# LIQUIDITY IMPACT ON SECTOR RETURNS OF STOCK MARKET: EVIDENCE OF CHINA

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**ABSTRACT**
Based on the model of weighted nonparametric estimation, the study aims to investigate liquidity impact on sector returns in Stock Exchanges in China. The two results are empirically shown using the data of financial services, traffic facilities, and nonferrous metals sectors from Shanghai and Shenzhen Stock Exchanges. First, negative relationship between return and liquidity is found and the expected returns of sectors are obviously reduced with liquidity impact. Second, the expected return of finance sector witnesses a weaker liquidity impact than the ones of traffic facilities and nonferrous metal sectors.

**JEL Classification code:**
G 14 – Information and Market Efficiency, Event Studies
G 15 – International Financial Markets
**Keywords:** Liquidity impact, weighted nonparametric estimation, sector returns, negative relationship.

## INTRODUCTION

The liquidity here is generally described as the ability to trade large quantities quickly at low costs with little price impact, although the definition of liquidity varies a lot in researches under different application backgrounds. Large numbers of literatures have investigated how the liquidity impacts on stock returns, since the liquidity in stock market has attracted public attention in

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recent years (Fama and MacBeth, 1973; Chan and Faff, 2003; Ben R. Marshall, 2006; etc.) The relationship between return and liquidity in the large hybrid quote driven markets in US (the NYSE, AMEX and NASDAQ) is well documented (Amihud and Mendelson, 1986; Chen and Kan, 1996; Brennan, Chordia and Subrahmanyam, 1998; Easley et al., 2002; etc.). However, the findings may not be directly applicable to Shanghai and Shenzhen stock markets in China, due to the differences in trading mechanisms.

More specifically, the literatures on liquidity can be split into two parts: the studies of liquidity measures and the researches of liquidity impact on returns.

On one hand, earlier studies of liquidity measures focus exclusively on bid-ask spreads. Aimhud and Mendelson (1986), and Eleswarapu and Reinganum (1993) measured liquidity with bid-ask spreads. Jin and Yang (2002), and Qu and Wu (2002) constructed a spread model with high-frequency data to investigate the microstructure of the stock market in China and a variety of factors that result in liquidity.

Bid-ask spread is a simple measure of liquidity, yet it is non-sensitive to the trading scale and many other aspects. It is an effective liquidity measure for small investors because they are likely to have all their orders filled at the bid or ask price. However, it fails to reflect the impacts that the large orders lay on prices. It is actually an index to measure transaction costs, rather than liquidity.

To remedy the problem, several liquidity measures on trading volume and market depth were developed. The market-depth model, brought forward by Kyle (1985), offers a relatively complete index for measuring liquidity; however, its linear assumption may not conform to the actual relations between price and volume in stock market. Lee, Mucklow, and Ready (1993) pointed out that spread alone was insufficient to measure liquidity, and liquidity must also be indicated by the depth of dealers' interest at the stated bid and ask. Datar et al. (1998) took the turnover as a cornerstone of a newly developed liquidity measure. Based on the study of liquidity measurement indices by Kyle (1985), Back and Pedersen (1998) proposed the concept of market depth indicators. With consideration of the specific situation in Chinese stock market, Jiang (2004) put forward an index to measure the market depth and short-term changes of liquidity by means of the model proposed by Engle and Lange (2001), so as to find the changes of net trading volume when changes in price reached a certain level. The index was validated to be an effective short-term liquidity measure with empirical results.

Trading volume and market depth are all trade-based measures. They indicate what people traded in the past, while are not necessarily effective indications of what will be traded in the future, particularly for small stocks. Moreover, two main disadvantages emerge among the volume-based measures. First, the volume-based measures ignore the changes in prices, which is often the most important factor in measuring the liquidity. Second, the volume itself has some relations with volatility, which hampers the measure of market liquidity.

The liquidity measures are developed with combination of price and volume, such as a price impact model, in order to overcome the inadequacies caused by bid-ask spread measure and volume-based measures. It measures the instant transaction costs, that is, the impacts that trading volume laid on price changing. Taking into account the large transactions and the depth indices of bid-ask spreads, Hegde and McDermott (2003) applied both spread and depth to investigate the effect of revisions to the S&P 500 index on liquidity. With combination of both bid-ask spreads and market depth, Ben R. Marshall (2006) proposed the Weighted Order Value (WOV) method to measure the liquidity.

The studies on liquidity measures show that the liquidity measures are closely related to the microstructure of a market, and no absolutely unequivocal definition of liquidity can be found across various models and empirical studies, as a consequence of different liquidity measures in different studies. Generally, bid-ask spread, trading volume, market depth and the turnover ratio are commonly used in measuring liquidity. An accurate liquidity measure should correctly classify an asset as being more liquid than another if it is more certainly realizable at short notice without loss, however, the liquidity measures listed above may fail to achieve this goal under certain conditions.

On the other hand, the relationship between return and liquidity in stock markets is well documented. Eleswarapu and Reinganum (1993) discovered a positive relationship between return and price spread, however, the relationship only held true in January. With the volume and turnover ratio-based measures of liquidity, Brennan, Chordia, and Subrahmanyam(1998), and Datar, Naik, and Radcliffe (1998) took an empirical test in relations between liquidity and returns based on the three-factor model of Fama and French (1992), and found the existence of the liquidity premium. Brennan, Chordia and Subrahmanyam (1998) also found a negative relationship for both NYSE and NASDAQ stocks, and Datar, Naik and Radcliffe (1998) illustrated that the liquidity effect did not take place in January exclusively, which was inconsistent with Eleswarapu and Reinganum (1993). Brennan and Subramanyam (1996) partitioned the transaction costs into a fixed part and a variable one, and studied relations between spread and expected returns. The empirical results indicated that the expected returns were positively related to the variable costs, and negatively related to the spread. In a related study, Easley et al. (2002) showed that a trade-based measure of information risk is positively related to returns using NYSE data. This information risk measure was shown to be positively correlated with spreads and negatively correlated with turnover, which suggests that it too is a proxy for liquidity. Using Australian Stock Exchange (ASX) data, Marshall and Young (2003) found a negative relationship between returns and turnover ratio indicating a positive liquidity premium. Ben R. Marshall (2006) found liquidity was negatively related to returns with a new WOV liquidity measure.

Compared with major stock exchanges such as the NYSE, Shanghai and Shenzhen stock exchanges present significant differences in price fluctuation and formation mechanism; moreover, Chinese stock markets are completely order-driven and there are no market makers. Since the most of stock markets in the world subject to the order-driven system, the research in order-driven stock markets is of great interest (Ahn, Cai, Hameo, & Ho, 2002). And the research on market liquidity comes across several problems.

First, the problem concerns market liquidity is that how many trading volume are traded when the stock price keeps almost the same. Back and Pedersen (1998) defined the market liquidity by the first-order partial differential coefficient of price relative to trading volume, which reflected the size of trading volume when the market price changes by a unit. They presented a brief and clear measure on the market liquidity. However, its computability challenges its application because it needs a derivable function of price relative to trading volume as the basis of computation.

Second, most of researches on market liquidity put their emphasis on how to estimate the market liquidity itself overall stock returns, while few on the liquidity impacts on the sector stock returns, which may be sensible to the investment of the fund companies.

The study aims to obtain the liquidity in the study of Back and Pedersen (1998) with nonparametric method, which is defined as the partial differential coefficient of price relative to trading volume. And the nonparametric measured liquidity is applied to explore how the liquidity impacts on sector stock returns in Chinese stock market.

The paper is outlined as follows. In Sect. II, after a brief description of the original data, the liquidity weighted kernel density estimation is presented. In Sect. III, the empirical results of nonparametric regression and weighted kernel density estimator are illustrated. Section IV briefly summarizes and concludes.

## I. DATA AND METHODOLOGY

Data of daily trading volumes and closing prices are employed in this study from http://www.stockstar.com/. Because finance, traffic facilities and nonferrous metal sectors are hot in Chinese stock markets, the study selects these sectors. The data covers 143 trading days from February 1 to September 22 in 2007 because the stock market presents an astonishing prosperous vision since the Spring Festival 2007.

## A. Liquidity Measure Model

Back and Pedersen (1998) proposed the concept of market depth on the basis of Kyle's liquidity measure (1985), and the definition of market depth index is the first partial derivative of price with respect to the amount of the trading volume. The specific form is given as follows:

$$\lambda(t, y) = \frac{\partial}{\partial y} p(t, y) \tag{2-1}$$

where, when trading volume is $y$ at time $t$, $p(t, y)$ implies the market price, which is a differentiable function for $t, y$, and $\lambda(t, y)$ indicates the market depth.

The economic implications of the index are very clear, however, it demands the price function is differentiable for any $t$ and $y$. It is difficult to express the differentiable function of price relative to trading volume, which is the key issue to realize equation (2-1). Generally, the differential equation is applied to solve the price function relative to trading volume. However, the stock price is the result of combined action of various dynamic factors in a complicated system, the precise expression of the price function relative to trading volume is hard to get. Many strict conditions are required on the price function: its property of Brown Movement, the error item subjected to normal distribution (Back and Pedersen, 1998), and so on. Unfortunately, the assumptions can hardly be satisfied commonly in the actual stock market, it explains why the market liquidity index by Back and Pedersen (1998) is hard to be applied in the actual stock market.

In the following section, the study first obtains the liquidity of sector stocks with the nonparametric regression (Nadaraya, 1964; Watson, 1964) estimation method, and then applies the liquidity to reveal how it impacts the sector stock return with liquidity-weighted kernel density estimation in Chinese stock market. The liquidity is found to be an important determinant of returns.

Since the kernel estimated function is continuous and differentiable, the study with nonparametric kernel regression model successfully settles the computability issue of market depth index, and finally gets the derivable function of price relative to trading volume.

The nonparametric kernel regression is used to express the theoretical closing price $p(t)$ and the theoretical trading volume $q(t)$, which are given as:

$$p(t) = \sum_{i=1}^{n} \frac{K\left((i-t)/h_n\right)}{\sum_{j=1}^{n} K\left((j-t)/h_n\right)} p \tag{2-2}$$

$$q(t) = \sum_{i=1}^{n} \frac{K\left((i-t)/h_n\right)}{\sum_{j=1}^{n} K\left((j-t)/h_n\right)} q_i \tag{2-3}$$

where $K(x) = (2\pi)^{-1/2} \exp\left(-x^2/2\right)$ is kernel function and the bandwidth is selected by Silverman's rule ( Silverman, 1986), which leads to the minimization of $MISE = E\int(\hat{f}(x)^2 - f(x))^2 dx$. That is, $h = 1.06\min\{\hat{\sigma}, R\}n^{-1/5}$, where $\hat{\sigma}$ is the standard deviation of the sample, $n$ is the sample size, $R = X_{[0.75n]} - X_{[0.25n]}$. Also, the $h_n$ in equations (2-2) to (2-7) is given by $cn^{-1/5}$, where $c$ is independent of $n$ and is related to the regression function.

Since equations of stock price and trading volume are continuous functions with respect to the trading day, equation (2-1) can be rewritten as:

$$\lambda(t.q) = \frac{dp(t)}{dq(t)} = \frac{dp}{dt}.\frac{dt}{dq} = \frac{dp}{dt} / \frac{dq}{dt} = \frac{p'(t)}{q'(t)} \quad (2\text{-}4)$$

Differentiate $p(t)$ and $q(t)$ with respect to $t$, and get:

$$p'(t) = \sum_{i-1}^{n} \frac{\exp\left(-\frac{1}{2}\left(\frac{i-t}{h_n}\right)^2\right) \cdot \left[\frac{i-t}{h_n^2} \cdot \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) - \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) \cdot \frac{j-t}{h_n^2}\right]}{\left[\sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right)\right]^2} p_i \quad (2\text{-}5)$$

$$q'(t) = \sum_{i-1}^{n} \frac{\exp\left(-\frac{1}{2}\left(\frac{i-t}{h_n}\right)^2\right) \cdot \left[\frac{i-t}{h_n^2} \cdot \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) - \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) \cdot \frac{j-t}{h_n^2}\right]}{\left[\sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right)\right]^2} q_i \quad (2\text{-}6)$$

In other words, the liquidity in equation (2-1) can be measured by equation

$$\lambda(t) = \frac{\sum_{i-1}^{n} \exp\left(-\frac{1}{2}\left(\frac{i-t}{h_n}\right)^2\right) \cdot \left[\frac{i-t}{h_n^2} \cdot \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) - \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) \cdot \frac{j-t}{h_n^2}\right] p_i}{\sum_{i-1}^{n} \exp\left(-\frac{1}{2}\left(\frac{i-t}{h_n}\right)^2\right) \cdot \left[\frac{i-t}{h_n^2} \cdot \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) - \sum_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{j-t}{h_n}\right)^2\right) \cdot \frac{j-t}{h_n^2}\right] q_i} \quad (2\text{-}7)$$

**B. Liquidity Impact on Sector Returns Model**

Given $x_1, x_2, \cdots x_n$ the daily returns of finance, traffic facilities and nonferrous metal sectors, the study defines the standard kernel density estimation of sector return as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - x_i}{h}) \tag{2-8}$$

where $K(\cdot)$ is a kernel function, which is usually a symmetrical probability density function, $h$ is bandwidth, which controls the trade-off between bias and variance of the estimator.

Model (2-8) investigates the daily sector returns with standard kernel density estimation, yet it does not take the liquidity into consideration and assumes each observation makes the same contribution (1/n) to sector return. Since existing literatures have validated that liquidity inevitably impacts on the stock return, the neglect of liquidity impact on sector return is unreasonable. In order to overcome such misleading deviations, enlightened by the population-weighted idea by Francisco (2003), the study puts forward the liquidity weighted kernel density estimation to measure the liquidity impact on sector returns.

The study standardizes the liquidities of each observation with their absolute values to illustrate their respective significance. $\omega_1, \omega_2, \cdots \omega_n$, satisfying $\sum_{i=1}^{n} \omega_i = 1$, are the respective standardized weights of observations $x_1, x_2, \cdots x_n$, respectively.

Replace the equal weight $1/n$ by $\omega_i, i = 1, \cdots, n$, the kernel density weighted estimation with liquidity is given:

$$\hat{f}_{\varpi}(x) = \frac{1}{h}\sum_{i=1}^{n} \omega_i K(\frac{x - x_i}{h}) \tag{2-9}$$

where the bandwidth $h$ and kernel function $K(\cdot)$ are same to the ones in (2-8).

Model (2-9) involves different information of each observation. The contribution to overall density function of sector return on the $i$ th day is $\omega_i / h$, and the change of $\omega_i$ reflects the difference which the liquidity in each trading day contributes to the whole sector return. Model (2-9) is taken as the liquidity weighted kernel density estimation.

Since the choice of kernel function and selection of bandwidth are the premise of nonparametric estimation, the study obtains them as follows. The Gauss kernel function $K(u) = (2\pi)^{-1/2} \exp(-u^2 / 2)$ is chosen to estimate $p(t)$, $q(t)$,

$\hat{f}(x)$ and $\hat{f}_\omega(x)$ and the bandwidth $h$ is selected by Silverman's rule (Silverman 1986), The calculation of both selection of bandwidth $h_n$, and the estimation of $\lambda(t)$, $\hat{f}(x)$ and $\hat{f}_\omega(x)$ are implemented in Matlab 7.0.

## II. EMPIRICAL RESULTS

This section is spent to illustrate how the liquidity impacts on the sector returns with standard kernel density estimation and liquidity weighted kernel density estimation. Figures 1 and 2 present the estimations of sector returns with models (2-8) and (2-9), respectively.

**Figure 1. Standard kernel density estimation of return in each sector**

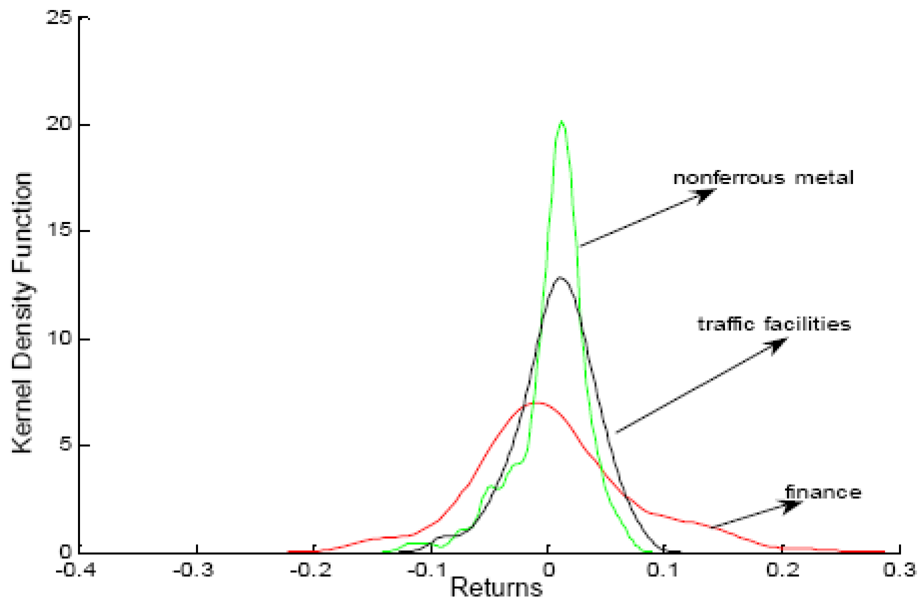



Figure 1 presents the standard kernel density estimations of returns for finance, traffic facilities and nonferrous metal sectors. The expected returns of these sectors are 0.0048, 0.0043 and 0.0084, respectively. The expected return of the nonferrous metal sector is nearly twice as much as the ones of both the finance and traffic facilities sectors. It is easily to notice that the expect returns of the traffic facilities sector and finance sectors are nearly equal, while the latter sector exhibits fat tails, which means return in the finance sector involves higher risk.

Figure 2 gives the weighted kernel density estimations of returns for each sector. Taking the liquidity impacts on sector returns into account, the expected returns are reduced to -0.0061, -0.0068 and -0.0261, with relative decrease by 227%, 258% and 411% for the finance, traffic facilities and nonferrous metal sectors, respectively. On one hand, the non-ferrous metal sector experiences the biggest change, which reflects the liquidity impact on this sector is the strongest among the three sectors within the studied period. On the other hand, the expected return of the finance sector experiences the least change, which may due to the large stock market value in this sector and hence liquidity plays little role on it. Moreover, because of the liquidity impact, two peaks of the estimations for the traffic facilities and nonferrous metal sectors are identified.

**Figure 2. Liquidity weighted kernel density estimation of return in each sector**

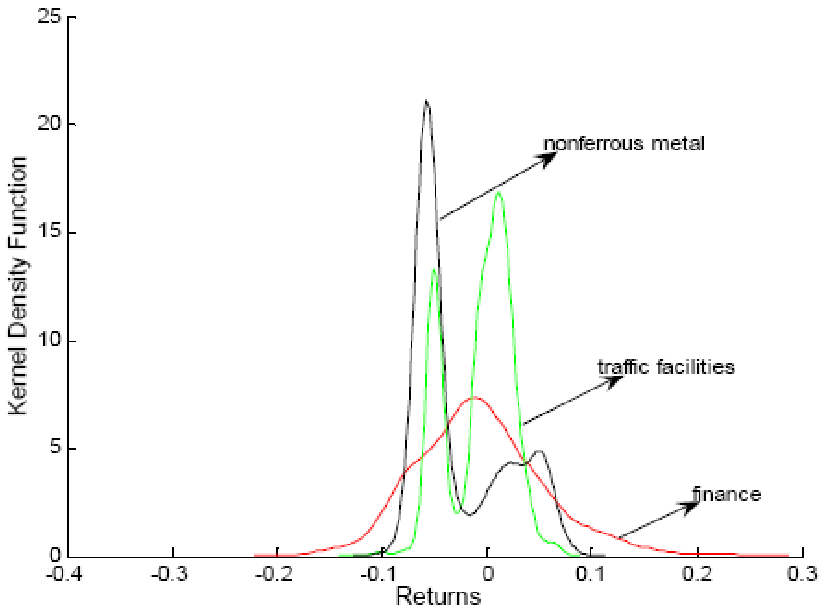


**Figure 3. Standard and liquidity weighted estimations of return for finance sector**

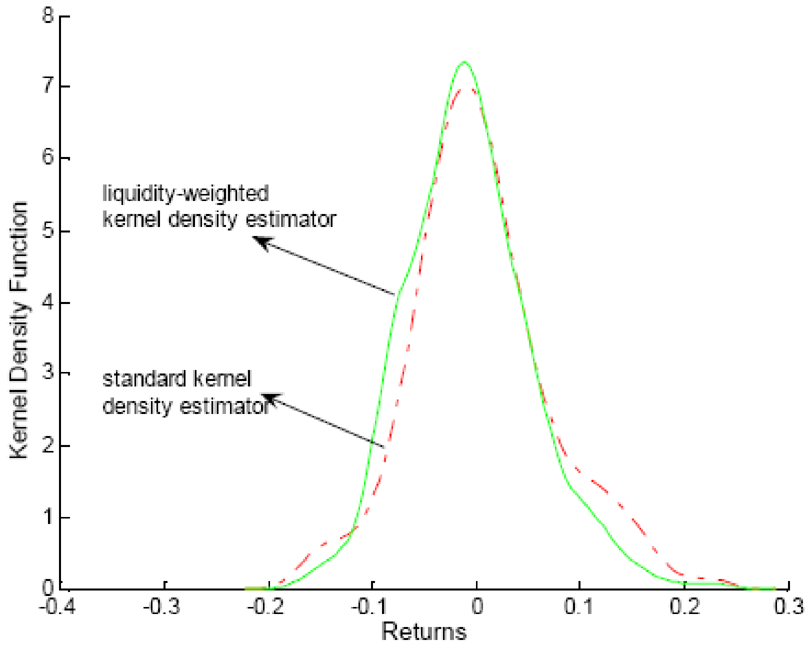



**Figure 4. Standard and liquidity weighted estimations of return for traffic facilities sector**

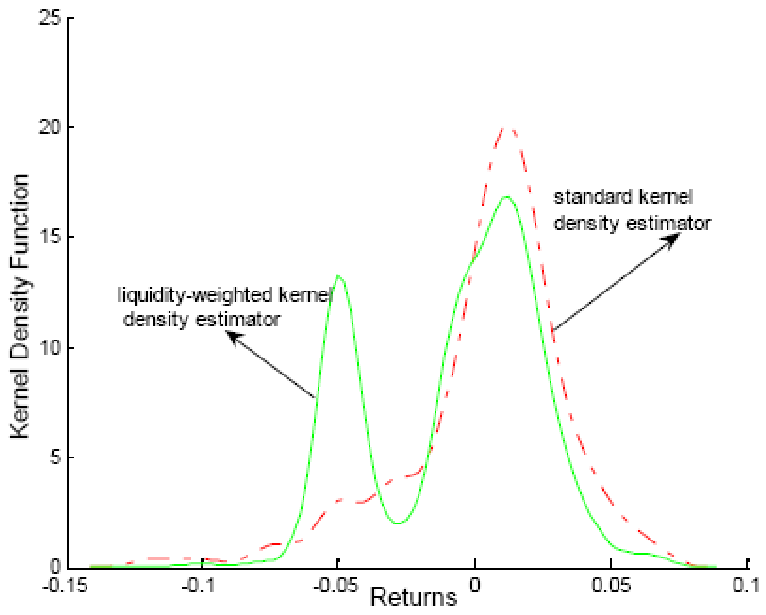
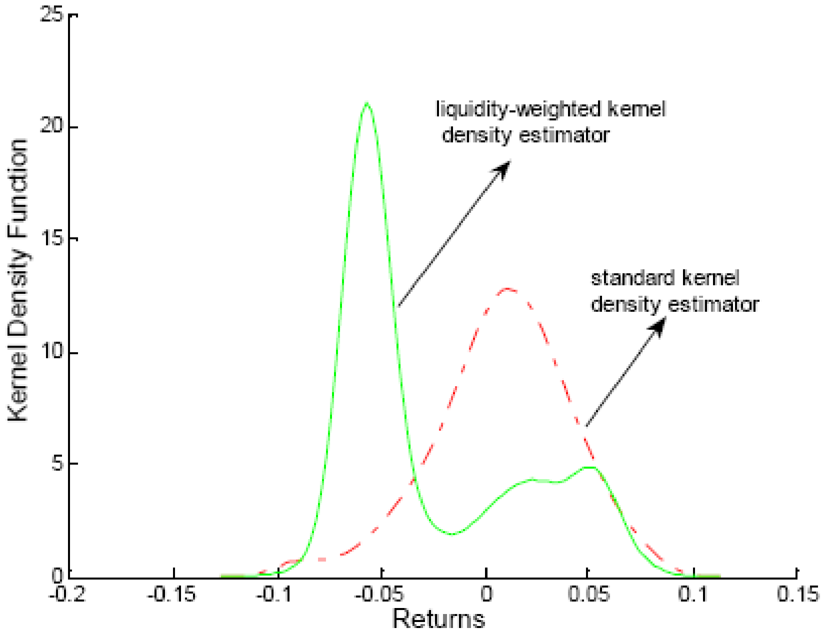


**Figure 5. Standard and liquidity weighted estimations of return for nonferrous metal sector**




In addition to the comparison of standard estimations and the liquidity weighted estimations among three sectors in Figures 1-2, Figures 3-5 give the respective comparison of standard and liquidity weighted estimations of returns for each sector, which focus on the liquidity impacts on sector returns at the entire sample interval.

Several findings are obtained by Figures 3-5. First, the distribution shapes of liquidity weighted estimation of return for each sector locate at the left of the ones of standard estimation, which indicates that the liquidity impact reduces the expected returns in each sector. Second, the distribution shape of the standard kernel density estimations possess fat tail while the liquidity weighted kernel density estimations do not, which illustrate the extreme returns for the sectors are reduced with the liquidity impact. Third, the liquidity impacts on the returns for the traffic facilities and nonferrous metal sectors are more obvious than the one for the finance sector. In detail, little changes are observed of the liquidity weighted estimation of return for the finance sector, which may be explained that the liquidity impact is relatively minor on the large market values in the finance sector; however, two peaks are presented in the liquidity weighted kernel density distributions of returns for both the traffic facilities and nonferrous metal sectors, illustrating these sectors suffer from stronger impacts of liquidity.

Furthermore, the study tests the difference of liquidity impacts among different return intervals and leads to the following results. The return of the finance sector exhibits two extreme cases with the liquidity impact. 1. The return ratio more than 10%, ranging from 0.1019 to 0.0559, is decreased by 45.1%. 2. The return ratio less than -12%, ranging from 0.0345 to 0.0215, is decreased by 37.7%. Both cases indicate the liquidity impact decreases the revenues in extreme cases and reduces the return volatility. The return of the traffic facilities sector with the liquidity impact witnesses the positive return shifts from the original 67% to present 52%; a peak emerges out when the return reaches about -0.05; however, the return at interval [-0.07, -0.035] increases from 8% to 25.5%. The return of the non-ferrous metal sector with liquidity impact reflects that the liquidity impact reduces the positive return obviously. Because the positive returns change from the original 80% to present 30%; a peak emerges out when the return reaches -0.05, yet the return in [-0.0881, -0.0333] increases from 10% to 62%.

## III. CONCLUSION

Shanghai and Shenzhen stock exchanges present significant differences in price fluctuation and the formation mechanism with the major stock exchanges such as the NYSE; moreover, Chinese stock markets are completely order-driven and there are no market makers. Based on the liquidity measure of Back and Pedersen (1998), the study brings forward a liquidity weighted kernel density estimation to investigate how liquidity impacts on the returns with sector data in Shanghai and Shenzhen Stock Exchanges.

Two innovations are embodied in the study. First, the liquidity is estimated by nonparametric regression (Nadaraya, 1964; Watson, 1964) model, which solves the computability issue in the model given by Back and Pedersen (1998) and can be taken as a better liquidity measure in stock market. Second, the study emphasizes particularly on the liquidity impact on sector returns rather than overall stock returns with the liquidity weighted model, which may be sensible to the investment of fund companies.

Using the data of financial services, traffic facilities, and nonferrous metals sectors from Shanghai Stock Exchange and Shenzhen Stock Exchange, two results are empirically obtained.

First, the liquidity impact reduces the expected returns for each sector and there is a negative relationship between return and liquidity. The expected returns of standard kernel density estimations for the finance, traffic facilities and nonferrous metal sectors are 0.0048, 0.0043 and 0.0084, respectively. With consideration of liquidity impact, expected returns are reduced to -0.0061, -0.0068 and -0.0261, with relative decrease by 227%, 258%

and 411%, respectively. Moreover, the extreme values of sector returns are reduced with consideration of liquidity impact; the distribution shapes of liquidity weighted estimation of return for each sector are located at the left of the ones of standard estimation. The facts conform to the ideas that investors had better hold less liquid stocks so as to gain higher returns.

Second, the expected return of the finance sector witnesses a weaker liquidity impact than the ones of the traffic facilities and nonferrous metal sectors. In detail, little changes are observed of the liquidity weighted estimation of return for the finance sector, which may be explained by the large stock market value in this sector; however, two peaks are exhibited of the liquidity weighted kernel density distributions of returns for both the traffic facilities and nonferrous metal sectors, illustrating the sectors experience stronger impacts of liquidity.

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