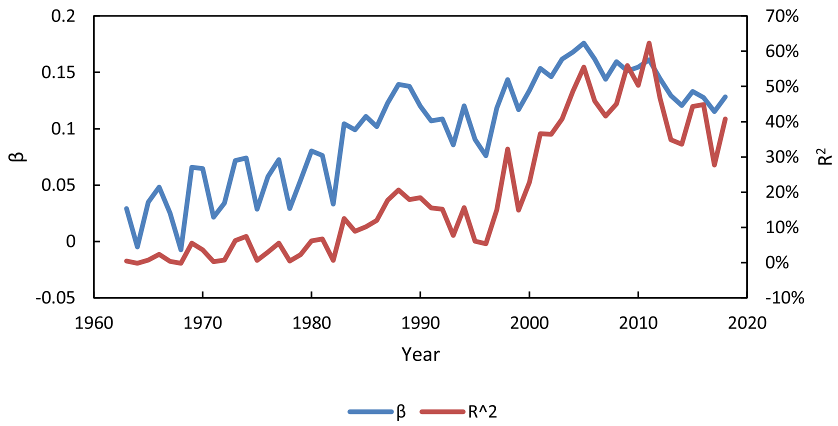
$$\ln(\bar{L}_t) = \alpha + \beta \cdot \ln(C_t) + e_t \qquad (1)$$

Where $\bar{L}_t$ is the average liquidity of comoved stocks on day-t. The liquidity is defined as the ratio of absolute normalized return divided by normalized volume as mentioned above. C_t is the return comovement on day-t, i.e. the percentage of stocks with negative returns less than -1 or positive returns greater than $+1$. e_t is the regression residual on day-t. Logarithm is taken on both independent and dependent variables in Equation (1) because the relationship between liquidity and comovement is nonlinear (one will see it later). β is the regression coefficient of logarithmic liquidity on logarithmic return comovement, and note that it is different from the liquidity beta in both mathematical form and economical meaning.

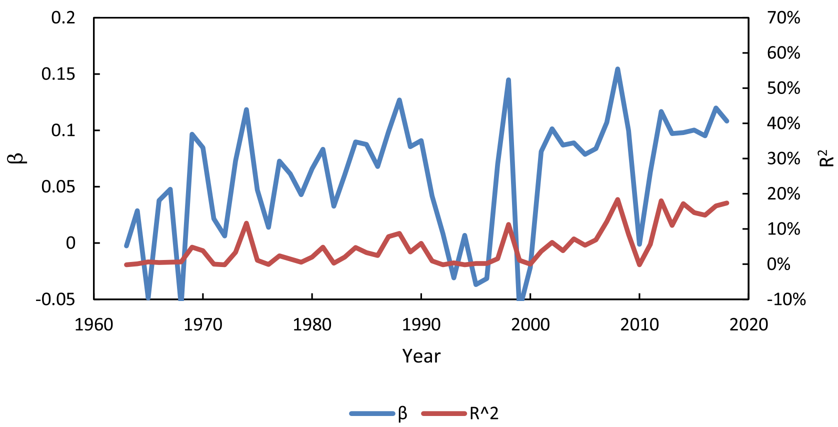
Figure 2(A and B) shows that the comovement coefficient β and R^2 are based on Equation (1) from 1963 to 2018 for large and small stocks, respectively. For large stocks, the impact of comovement on liquidity has gradually increased and it peaked around 2000. The increased β is consistent with the increased basket trading over the same period. The explanatory power of comovement (R^2) has also significantly increased after the 1990s. The R^2 reaches nearly 62% in 2011. The average R^2 from 2000 to 2018 is 43%, significantly higher than the average R^2 of 8% from 1963 to 1999.

In contrast, both the comovement coefficient (β) and R^2 show a similar but much less significant uptrend for small stocks. The average R^2 from 2000 to 2018 is 10%, while the average R^2 is 2% from 1963 to 1999. It indicates that the impact of comovement on liquidity is less for small stocks.

Detailed dynamics about the impact of increased basket trading on the relationship between comovement and liquidity is plotted in Figure 3 (A for large stocks and B for small stocks), where negative comovements are separated from positive ones. To illustrate the relationship change over time, the 56-year data are split into six charts: (a) 1963–1970; (b) 1971–1980; (c) 1981–1990; (d) 1991–2000; (e) 2001–2010; and (f) 2011–2018. Specifically, Figure 3A(a) aggregates eight-years of average daily liquidity and comovement data for both negative and positive returns from 1963 to 1970. Similarly, Figure 3A(b) aggregates ten-years of data from 1971 to 1980, and Figure 3A(f) aggregates eight-years of data from 2011 to 2018.[6]



(a) Large Stocks



(b) Small Stocks

Figure 2 The comovement coefficient (β) and R^2 for the regression of liquidity on comovement for (A) large stocks; and (B) small stocks.

Starting from Figure 3A (a. 1963–1970) for large stocks, the liquidity for both negative returns and positive returns has no strong correlation with comovement (the slope is nearly flat). As time moves forward from 1963 to 2018, four observations emerge in Figure 3A:

(1) The difference of the liquidity–comovement relationship between negative and positive returns is disappearing (we will go back to this point in the last section);
(2) The slope of the liquidity–comovement relationship is increasing and concaved for both negative and positive returns;
(3) The curve is much less scattered after 2000 for both negative and positive comovements, suggesting that the explanatory power of comovement is much higher (see Table 1 for a high R^2 of 84%). It also indicates a more mechanical relationship between liquidity and comovement after 2000;[7]
(4) The chance that the comovement exceeds 0.5 is increased from 1% (1963–1970) to 4.3% (2011–2018) for negative returns as mentioned earlier. The tendency to have a large comoved negative returns in the last two decades is meaningfully increased.

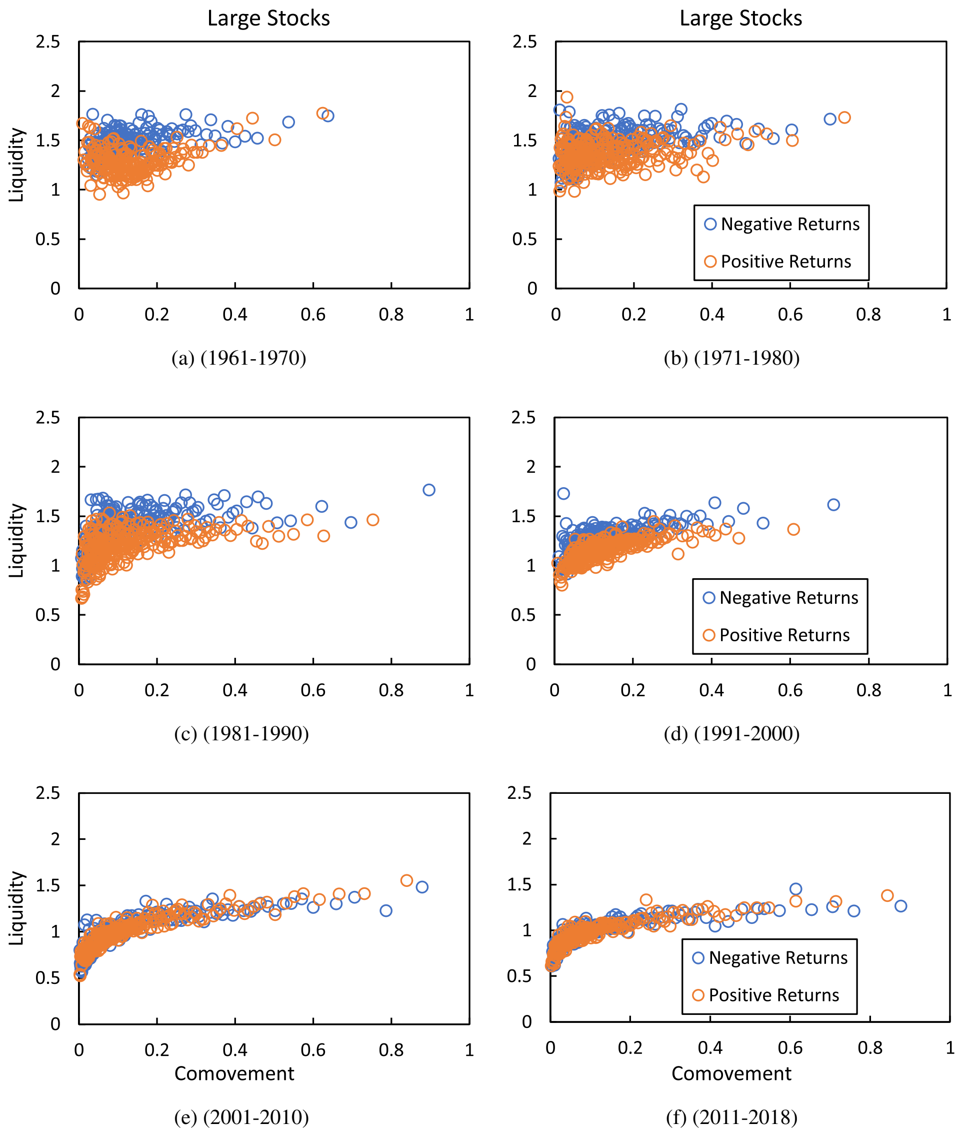
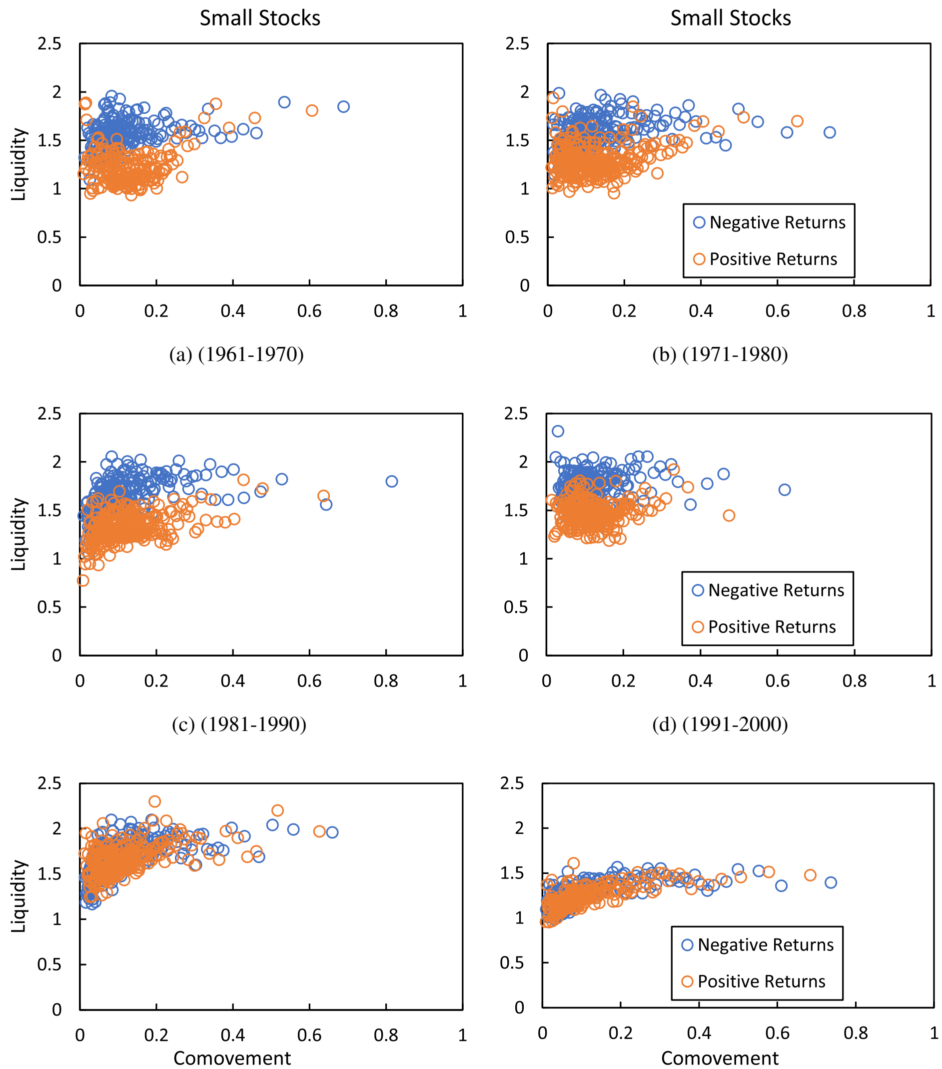


Figure 3A The time-series relationship between liquidity and comovement for large stocks from 1963 to 2018.

The above-mentioned four observations also appear in small stocks as shown in Figures 3B (a–f), however, the overall relationship between liquidity and comovement for small stocks is more scattered and less significant than large stocks, indicating that comovement has a less impact on liquidity for small stocks. Since basket trading is less concentrated in small stocks, the impact of comovement on liquidity is expected to be smaller.

Next, we dive into two representative charts: Figure 3A(a) for a smaller impact of comovement on liquidity and Figure 3A(f) for a larger impact of comovement. Since positive comovements show a similar story, we focus on negative comovements. In Figure 3A(f), it is clear that illiquidity increases at a decreasing rate with comovement — a concave function. The average liquidity for comoved stocks can be fit by Equation (1) very well, which implies the average



(a) (1961-1970) (b) (1971-1980)

(c) (1981-1990) (d) (1991-2000)

(e) (2001-2010) (f) (2011-2018)

Figure 3B The time-series relationship between liquidity and comovement for small stocks from 1963 to 2018.

liquidity is a power-law function of the comovement (subscript-t and residuals are omitted):

$$\bar{L} = e^{\alpha} \cdot C^{\beta} \tag{2}$$

Equation (2) is derived by taking exponential on both sides of Equation (1). The fitted curves for negative returns are shown in Figure 4(A and B) for 1963–1970 and 2011–2018, respectively.[8] The corresponding fitted parameters are listed in Table 1. The exponent (β) of the comovement is 0.06 and 0.13 in 1963–1970 and 2011–2018, respectively. To give an estimate, assuming a comovement from 0.03 to 0.1 and all else the same, the illiquidity during 2011–2018 is increased by about 16.9% ($= \frac{0.1^{0.13} - 0.03^{0.13}}{0.03^{0.13}}$). In contrast, the illiquidity during 1963–1970 is increased by a much lower 7.5% ($= \frac{0.1^{0.06} - 0.03^{0.06}}{0.03^{0.06}}$). In other words, the impact of comovement on liquidity is more than doubled from 1963 to 2018 assuming a comovement from 0.03 to 0.1. In the meantime, the explanatory power of comovement (R^2) during 2011–2018 is

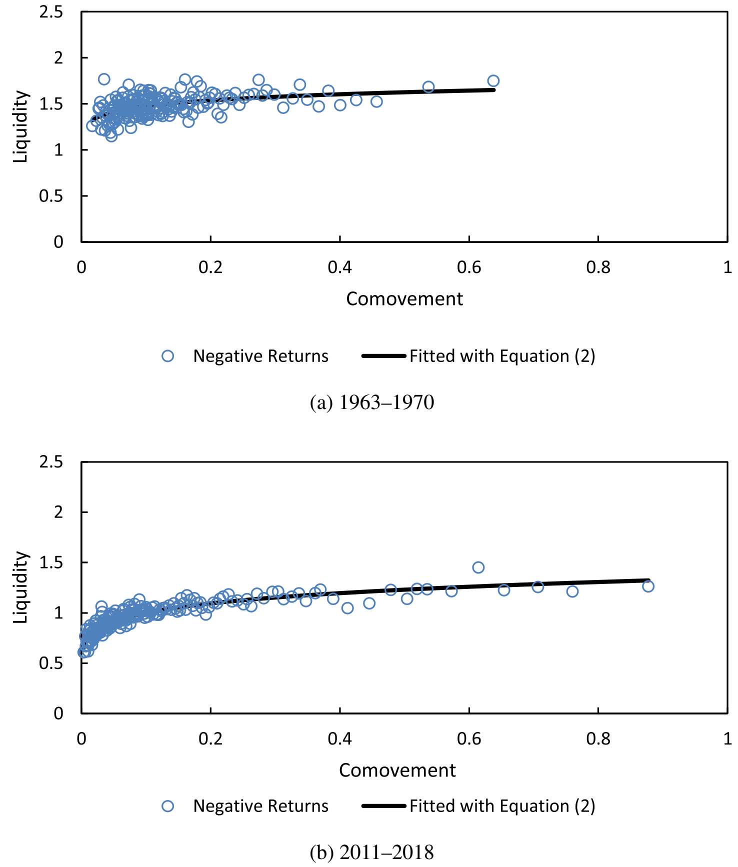


Figure 4 Empirical and fitted relationship between liquidity and comovement for negative returns during (a) 1963–1970, and (b) 2011–2018.

Table 1 The fitted parameters for the liquidity–comovement relationship for negative returns (Equation (2)).[a]

	α	β	R^2
1963–1970	0.53	0.06	25%
2011–2018	0.30	0.13	84%

[a]All α and β values are statistically significant at the 1% level.

84%, much higher than the R^2 of 25% during 1963–1970.[9]

A good fit on Equation (2) is economically meaningful because it allows one to forecast the average liquidity, given the return comovement.

Next, we explain why the mechanical relationship between liquidity and comovement follows the power-law function.

5 Explaining the mechanical liquidity–comovement relationship

Recall that liquidity is the ratio of absolute return divided by volume, thus volume plays a critical role in explaining the liquidity–comovement relationship. Figure 5 shows that the liquidity–comovement relationship is mainly driven by the volume–comovement relationship because the average return of comoved stocks does not vary much with comovement during both time periods (A. 1963–1970 and B. 2011–2018). Smaller

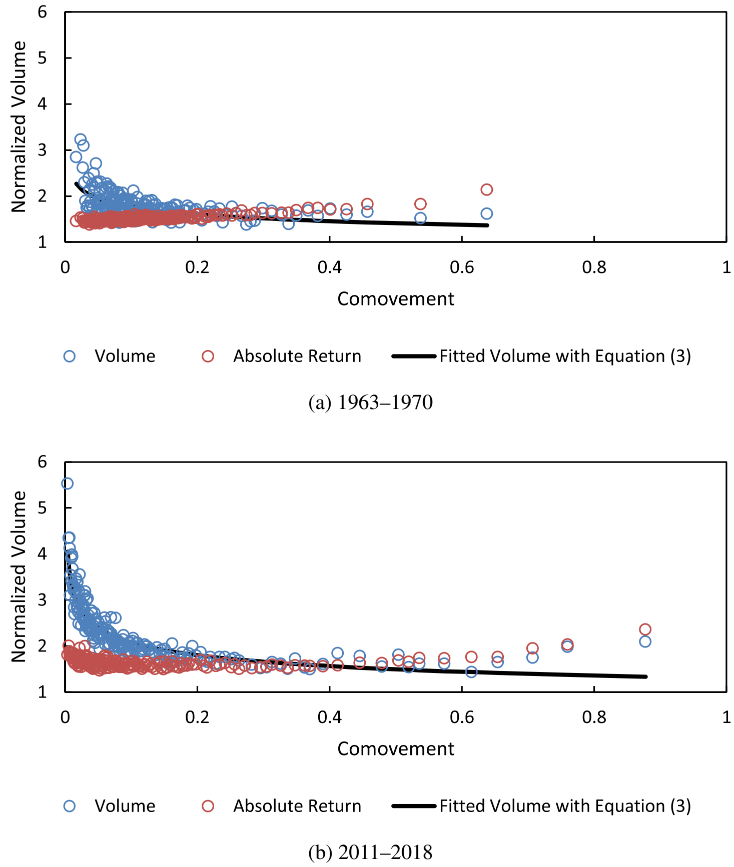


Figure 5 Average volume and average absolute return as a function of comovement for negative returns for (A) 1963-1970, and (B) 2011−2018.

variation in the average return of comoved stocks is not surprising because (1) the threshold for return comovement is −1, and (2) the return distribution quickly decays beyond −1. The volume–comovement relationship can be also fit by the power-law function (fitting parameters are shown in Table 2):

$$\bar{V} = e^{\alpha} \cdot C^{\beta} \tag{3}$$

Where $\bar{V}$ is the average trading volume of comoved stocks. C is the return comovement. Equation (3) is similar to Equation (2) because liquidity is a reciprocal function of volume ($\bar{L} \propto 1/\bar{V}$). Note that β in Equation (3) is negative, and in contrast, β in Equation (2) is positive.

Table 2 shows that βs for the regression of volume are negative (−0.14 for 1963–1970, and −0.20 for 2011–2018), which correspond to positive βs (0.06 for 1963–1970, and 0.13 for 2011–2018) for the regression of liquidity shown in Table 1. The decreased β for volume by 0.06 (from −0.14 to −0.20) is consistent with the increased β for liquidity by 0.07 (from 0.06 to 0.13). The R^2 is 38% and 84% for 1963–1970

Table 2 The fitted parameters for the volume–comovement relationship for negative returns (Equation (3)).[a]

	α	β	R^2
1963–1970	0.25	−0.14	38%
2011–2018	0.26	−0.20	84%

[a]All α and β values are statistically significant at the 1% level.

and 2011–2018, respectively. Overall, the fitting in Figure 5B is good except for a few points at the high comovement end.[10]

Equation (3) and Figure 5B clearly show that during 2011–2018, when comovement is high, average trading volume is relatively thin and thus liquidity is relatively low.

The volume–comovement relationship in Equation (3) can be explained by a liquidity supply model. Consider the following two extreme cases:

(1) If stocks are traded independently and if the supply of liquidity is infinite, the average volume is independent of comovement, i.e. $\bar{V} \propto C^0$ so $\beta = 0$.
(2) If stocks are traded in baskets and if the supply of liquidity is fixed, the total trading volume $(N^* \bar{V})$ is a constant, where N is the number of comoved stocks which is proportional to comovement C, i.e. $\bar{V} \propto C^{-1}$so $\beta = -1$.

β Values from -0.14 to -0.20 shown in Table 2 suggest that the supply of the liquidity for an average stock lies between infinite ($\beta = 0$) and fixed ($\beta = -1$). We argue that, in reality, the supply of liquidity is neither fixed nor infinite, so β should be somewhere between 0 and -1. Moreover, as more and more stocks are traded in baskets, β should move in the direction from 0 to -1 because the supply of liquidity is limited. In other words, the volume—comovement relationship in Equation (3) and Figure 5 can be explained by a realistic supply of liquidity. Since liquidity is reciprocal function of volume, the liquidity supply model can also explain the liquidity—comovement relationship (Equation (2)).

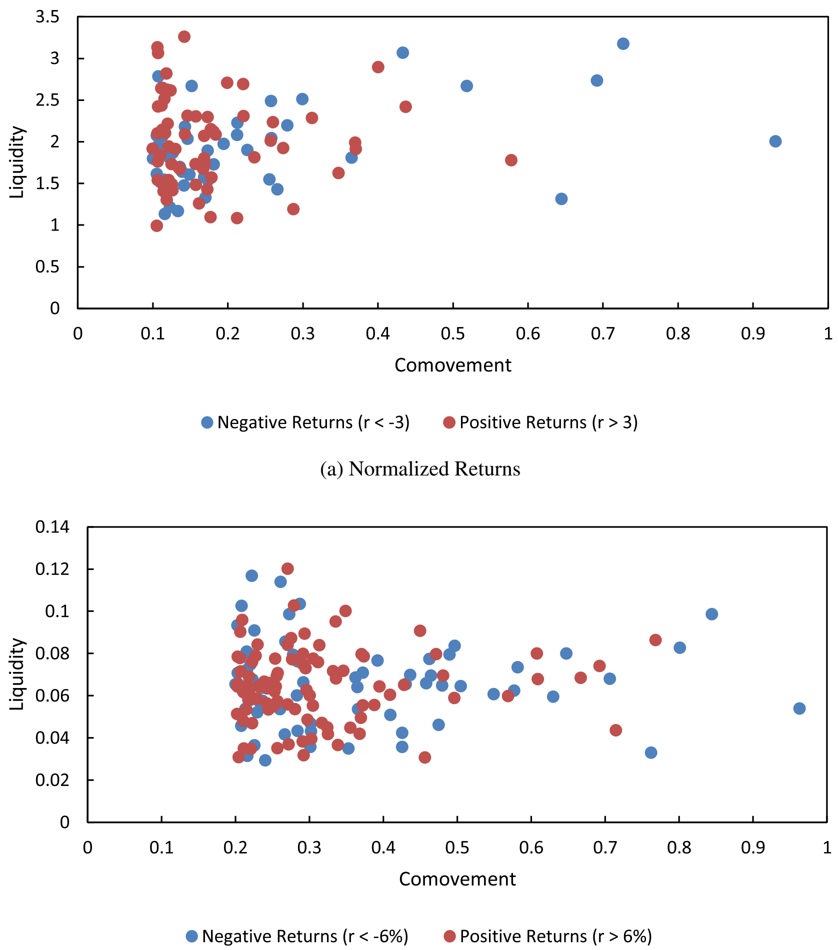
In short, the liquidity level has dramatically increased over the last half-century due to increased trading volume, but in the meantime, the impact of comovement on liquidity has also increased for large stocks as a result of increased basket trading. The impact of comovement on liquidity can be quantified by a power-law function and explained by a liquidity supply model. On the other hand, the impact of comovement on liquidity is similar but smaller for small stocks.

6 Liquidity under three-sigma return comovements

Comovements of large returns are closely related to market crash or crisis (e.g. Black Monday of 1987, and the financial crisis in 2008). Figures 6A and 6B show the average daily liquidity for comovements with extreme negative or positive returns for large stocks (one data point corresponds to one trading day). The threshold of the comovement is chosen as ± 3 for normalized daily returns, and $\pm 6\%$ for raw daily returns, so they are three-sigma comovements.[11]

Figures 6A and 6B plot the average daily liquidity under three-sigma comovements for large stocks from 1963 to 2018 for both normalized and raw returns, respectively. To focus only on meaningfully large comovements, Figure 6A and 6B plot all daily three-sigma comovements that are greater than 0.1 and 0.2, respectively. There are 50% and 76% of the negative three-sigma comovements coming from 2000 to 2018 (34% of the 56-years) for normalized and raw returns, respectively. It indicates an increased negative three-sigma comovements with the increased basket trading, which is consistent with the higher probability of negative one-sigma comovements from 2000 to 2018 shown in Figure 1. Like Figure 1, Figure 6A adopts normalized returns in each year, which isolate the overall market volatility, and thus it provides clearer evidence that increased negative three-sigma comovements are associated with increased basket trading.[12]

In Figure 6A, the daily liquidity varies widely from 1 to 3 for both negative and positive



(a) Normalized Returns

(b) Raw Returns

Figure 6 Liquidity under three-sigma comovement for large stocks from 1963 to 2018 for (A) normalized returns and (B) raw returns.

three-sigma returns, reflecting a large uncertainty in price impact under extreme markets. It is interesting to observe that the average liquidity level is approximately the same for both negative returns (1.92) and positive returns (2.00) under the three-sigma comovements, but the three-sigma comovements for negative returns tend to be larger. For example, Figure 6A shows that five comovements are greater than 0.5 for negative three-sigma returns, but only one comovement is greater than 0.5 for positive three-sigma returns. Figure 6B shows a similar picture to 6A. The largest comovement for negative three-sigma returns in both Figure 6A and 6B is Black Monday on 10/19/1987.

Some empirical researches appear to support the observation that comovement tends to be larger in three-sigma negative returns. For example, Lou (2012) finds that fund managers invest only 62% of capital inflows in their existing holdings, however, they would have to sell 97% of their holdings to pay for redemptions. This flow-induced asymmetric trading suggests that a larger comovement in negative returns is more likely to happen than that in positive returns. In another research, Hameed *et al.* (2010) document that liquidity commonality within an industry increases significantly when the returns on other industries are large and negative, suggesting contagion in illiquidity: illiquidity in one industry spills over to other industries.

In short, the average liquidity level is approximately the same for both negative three-sigma comovements and positive ones, however, negative three-sigma comovements tend to be larger than positive ones. In addition, large negative three-sigma comovements are increased with basket trading.

7 Asymmetric correlation and asymmetric three-sigma comovement

Asymmetric correlation is well-documented in literature. For example, Longin and Solnik (2001) document that international markets (UK, France, Germany, and Japan) have a higher correlation with the US market when prices fall in the US market. Ang and Chen (2002) find strong evidence of an asymmetric correlation between the US market and stock portfolios formed by sorting on size, book-to-market ratio, past returns, and industry. Among individual stocks, Chordia *et al.* (2011) report that pairwise stock correlations are on average higher when market returns are negative.

Higher correlation in downturned markets implies a tendency of a higher comovement for negative returns than positive returns, which suggests a positive relationship between asymmetric comovement and asymmetric correlation. We examine this relationship next.

We first measure the asymmetric pairwise correlation among large stocks. We follow the literature and use raw returns instead of normalized returns in this section. The asymmetric correlation is measured as the difference between the average pairwise correlation when the market return is negative and the average pairwise correlation when the market return is positive. The market return is defined as the equally-weighted returns across large stocks. The asymmetric pairwise correlation is calculated for each year as shown in Figure 7. The average pairwise correlation from 1963 to 2018 is 13.7% when market returns are negative, and 11.1% when market returns are positive. Therefore, the average asymmetric correlation is 2.6% for large stocks.

Similarly, we calculate the asymmetric three-sigma comovement as the difference between

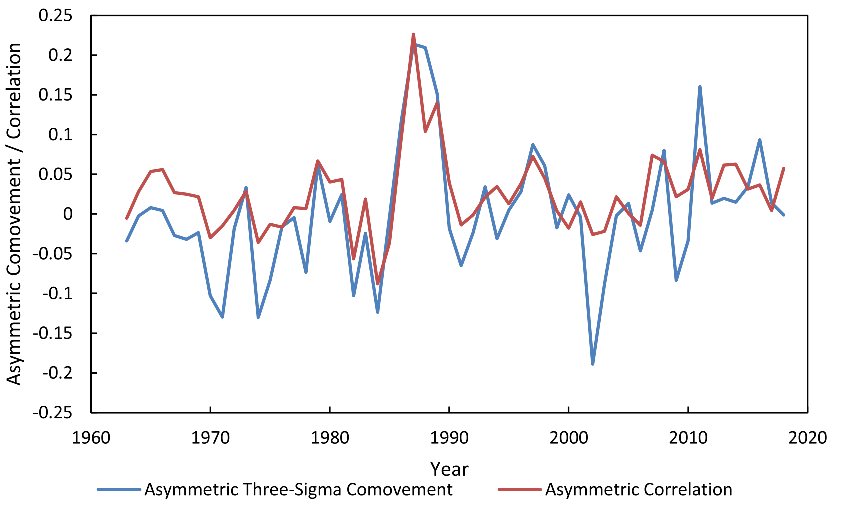


Figure 7 Asymmetric three-sigma comovement and asymmetric correlation for large stocks.

the average of the three largest *negative* three-sigma comovements and the average of the three largest *positive* three-sigma comovements for each year. Figure 7 shows that the correlation between asymmetric three-sigma comovement and asymmetric correlation is 83%. Both asymmetric comovement and asymmetric correlation have a positive but insignificant trend over time. A linear regression of asymmetric correlation on asymmetric comovement suggests that asymmetric three-sigma comovement can explain 68% of the variation in asymmetric correlation. More importantly, in years with stressed markets (e.g., 1973, 1987, 2000, 2008, and 2011), the average of negative three-sigma comovements was greater than the average of positive ones.

8 The disappearance of three asymmetries

Karpoff (1987) reviews previous researches on the relationship between price changes and trading volumes in financial markets. Numerous empirical findings seem to support a positive volume — *absolute return* correlation. However, the relationship between volume and *signed return* is more puzzling. It has been documented that the volume is relatively heavy in positive returns and light in negative returns — we call it asymmetric volume here. An interesting hypothesis, described in Karpoff (1988), is that constraints on short selling raise the costs of trading when stock prices are falling so that volume is lower for negative returns.

Duffee (2001) documents that the positive relationship between the market return and non-market volatility (i.e. asymmetry in non-market volatility) can help explain the asymmetric volume. He argued that the asymmetric volume is driven primarily by greater non-market news arrival, and thus more non-market volatility and volumes, on days when the market rises. He further argued that the source of this asymmetry in non-market volatility is another asymmetry—positive skewness in sector-specific or firm-specific return shocks. Albuquerque (2012) argues that during earnings announcement periods, stocks tend to have high expected returns and high volatility, which causes positive skewness for an average individual stock.

Interestingly, Duffee (2001) observes that the asymmetric volume, along with the asymmetry in non-market volatility, was disappearing in the 1990s. Xiong and Idzorek (2019) observe that the average skewness for individual stocks was declining from positive to negative, which is consistent with the disappearance of the asymmetry in non-market volatility. Therefore three well-documented asymmetries (asymmetric volume, asymmetry in non-market volatility, and positive skewness for individual stocks) have simultaneously disappeared.

In order to shed some light on why the three asymmetries have disappeared, we start by updating the three asymmetries using the same data sample from 1963 to 2018.

First, the test of the asymmetric volume is whether b_1 differs from zero in the following Equation (4):

$$\bar{V}_t = b_0 + b_1 \cdot \bar{R}_t + b_2 \cdot |\bar{R}_t| + e_t \qquad (4)$$

Where $\bar{V}_t$ is the average volume for negatively or positively comoved stocks on day-t, and $\bar{R}_t$ is the average return (negative or positive) for comoved stocks on day-t. e_t is the regression residual on day-t. The regression setting in Equation (4) is similar to Footnote 5 except that the threshold for return comovement is set to zero.

A positive regression coefficient b_1 in Equation (4) indicates that trading volumes are on average higher when returns are positive. Figure 8 shows that b_1 from 1963 to 2018 for both large and small stocks. It shows that the coefficient b_1 for large stocks is largely positive prior to 2000

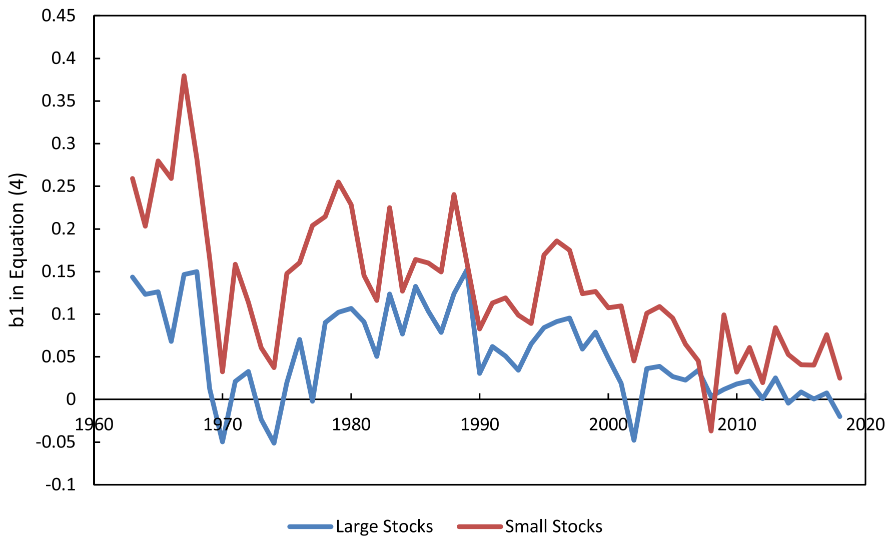


Figure 8 The disappearance of asymmetric volume.

but it is approaching zero afterwards. The corresponding t-statistic for b_1 becomes consistently insignificant at the 5% level after 2000. Therefore Figure 8 confirms the disappearance of the asymmetric volume.

As mentioned earlier in Figure 3A, we have observed that the difference of the liquidity–comovement relationship between negative returns and positive returns is gradually disappearing over time, which is consistent with the disappearance of asymmetric volume because liquidity is a reciprocal function of volume.

Second, similar to Duffee (2001), a simplified test of the disappearance of the asymmetry in non-market volatility is whether b_1 differs from zero in Equation (5):

$$|\bar{\omega}|_t = b_0 + b_1 \cdot R_{M,t} + b_2 \cdot |R_{M,t}| + e_t \quad (5)$$

Where $|\bar{\omega}|_t$ is non-market volatility, i.e. the equally-weighted average of absolute residual return across large or small stocks on day-t.[13] $R_{M,t}$ is the cap-weighted market return (negative or positive) on day-t. e_t is the regression residual on day-t.

A positive regression coefficient b_1 in Equation (5) indicates that non-market volatilities are on average higher when market returns are positive. Figure 9 shows that the b_1 from 1963 to 2018 for both large and small stocks. It shows that the coefficient for both large and small stocks is gradually declining. For large stocks, b_1 becomes negative after 2015, and its corresponding t-statistic is consistently insignificant at the 5% level after 2002, which confirms the disappearance of the asymmetry in non-market volatility.

Third, Figure 10 shows that the average skewness from 1963 to 2018 is declining for both large and small stocks. For large stocks, the average skewness becomes negative after 2015, which is consistent with Figure 1 of Xiong and Idzorek (2019).

All three asymmetries in Figures (8–10) show a statistically significant negative trend over time at the 1% level for both large and small stocks, indicating that the disappearances of the three asymmetries are all associated with increased basket trading although no causality is implied. We argue that the increased basket trading can make the volume–comovement relationship more

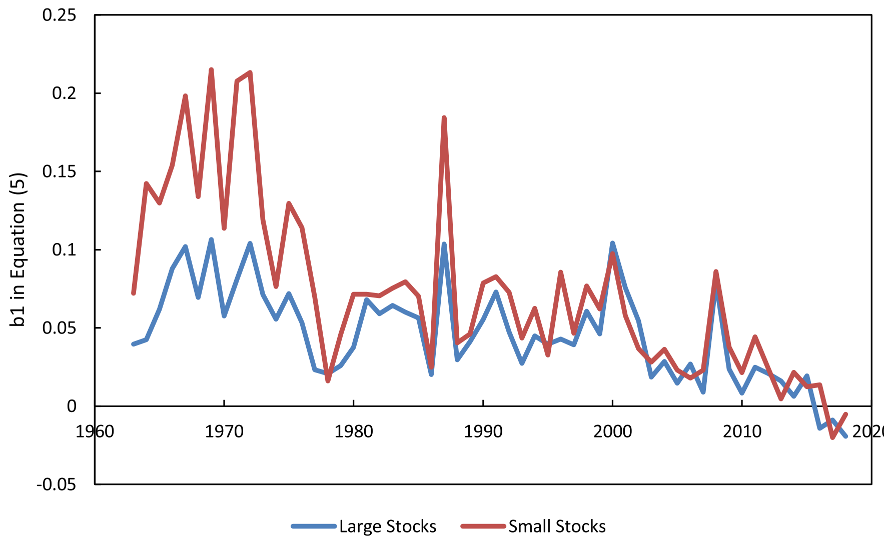


Figure 9 The disappearance of the asymmetry in non-market volatility.

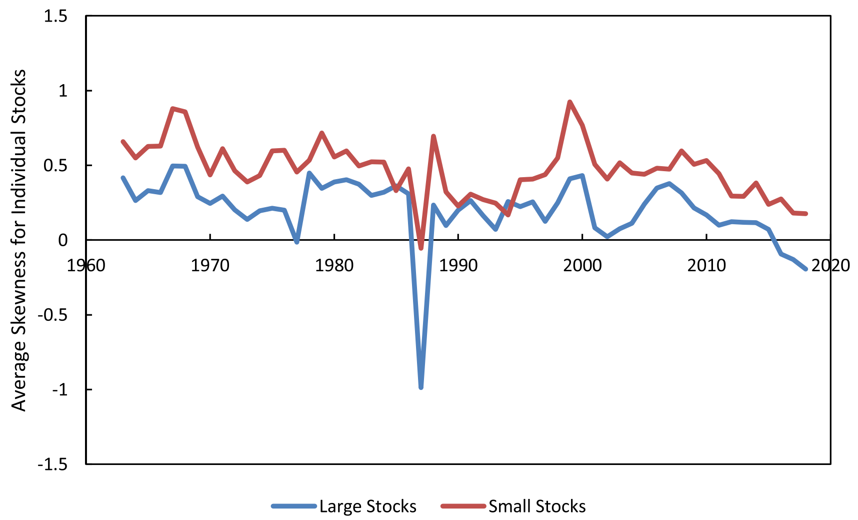


Figure 10 The declining average skewness for individual stocks.

mechanical (Equation (3)) for both negative and positive returns, which can help explain the disappearance of the asymmetric volume. In other words, both buying and selling can face similar liquidity pressure under basket trading. Fund managers (in particular, index fund managers) must simultaneously buy or sell a large number of stocks in the proportion, otherwise the rapid price movements of the stocks would prevent the managers from holding the stocks in correct weights. On the other hand, intuitively, basket trading (in particular, index trading) can reduce the impact of earnings announcement on positive skewness for individual stocks by trading many stocks simultaneously, which can explain the disappearances of positive skewness and asymmetry in non-market volatility.

Another factor that can contribute to the disappearance of asymmetric volume is the increased short selling. Karpoff (1988) argues that the asymmetric volume was not observed in various commodity future contracts, which have no asymmetry in costs for going long versus going short. In fact, short selling has increased significantly in our sample period due to the development of the equity lending market and growth of the hedge fund industry (e.g., Rapach *et al.*, 2016). On the other hand, ETFs can be easily sold short, and short selling activities of ETF products have dramatically increased since 2000 (e.g. Li and Zhu, 2018), which goes hand in hand with increased index trading.

It is interesting to contrast the asymmetric correlation with the three asymmetries. The three asymmetries gradually disappear, but the asymmetric correlation remains stable (Figure 7). The disappearances of the three asymmetries are likely driven by increased basket trading, along with increased short selling. In contrast, the asymmetric correlation still survives because it is mostly driven by a different force: a tendency of larger negative three-sigma comovements than positive ones. Specifically, the average liquidity level is similar for large negative and positive three-sigma comovements, but the number of stocks that suffer large losses tends to be larger than the number of stocks that experience large gains due to a more contagious selling in downturned markets.

9 Conclusions

Institutional investing and index trading have increased significantly over the last half-century. It has meaningful implications for the relationship between liquidity and return comovement. Through appropriately normalized returns and trading volumes, we directly measure this mechanical relationship across stocks over time and report a few interesting findings.

First, return comovement has increased with basket trading. The average probability of having comovement greater than 0.5 is 1.0% during 1963–1970 for one standard deviation loss, and it increases to 4.3% during 2011–2018. It indicates an increased downside comovement risk for investors.

Second, the liquidity level has dramatically increased due to increased trading volume, but in the meantime, the impact of comovement on liquidity has also increased. More importantly, the impact of comovement on liquidity can be quantified by a power-law function and explained by a liquidity supply model. Specifically, assuming a comovement from 0.03 to 0.1 and all else the same, the impact of comovement on liquidity is more than doubled from 1963 to 2018 for large stocks. On the other hand, the impact of comovement on liquidity is smaller for small stocks because basket trading is more concentrated on large stocks.

Third, the average liquidity level is nearly the same under large comovements with negative and positive three-sigma returns, however, negative comovements tend to be larger than positive ones. This asymmetric three-sigma comovement can explain 68% of asymmetric correlation.

Finally, we show that the disappearances of the three well-documented asymmetries (asymmetric volume, asymmetry in non-market volatility, and positive skewness for individual stocks) are associated with increased basket trading and short selling. In contrast, asymmetric correlation still survives, and it is mainly driven by a larger negative three-sigma comovement because selling is more contagious in downturned markets.

Appendix. Normalization of returns and trading volumes

In order to better isolate the comovement from other factors such as individual stock's volatility and overall market volatility, we normalize daily returns for each stock in each calendar year as follows:

$$R_{i,t} = \frac{r_{i,t} - \mu_i}{\sigma_i} \tag{A.1}$$

Where $r_{i,t}$, μ_i, and σ_i are the daily raw return on day (t), mean and standard deviation of returns for stock (i) in a given calendar year, respectively.

Another way to normalize the returns is to replace μ_i in Equation (A.1) with a long-term average daily stock return across all stocks and all years, which is a constant. Conclusions do not change much with this return normalization method.

Trading volumes over the last half-century have increased dramatically due to improved technology, increased competition in the provision of market-making services, and structural changes in the market. The average turnover rate for an individual stock is increased by 30-fold, from 0.03% in 1963 to 1.0% in 2018. Likewise, the average trading volume is increased by 410 times from 1963 to 2018. Therefore, it is critical to normalize the trading volume for our study.

Since trading volume has an infinite standard deviation (see Gabaix *et al.*, 2006), it is normalized as:

$$V_{i,t} = \frac{v_{i,t}}{v_i} \tag{A.2}$$

Where $v_{i,t}$ is raw volume for stock (i) in day (t), and v_i is the median of $v_{i,t}$ in a given calendar year. Gabaix *et al.* (2003) use the average (instead of median) of $v_{i,t}$ to normalize volume, which essentially gives the same results. Another similar normalization method is given in Gabaix *et al.* (2006) in which v_i is the average absolute deviation $v_i = \overline{|v_{i,t} - \overline{v_{i,t}}|}$.

After each stock's volume is normalized based on Equation (A2), the average normalized volume for all stocks (including large and small) varies slightly around its average value of 1.4 over the 56-years. We then scale the normalized volume so that the average normalized volume across large or small stocks is 1.4 in every calendar year. More importantly, we observed that the distribution of volumes has gradually moved away from tails (both low and high) to the middle from 1963 to 2018, which is consistent with increased commonality in trading volumes reported in Sullivan and Xiong (2012).

Notes

1 Index trading is treated as a kind of basket trading in this study.

2 Other thresholds, such as ± 0.5, ± 1.5, ± 2, etc. are tested for robustness. Conclusions do not change much with different thresholds.

3 Return comovement defined in this way is correlated with equally-weighted market returns (correlation of -86% for negative returns and $+87\%$ for positive returns from 1963 to 2018).

4 As a robustness check, we use Amihud's liquidity measure and normalize the dollar volume using Equation (A2), and the conclusions remain unchanged and thus not reported for brevity.

5 In each trading day, we split the stocks into two comoved groups, one with returns less than -1 for negative comovements, and another with returns greater than $+1$ for positive comovements. We compute the average liquidity and comovement for each group, and then combine them in one regression for each year. For example, for a year with 252 trading days, there are 504 pairs of liquidity and comovement data points in each year's regression.

6 In order to clearly show the relationship between liquidity and comovement, we first sort the (average daily liquidity–daily comovement) pairs on comovement and then compute the 10-day average for both liquidity and comovement, separately for negative and positive returns. Each of the 10-day averaged liquidity–comovement pairs corresponds to one data point in Figure 3A(a–f). The number of data points ranges from 199 to 252 in the six charts.

7 Note that the more mechanical relationship after 2000 is not impacted much by the data aggregation and 10-day averaging (Footnote 6), as Figure 2A shows that R^2

(for single-year and non-averaging) is much higher after 2000 for large stocks.

[8] Note that the average illiquidity in 1963–1970 is higher than that in 2011–2018 in Figure 4, and the main reason is that the trading volume distribution is wider in 1963–1970 than that in 2011–2018 (see Appendix). About 25% of the normalized volumes are from 0.1 to 0.75 in 1963–1970, while only 9% of the normalized volumes are from 0.1 to 0.75 in 2011–2018. The average liquidity is dominated by small volumes assuming that returns are equal. The average liquidity is 3 for small volumes (0.1–0.75), so it results in an averaged liquidity difference of $0.16 * 3 = 0.48$, which is pretty close to the average liquidity difference between Figure 4A and 4B.

[9] The R^2s in Table 1 are higher than those in Figure 2A because each data point in Figure 3A is averaged over 10 daily comovements as mentioned in Footnote 6.

[10] When return comovement is high, absolute returns tend to be high. Higher absolute returns are driven by higher volumes. In other words, when absolute returns are included or controlled in Equation (3), higher volumes than calculated volumes by Equation (3) are expected.

[11] The average daily standard deviation for individual large stocks is about 2% for raw returns from 1963 to 2018, so 6% corresponds to a three-sigma event for raw returns.

[12] The negative three-sigma comovements for raw returns in Figure 6B are dominated by the 2008 financial crisis, which accounts for 44% of the negative three-sigma comovements.

[13] The residual return for stock-i is: $\omega_{i,t} = R_{i,t} - \beta_i \cdot R_{M,t}$, where β_i is the beta of stock-i and it is estimated for each year.

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