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The Impact of the Shanghai-Hong-Kong Stock Connect Program on the Liquidity of Shanghai A-Shares

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Summary

Master Thesis submitted with the view of getting the degrees of:

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The Impact of the Shanghai-Hong-Kong Stock Connect Program on the Liquidity of Shanghai A-Shares

Market liquidity has a central role in many areas of finance and has been studied in depth, both in order to identify its sources and to find out its impacts. The first aspect generally touches the area of market microstructure.

In this paper, we broadly review the existing literature related to the microstructure approach to liquidity and discuss various ways to measure it. We also detail the impact of the Shanghai-Hong Kong Stock Connect Program (here-after denominated the Program) on the liquidity of A-shares traded in the Shanghai Stock Exchange (SSE). The Program allows Hong Kong investors to trade Shanghai A-shares directly through their broker in Hong Kong – and reversely from Hong Kong to Shanghai which constitutes a new step in the opening of Chinese stock markets to foreign investors.

We then test the impact of the program in term of intraday patterns of liquidity measured as bid-ask spread, depth and trading volume using graphical exploration and linear regressions on 104 A-shares during two periods of 20 days using intraday minute-by-minute data.

The key findings show that liquidity is slightly better for stocks included in the program. In addition, we observe L-shaped patterns of spread for both the stocks included in the program, and those not included in it. Regarding depth, we find out different results for stocks in- and out-the Stock Connect Program. Depth of stocks part of it follows an inverted L-shaped pattern while depth of stocks out of the program follows a U-shaped pattern. In addition, trading volume of all stocks follows a U-shaped pattern. All the patterns mentioned are explained by the market microstructure theory (order handling, inventory management and asymmetric information costs).

Finally, we conclude that stocks included in the program exhibit better market liquidity and different trading behavior without being able to affirm that the program can solely explain those differences.

Key words: market liquidity; market microstructure; liquidity proxies; intraday patterns of liquidity; bid-ask spread; depth; trading volume; Shanghai-Hong Kong Stock Connect Program

Table of Contents

List of Figures

List of Tables

Chapter 1 – Introduction

Context

It is commonly accepted that market participants around the world are known to be worried about three factors when making transactions: the return, the risk and the ease with which they will sell or buy the asset. This third factor refers to market liquidity. Though this last topic has received much less attention in traditional financial classes than return and risk, its study still goes back to more than eighty years (Keynes already mentioned it in 1935). However, despite its central role in many areas of finance and the substantial literature around it, no strict definition emerges. Thereby, O'Hara (1995) drew on an analogy with pornography: "it is hard to define but you know it when see it". Nevertheless, this ambiguity around its definition does not prevent authors, regulators and market participants as a whole to agree on its importance in the operation of the market. Thus, research on the relation between market liquidity and asset pricing is numerous, and a large part of it covers volatility as well. Additionally, extensive literature takes care of the sources of liquidity. This discussion generally touches to the realm of market microstructure. This is the view we are going to explore here as it is of great importance for traders or regulators. Whether studied for its consequence or its sources, the conclusion remains the same; market liquidity is a key in capital markets, therefore, we need to understand it properly.

In addition to market liquidity, this thesis looks into a recent development in the stock exchanges ecosystem worldwide; the "Shanghai-Hong Kong Stock Connect Program". This program officially launched on November 17, 2014 - together by the Hong Kong Exchanges and Clearing, the Shanghai Stock Exchange (SSE) and ChinaClear - is an innovative mutual market access scheme that represents a historic development for Chinese capital market (BNP Paribas, 2014). Indeed, so far, China has only given limited access to its capital markets to foreign investors. The possibility to trade Chinese Stocks existed but was restricted, especially to access directly A-shares traded inside the mainland. At the same time, this market represents one of the biggest traded volume and value since a few years; Shanghai Stock Exchange was the seventh biggest capital market by volume in 2013 before the launch of the program. The program now allows all oversea investors – individuals or institutional – to gain access to the Shanghai Stock Exchange through a broker in Hong Kong, which constitutes a substantial step forward in the liberalization of China capital markets[1] and new opportunities of investment for foreign investors. Therefore, the importance of the program covers multiple areas. From the regulators' point of view, it is crucial to understand the impact of such an innovative program. As far as investors are concerned, it is crucial to determine which opportunities this new access to Chinese stocks offers. Finally, no one can ignore the impact of China on the global economy, which makes its new opening even more significant.

Purpose of the Paper

The goal of this thesis is to capture the impact of the Shanghai-Honk Kong Stock Connect Program on market liquidity. Indeed, one of the purposes the program is to improve the liquidity of the Shanghai A-shares. A first motivation is thus to verify whether or not the program reaches its goal. More generally, it is highly interesting to understand what impact a mutual program can have on stock exchanges in particular in term of liquidity, both for regulators and market participants.

In this paper, we have based our analysis on intraday minute-by-minute data (extracted form Bloomberg database). Based on those, we have been able to study the evolution of liquidity during the day. Basically, we have built two samples of A-Shares traded in Shanghai: one sample of 52 stocks included in the Shanghai-Honk Kong Stock Connect Program, and one sample of 52 stocks not part of the program. For each sample, we have computed liquidity measures[2], have then compared the two samples and analyzed the intra- and inter day patterns highlighted.

Research Questions and Hypotheses

We have formulated three sub-questions in order to analyze the impact of the program on liquidity of Shanghai A-shares. The first one focuses on liquidity proxies such as bid-ask spread, depth or turnover. It is formulated as follows:

"Are liquidity proxies of stocks included in the program different from the ones of stocks that are not part of the program?"

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[1] And in particular, an important increase of the use of the RMB - the Chinese currency.
[2] Such as bid-ask spread, depth, turnover, trading volume, etc.

To answer this first question, we have computed the different measures over the studied periods[3] and compared the values for stocks included in the program – called in-the-program sample – and stocks not part of it – called out-the-program sample. Therefore, based on the previous statements above, we have formulated the following hypothesis:

(i) Liquidity proxies of "in-the-program" stocks are better than the ones of "out-the-program" stocks.

Afterwards, we have focused on intraday pattern of liquidity proxies. This subject relates closely to market microstructure and has been studied in several occurrences of the literature. Among others, Guo and Tian (2005) have demonstrated the existence of significant intra- and inter day pattern of bid-ask spread and depth during the course of the day in the SSE. More specifically, they have showed that bid-ask spread and depth follow a L-shaped pattern over the day. Such intraday patterns have been observed on other stock exchanges – for example the Tunisian Stock Exchange (Tissaoui, 2012) or the Istanbul Stock Exchange (Köksal, 2012) – and can be explained by inventory cost, adverse selection problem and order processing costs that we describe more in depth in our literature review[4]. Therefore, still in accordance with the initial goal of this thesis, our second sub-question is formulated as follows:

"*Are liquidity patterns of stocks included in the program different from the ones of stocks that are not part of the program?"*

The existing literature on the subject lets us think that liquidity pattern of both in- and out-the-program samples should follow traditional patterns and leads us to propose the following hypothesis:

(ii) Stocks in-the-program and out-the-program both exhibit liquidity intraday patterns consistent with previous researches (L-shaped spread, U-shaped volume Etc.).

Practically, we have verified this hypothesis with graphical exploration mostly. In a few words, we have created the average intraday patterns of spread, depth and trading volume over each period using Excel[5] and compared them.

[3] We used two periods of 20 days, selected according to the values and the volatility of the market returns – one period of "normal return/volatility" and one period of "abnormal" return/volatility.

[4] And what constitutes basically the basement of market microstructure theory.

[5] In other words, we have determined the average value of spread and depth for each minute of the day and drew the curve of their evolution over the day.

Ultimately, we have looked for the determinants of the liquidity patterns observed still following the methodology proposed among others by Guo and Tian (2005). This leads to our last sub-question:

"*What are the determinants of intraday liquidity patterns?*".

The literature usually suggests that liquidity measured by spread or depth can be explained by three determinants: the stock price, the level of risk and the trading activity. Therefore, based on previous works, we have determined the following three hypotheses:

(iii) *There is an inverse relationship between stock price and spread;*

(iv) *There is a positive relationship between return volatility (level of risk) and spread;*

(v) *There is an inverse relationship between trading activity and spread.*

Again, those relationships can be explained by market microstructure theory. In practice, we have verified those hypotheses via linear regression using the SPSS software. In addition, we have used our model to verify the statistical robustness of the patterns exhibited before by including dummy variables to test the significance of the time-of-the-day effect[6]. Finally, we have included a dummy variable in our model to test if the inclusion in the program is indeed a source of better liquidity. In other words, we have verified the following last hypothesis:

(vi) *The Stock Connect Program has a positive impact on liquidity measures by spread and depth.*

Thus, we have finally reached a linear model of the form:

$$Log(Spread_{i,t}) = \beta_0 + \beta_1 \log(Price_{i,t}) + \beta_2 \log(Volatility_{i,t}) + \beta_3 \log(Trading\ volume_{i,t}) + \sum_{h=1}^{3} \delta_h Market\ Cap_i + \sum_{j=1}^{4} \alpha_j Day_{i,t} + \sum_{k=1}^{23} \gamma_k Time_{i,t} + \beta_4 Dummy\ Program_i + \varepsilon_{i,t}$$

Structure of the Thesis

The paper is organized as follows:

Chapter 2: We will begin by reviewing the literature related to market liquidity. There are three sections in this chapter, each of them answering one of the following questions: *What is liquidity? What are the sources of liquidity?* And*, how to measure it?* In doing so, we will review the different definitions of market liquidity and extract from the literature the

[6] As well as the day-of-the-week effect and the market capitalization effect, although these parameters do not constitute a significant source of interest for the purpose of this paper.

attributes which are most commonly linked to the liquidity concept. Next, we will elaborate on the importance of market liquidity and its relation with various areas of finance. In the second section, we will develop the microstructure view of liquidity to understand its sources. We will analyze both dealer and order-driven markets using a unified model. Finally, we will propose a panel of liquidity measures in the third section.

Chapter 3: The third chapter of this thesis is dedicated to the description of the Chinese financial markets. To understand it accurately, we will begin with an historical perspective. Then, we will describe the different share classes, an important but confusing feature of Chinese markets. After that, we will focus on the Shanghai and the Hong Kong stock exchanges by describing them and identifying their similitudes and differences. Obviously, we will discuss largely the Shanghai-Hong Kong Stock Connect Program. Finally, we will discuss the investors' profiles of market participants acting in China, another key feature given the proportion of individual investors on the market.

Chapter 4: In this chapter, we develop our three sub-questions and their hypotheses. We will explain the reasons and the pertinence of our choices. In addition, we will discuss the concepts and theories that conduct us to propose our hypotheses.

Chapter 5: The fifth chapter details our data and methodology. We will pay particular attention to how we selected our data – which stocks, which periods – and describe more in depth how we will build our analysis.

Chapter 6: This chapter presents the results of our analysis. It is organized in two sections. The first one proposes descriptive analyses – values of the liquidity proxies studied, plots of the liquidity patterns during the day – for stocks included in the program and for stocks that are not part of it. Then, we will suggest hypotheses to explain our results based on the microstructure theory, and compare in- and out-the-program samples, trying to highlight similitudes and differences. After that, we will present the results of our regression analysis. In this section, we will verify the meaning of the patterns observed before and search the determinant of the liquidity of Shanghai A-shares. Again, we will look after significant differences between results of stocks in- and out-the-program.

Chapter 7: The final chapter highlights the conclusions of the thesis. We will look back at our process and emphasize our main results and their implications. Ultimately, we will point out the limitations of our work and propose some suggestions for future research.

Chapter 2 – Literature Review

Section 1: Introduction to Liquidity

i. Market Liquidity Definition

Defining market liquidity is not an easy task, there are many studies related to it – liquidity and volatility, liquidity and asset pricing, liquidity risk etc. – but no strict definition emerges from the literature so far. Nevertheless, some have given the intuition of its meaning, for example, O'Hara (1995) defined it as "the ability to buy or sell significant quantities of a security quickly, anonymously, and with minimal or no price impact" (in O'Hara, 2004, p.1). Harris (1990) also gives an interesting definition to the concept; he argues that

> *a market is liquid if traders can buy or sell large number of shares whenever they want and at low transaction costs. Liquidity is the willingness of some traders (often but not necessarily dealers) to take the opposite side of a trade that is initiated by someone else, at low cost. (in Vo, 2004, p.14).*

In a straightforward way, Brunnermeier and Pedersen (2008) state that market liquidity is "the ease with which an asset can be traded". (Brunnermeier and Pedersen, 2008, p.1). Other words, same message, Schwartz and Francioni (2004) defined a liquid asset as "the one that is in cash or that is readily convertible into cash". (Schwartz and Francioni, 2004, p.60). These definitions probably sound obvious to the reader but remain particularly evasive and as O'Hara (2004) says liquidity is easy to identify when seen but is difficult to define strictly. In effect, many concepts used in these definitions must be quantified; for example, what is a "*significant quantity of a security"*, or what are "*low transaction costs"?* The difficulties implied by this state of art have lead researchers to focus on the attributes of liquidity. The most common attributes used to define liquidity are depth, breadth and resiliency, according to Black[7] (in O'hara, 2004).

Illiquidity is obviously the contrary of liquidity. Illiquidity refers to the frictions that hamper trading of asset and that leads to liquidity risk, the harmful consequences of illiquidity. According to The Bank of England (in Hibbert, Kirchner, Kretzschmar & McNeil, 2009, p.6), market liquidity risk is the fact that "traders cannot easily offset or eliminate a position without significantly affecting the market price". Alternatively, Schwartz and Francioni (2004, p.61) describe the cost of illiquidity as "the price concession that has to be paid to

[7] Black, F. (1971). Toward a Fully Automated Stock Exchange, Part I. *Financial Analysts Journal*, *27*(4), 28-35.

execute an order quickly, by a buyer who incurs higher price or by a seller who receives lower price."

Finally, market liquidity should not be confused with funding liquidity. Funding liquidity is, as defined by Brunnermeier and Pedersen (2008), "the ease with which traders can obtain funding". (in Hibbert, Kirchner, Kretzschmar & McNeil, 2009, p.6). However, the authors have proved the existence of a link between market liquidity and funding liquidity. Indeed, they showed that their interaction - particularly in crises period - can lead to "liquidity spiral". Their findings are summarized by Hibbert, Kirchner, Kretzschmar and McNeil (2009) who explain that firms with difficulties in obtaining funding may sell large holdings in order to satisfy cash-flows needs which may contribute to market illiquidity.

ii. Attributes of Market Liquidity

The use of depth, breadth and resiliency are largely suggested by literature of market microstructure. As soon as 1971, Black gave these definitions to the concepts:

- "**Depth** is the amount of stock that can be traded at a given price;
- **Breadth** is the ability to trade across assets without affecting the price;
- **Resiliency** is how quickly the price returns to the pre-trade price." (in O'Hara, 2004, p.2).

Kerry (in Hibbert, Kirchner, Kretzschmar & McNeil, 2009) has shown the relationship between these three dimensions - liquidity, price and quantity, bought or sold. He has derived

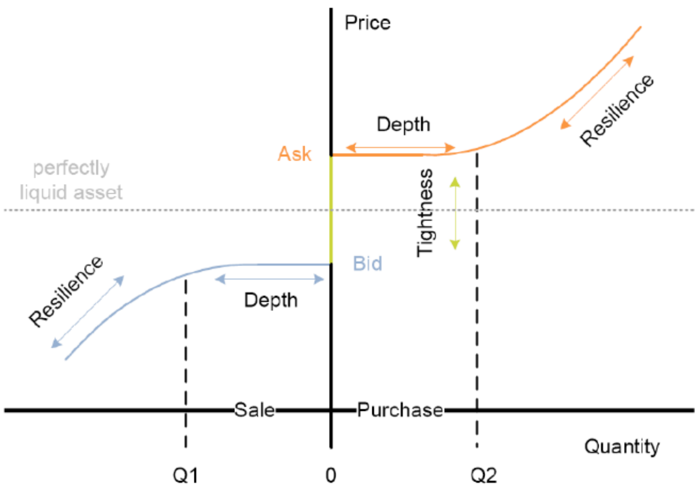

Figure 1 – Relationship between depth, breadth and resiliency
Source: Kerry (in Hibbert, Kirchner, Kretzshmar & McNeil, 2009, p.7)

the following supply-demand curve (*figure 1*).

The right-hand side can be interpreted as the per-unit prices by volume that would have to be paid to acquire assets; and the left-hand side, as the per-unit prices by volume that would be received when selling assets.

Kyle (1985) uses the concept of tightness instead of breadth. He defines it as "the cost of turning over a position in a short period of time" (Kyle, 1985, p.1330) or in other words, as the size of the bid-ask spread. The link between breadth, depth and bid-ask spread is highlighted by Schwartz and Francioni (2004) who state that a market has depth and breath if

> *orders exist at an array of prices in the close neighborhood above and below the price at which shares are currently trading and if the best buy and sell orders exist, in total, in substantial volume. Bid-ask spread is thus tighter and market impact is slighter when a market has depth and breadth. (Schwartz & Francioni, 2004, p.61)*

These are the most classical attributes of liquidity used as quantifiable measures. In the third section of this chapter, we will pay greater attention to the different proxies documented in the literature, which can be used to measure market liquidity.

iii. Importance of Market Liquidity

The capital asset pricing model (CAPM) is a two-dimensional (risk and return) tool used for asset pricing. The CAPM relies on the simplifying assumption that financial markets are a frictionless world in which trading is costless and where price discovery is trivial (Schwartz & Francioni, 2004). Such a marketplace would be a market of perfectly liquid assets. In actual markets characterized by divergent expectations, trading involves costs and frictions. Schwartz and Francioni (2004) make the following statements about financial markets:

> *(1) Perfect substitutes do not exist for individual stocks; (2) the demand to hold shares of an individual stock is not horizontal (infinitely elastic) at some intrinsic value and; (3) the price of each individual issue can be found only in the marketplace where its shares are trades. (Schwartz & Francioni, 2004, p.59)*

This introduction gives us the intuition that classical simple (but largely used) pricing models lack a dimension. Schwartz and Franchioni (2004) argues that market liquidity is the missing dimension. It represents the level of friction in the market and the costs incurred to complete transactions. Following the same logic, Amihud and Mendelson (1991) have divided illiquidity costs into four distinct dimensions: bid-ask spread (the difference between the best buy offer and the best sell offer); market impact (the price change incurred when a trader goes long or short on a large position); delay and search cost (the costs incurred when a trader delays execution of a transaction to get better trading conditions); and direct transaction costs (brokerage commissions, exchange fees and transaction taxes).

This would involve that liquidity is as important as risk and return as a concept, which seems to be confirmed by numerous studies. The following paragraphs summarize succinctly the major researches conducted on liquidity and its consequences.

The first and most obvious consequence of liquidity is its relationship with asset pricing. Intuitively, it seems clear that market participants will ask a premium for lower liquidity. Amihud and Medelson (1986) have studied early this relationship. They have shown that asset expected returns are increasing with the bid-ask spread (used as a proxy of liquidity). Their model has thus proven that investors require a higher expected return for less liquid asset and that market participants with longer investing time horizon tend to buy assets with higher spread (lower liquidity). Brennan and Subrahmanyan (1996) have investigated and confirmed these results. Using illiquidity measure based on intraday data, they have found a significant relation between expected rate of return and the used liquidity measure, after adjusting for Fama and French risk factors, and the effects of stock price level. These results are also confirmed by Eleswarapu (1997) and Loderer and Roth (2005) who used bid-ask spread as a liquidity-proxy as well. Some researchers have used other liquidity-proxies. They have found consistent results. Brennan, Chordia and Subrahmanyam (1998) have used stock trading volume and demonstrated the negative impact of volume on risk-adjusted return. Pastor and Stambough (2003) have used the same proxy and confirmed the findings. Datar, Naik and Radcliffe (1998) and Nguyen and Mishra (2005) preferred to use stock turnover as a measure of liquidity and have demonstrated the negative relationship between expected-return and stock turnover as well. Even if Eleswarapu and Reinganum (1993) have questioned the early results of Amihud and Medelson, we can argue that the further researchers listed here above have been sustaining the statement that investors require higher return for lower liquidity (the liquidity premium).

A second largely documented matter is the link between liquidity and volatility. Several researches have indeed showed that liquidity is the dominant determinant of volatility (Mike & Farmer, 2008); periods of low liquidity correspond to periods of high volatility and vice-versa. Understanding liquidity is thus most important subject to understand volatility. Schwartz and Francioni (2004) confirmed this and even stated that volatility can be used as a good (inverse) proxy for volatility. Earlier, Tuevo (2002) had investigated and proved the hypothesis that there is an inverse relationship between price volatility and market liquidity. O'Hara (2004) called the relationship "the Dark Side of liquidity" - in other words the negative view of liquidity. The idea is that liquidity leads to instable capital markets. There is in fact a long tradition in economics of viewing liquidity as a destabilizing force (see for example Tobin, 1978; Summers, 1989; Coffee, 1991; or Bhide, 1993; all in O'Hara, 2004). The "Dark Side" would lead to dramatic consequences for illiquid stock since investors only care for buying and selling (with short-term objective) and not for investing in the underlying asset (O'Hara, 2004). Moreover, according to the adepts of this negative view, the harmful effects of illiquid markets are not limited to their impact on single firms but lead to instability in the overall functioning of markets.

O'Hara (2004) opposes to this view "the Bright Side" of liquidity by which liquidity enhances market stability because investors are more willing to hold liquid assets. This is what he calls the microstructure view of liquidity (which is going to be discussed more in depth in the next section). In this view, more liquidity will lead to more stability because the price will be less affected by trades. Note that the "Dark Side" and the "Bright Side" of liquidity don't contradict each other on the underlying concepts (inverse relationship between volatility and liquidity) but disagree on the output: more volatility versus more stability. If there is still no agreement in the literature on the issue, it is particularly important for central bank to understand both views when making their policies.

Finally, market liquidity is frequently used as a measure of financial market development (the more liquid, the more developed), which can be linked to economic growth for example (Levine & Zervos, 1996) and to market efficiency (Chordia, Roll & Subrahmanyam, 2006).

Section 2: Market Microstructure

i. Overview

To understand the concept of liquidity, it is important to understand where it comes from. Therefore, before defining the possible measures of liquidity, we will focus on its sources. There are different ways to achieve this purpose as suggested by the literature. In this section, we will focus on the microstructure approach of liquidity, which is the most documented view so far. At the end of this section, the reader should have a good understanding of the mechanisms underlying liquidity as suggested by the market microstructure theory.

The term “market microstructure” was born in 1976 with Garman who studied market making and inventory costs (Wuyts, 2007). Later, the term has become “a collective term for the financial literature describing economic forces affecting trades, quotes and prices, i.e. the process by which investor demands are translated into transactions”. (Wuyts, 2007, p.287). Thereby, market microstructure theory is concerned with the trading mechanisms and processes used for financial securities (Hibbert, Kirchner, Kretzschmar & McNeil 2009); or, as Madhavan (2000, p.205) states, “market microstructure studies the process by which investors’ latent demands are ultimately translated into prices and volumes”.

As stated above, the first purpose of market microstructure was the study of market making and inventory costs. Later, researchers have given greater attention to the effect of asymmetric information on market prices, and so on the learning problem confronting market intermediaries that affect market prices (O’Hara, 1995). This information based-approach has greatly enhanced the understanding of the behavior of markets (and the nature of liquidity).

Reviewing the entire market microstructure literature is neither relevant neither interesting for the purpose of this paper. Therefore, a focus will be put on the aspects of microstructure that impact market liquidity and some fields of market microstructure will thus voluntary not be explored or only shortly described.

Finally, it should be noted that this section uses the Madhavan’s paper “Market microstructure: A survey” (2000) model as a basis for the understanding of market microstructure. We will confront and integrate other common views exposed in the literature to this model. This model takes into account most of the early microstructure theories and thus proposes an interesting unified approach for the purpose of this paper.

ii. The Model

Let us introduce the general model for the following sub-sections. The model we will present is borrowed to Madhavan (2000). It is a canonical model of security prices that assumes weak efficient market hypothesis (price reflects all public information) and no trading frictions (or costs). The model’s components are the following:

- V_t : is the log fundamental value or true value of a risky asset at some point in time t. V_t represent the full-information expected present value of future cash flows, which can vary with respect to variation in expected cash flows or discount rate.

- $\mu_t = E[V_t|H_t]$: is the conditional expectation of V_t given H_t, the set of public information at time t;
- P_t : is the log price of the risky asset at time t.

Given that agents are assumed to possess symmetric information and that frictions are negligible, the price simply reflects the expected value of the asset, and we have:

$$P_t = \mu_t \qquad (1)$$

Taking the log differences, we obtain the following simple model of stock returns:

$$r_t = P_t - P_{t-1} = \varepsilon_t \qquad (2)$$

With $\varepsilon_t = \mu_t - \mu_{t-1} = E[V_t|H_t] - E[V_{t-1}|H_{t-1}]$, the innovation in beliefs or the premium/discount resulting from the incorporation of new expectations in t. Since μ_t follows a martingale process[8], applying the law of iterated expectations, the returns are serially uncorrelated. Then, according to Madhavan, "markets are efficient in the sense that prices at all points in time reflect expected values". (Madhavan, 2000, p.209).

This canonical model will be the basis for our development of the microstructure theory, which is concerned with how various frictions and non-symmetric information affect trading process (Madhavan, 2000). The author then adapts his model to incorporate trading frictions and private information. In other words, he relaxes some of the model's constraints.

First, an error term representing the trading frictions, such as the bid-ask spread (a common proxy for liquidity), is added. Hence, we write: $P_t = \mu_t + s_t$, where s_t is the error term that reflects the effects of friction, with mean 0 and constant variance term $\sigma(s_t)$. Moreover, it is usual to model $s_t = sx_t$, where *s* is a positive constant term (one-half the bid-ask spread) and x_t is the signed order flow. For illustration purpose, we can take the simplest case of unit quantity: x_t= *+1* represents buyer-initiated trade; *-1* represents a seller-initiated trade and *0*, a cross at mid-quote (Madhavan, 2000). Based on these now components, we obtain:

$$r_t = \varepsilon_t + s_t - s_{t-1} = \varepsilon_t + s(x_t - x_{t-1}) \qquad (3)$$

[8] A martingale process X_t is a process such that $E[X_t] = X_0$ for all $t > 0$. In other words, the best guess (the expectation) about the future value of the process is its current value (at t=0).

The following statement summarizes well the implication of s_t :

> *The presumption of much of the early work in finance is that both the variance of* s_t*,* $\sigma(s_t)$ *and its serial correlation*[9] $\rho(s_t; s_{t-1})$ *are small in an economic sense. However, if the spread is not insignificant, there will be serial correlation in returns because of bid-ask bounce of the order of* $\sigma(s_t)$*. (Madhavan, 2000, p.209).*

Autocorrelation in returns means that historical data allow predicting future returns, what is a feature of non-efficient markets (Chordia, Roll & Subrahmanyam, 2006). Liquidity (representing by spread) can thus be already linked to market efficiency at this early point.

Furthermore, we can derive easily the spread estimator of Roll (1984) (in Madhavan, 2000) from equation 3. Indeed, the covariance between return in t and t-1 is given by: $cov(r_t; r_{t-1}) = -s^2$, and therefore, a simple measure of the implicit round-trip percentage bid-ask spread is given by:

$$\hat{S} = 2\sqrt{-cov(r_t\ ;\ r_{t-1})} \qquad (4)$$

The Roll estimator provides a method to estimate execution costs simply by using transaction prices data. Nevertheless, according to Madhavan (2000), the estimator must be used carefully since transaction costs are difficult to measure. Indeed, in many markets, quoted spreads may overstate (for investors who can extract favorable terms from dealers) or understate (for other trades, such as large-block trades) true costs as showed by Loeb[10] (in Madhavan, 2000).

Note finally that many questions deal with the properties of s_t over time and across markets because spreads may be functions of various parameters (Madhavan, 2000). For example, Roll's measure only takes into account the "handling costs" while "inventory costs" and "asymmetric information costs" could also be components of the spread (Wuyts, 2007). It is thereby unsurprisingly that spread components is largely discussed in the literature.

A second important extension to the model is the incorporation of private information impact. Indeed, some and only some market players can possess private information, creating information asymmetry in the market. In that case, the model need to be adjusted to reflect the revision in belief about asset values from time t-1 to time t due to information arrivals.

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[9] Serial correlation is equivalent to autocorrelation.

[10] Loeb, T. (1983). Trading Cost: The Critical Link Between Investment Information and Results. *Financial Analysts Journal*, *39*(3), 39-44.

Actually, this evolution in belief will be correlated with order flow x_t since informed traders will buy when price is under true value and sell when over. So, the derived model is:

$$\varepsilon_t = \lambda x_t + u_t \tag{5}$$

where λ is a strictly positive parameter and u_t is pure noise. Based on this new equation and our previous finding, we can derive that the price impact of the trade for a unit purchase is (Madhavan, 2000):

$$p_t - \mu_t = s + \lambda \tag{6}$$

According to Madhavan (2000), due to asymmetric information, the true cost of trading will exceed the quoted (half) bid-ask spread for large orders. This phenomenon is due to the price change related to large order. The total trading cost can therefore reduce significantly the gain of an investment strategy. Subrahmanyam[11] (in Madhavan, 2000) argues that information asymmetry is mainly a problem for individual stock. Indeed, it is less likely that investors have private information about the entire market (and as such, it should not be a problem for well-diversified portfolio). Again, we see the link of the model with liquidity since price impact - or breadth, the ability to trade across assets without affecting the price - is one of the main attributes of market liquidity.

Finally, it should be noted that this model is the most general one and that it could be adapted to specific market structures. Nevertheless, this model gives us sufficient knowledge to study further considerations of liquidity.

iii. Dealer Markets

In general, stock markets can be classified along two main lines: quote versus order driven; and continuous versus periodic systems. In the present and in the next sub-section, we are focusing on the first line. In a quote system, dealers (market makers) determine bid and ask prices at which they want to buy and sell securities. On the opposite, in an order driven market, traders interact directly with each other without intermediation (Wuyts, 2007). Frequently, both structures are used together to form a hybrid market, such as the NYSE, where market makers (specialists) compete with a public order book. Here below, we review

[11] Subrahmanyam, A. (1997). The ex ante effects of trade halting rules on informed trading strategies and market liquidity. *Review Of Financial Economics*, *6*(1), 1-14.

the role of market makers as liquidity provider; and in the next sub-section, we will confront this system with order-driven markets. Finally, it should be noted that in order to understand well the pricing process of dealers, we split this sub-section into their three main cost drivers: order handling, inventory and asymmetric information (usually defined as the three component of the bid-ask spread).

a. Order handling costs

Market makers or dealers quote two prices: the bid, at which they are willing to buy stocks and the ask, at which they are willing to sell. The difference between the two is obviously the bid-ask spread, a common measure of liquidity. The spread, which represents the cost of a roundtrip (buying a stock and re-selling it directly), can be seen as the cost of immediacy. Indeed, the dealer provides immediacy to market participants in exchange of what he receives a compensation; the bid-ask spread. Typically, the literature suggests three categories of model to explain the spread variations: models based on order handling costs, on inventory costs and on asymmetric information costs (Wuyts, 2007; Madhavan, 2000). As already discussed, Roll has proposed a simple measure for the bid-ask spread: $\hat{S} = 2\sqrt{-cov(r_t\ ;\ r_{t-1})}$ only based on transaction prices. This is in fact a measure for the order handling costs (Wuyts, 2007). Nevertheless, this measure, neither its extensions (see Choi, Salandro & Shastri[12]; or George, Kaul & Nimalendran[13] - both in Wuyts, 2007) take into account inventory or asymmetric information.

b. Inventory costs

A second flow of models analyzes inventory costs. In 1971, Smidt[14] argued, "market makers are not simply passive providers of immediacy, but actively adjust the spread in response to fluctuations in their inventory levels". (in Madhavan, 2000, p.213). In other words, dealers take an active role in price setting with the objective of achieving a rapid inventory turnover and not accumulating significant positions on specific securities (Madhavan, 2000). Therefore, prices may differ from expectations of value because the current position of the

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[12] Choi, J., Salandro, D., & Shastri, K. (1988). On the Estimation of Bid-Ask Spreads: Theory and Evidence. *The Journal Of Financial And Quantitative Analysis*, *23*(2), 219-230.

[13] George, T., Kaul, G., & Nimalendran, M. (1991). Estimation of the Bid–Ask Spread and Its Components: A New Approach. The *Review of Financial Stududies*, *4*(4), 623-656.

[14] Smidt, S. (1971). Which Road to an Efficient Stock Market: Free Competition or Regulated Monopoly?. *Financial Analysts Journal*, *27*(5), 18-20.

dealer in a specific stock is relative to its desired level of inventory. Further, this situation in addition to its price distortion effect will obviously lead to fluctuation in liquidity through spread variation. Indeed, inventory control implies the existence of bid ask-spread even if transaction costs are insignificant (Amihud and Mendelson, 1980). Various models coexist in the literature: in Garman (1976), market makers set lower ask prices and higher bid prices to avoid certain failure[15]. Amihud and Medelson (1980) explicitly incorporate inventory in the pricing decision of the market makers (in a unique market maker model), in this model the optimal bid and ask prices are a monotone decreasing function of the inventory position and exhibit a positive spread. Stoll (1978) focuses on portfolio risk and argues that risk adverse dealers want a well-diversified portfolio but allows diverging from this portfolio in exchange of compensation (the positive spread). The earliest model (of Garman) makes the link between dealer quotes and inventory levels. To understand the intuition beyond that, we can extend the canonical model exposed in sub-section ii, still based on Madhavan's development (2000). Recall that x_t represent the order flow in period *t* and that, for simplification mater $x_t \in \{-1; 0; 1\}$. Let's denote that I_t is the inventory level at time *t* with the convention that $I_t > 0$ denotes a long position and $I_t > 0$ a short one. So, the inventory position of the dealer at the start of the trading round is:

$$I_t = I_0 - \sum_{k=1}^{t-1} x_k \tag{7}$$

Where I_0 is the dealer opening position. Because dealers have limited capital *K*, we have the condition $|I_t| < K$. If there is no informed market participant and that market maker sets bid and ask prices (p_t) to equal expected demand and expected supply, we have $E[x_{t+1}|p_t] = 0$. And, from equation 7, it follows that $E[I_{t+1} - I_t|I_t] = 0$, and thus inventory follows a random walk with zero drift. Therefore, if dealer capital is finite, $Pr[|I_T| > k] = 1$ for some finite horizon *T*, market failure is certain. Note that this inventory-price relationship does not only alter spreads but also actual prices (Madhavan, 2000).

More advanced models (for example Zabel, 1981; O'Hara & Oldfield, 1986; or Madhavan & Smidt, 1993) include multivariate framework where order flow and portfolio returns are stochastic (Wuyts, 2007). Generally, these models consider that market makers face a large

[15] A market failure is a situation in which demanded quantity does not equal supplied quantity.

number of rounds of auctions during the day. At each auction, markets are cleared, prices and inventory levels change, and at the end of the day, dealers have to liquidate or store overnight at cost. Bid and ask prices are thus here quoted in order to “maximize the present expected value of trading revenue less inventory storage costs over an infinite horizon of trading days”. (Madhavan, 2000, p.214). Let us review the model exposed before to this new way of thinking, still in accordance with Madhavan’s development. In this setting, market makers set prices to control inventory and not anymore by equaling assets expected value. In a typical inventory model we have:

$$p_t = \mu_t - \phi(I_t - I^*) + sx_t \tag{8}$$

With I^* the target inventory level of the dealer.

In this model, the average of the bid and ask prices need to equal p_t, the equilibrium price. According to Madhavan, “the dealer cuts the price at the start of round *t* if he or she enters the trading round with a long position and raised price if short, relative to the inventory target”. (Madhavan, 2000, p.215). Anyway, we understand here that market makers are important providers of liquidity or illiquidity depending of their inventory strategy.

c. Asymmetric information costs

Finally, yet importantly, information-based models provide insights in the understanding of price formation and market liquidity. Bagehot (1971) has been the first to make a distinction between liquidity traders - or noise traders, who are uninformed traders - and informed traders, who possess private information. In information models, informed traders act to profit from their non-public information and the market maker wants thereby to compensate for the loss he incurs in trading with informed traders. As Madhavan argues, “while market maker loses to informed traders on average, but recoups these losses on noise trades, suggesting that the spread contains an informational component as well”. (Madhavan, 2000, p.216).

Again, numerous models of this type have been developed but some of them seems to receive greater attention in the literature. First, Glosten and Milgrom (1985) showed that “the presence of traders with superior information leads to a positive bid-ask spread, even when specialists are risk-neutral and makes zero expected profits”. (Glosten & Milgrom, 1985, p.71). Let’s extend the previous canonical model - but ignoring order handling and inventory costs - to the Glosten and Milgrom's set-up, with the following assumptions, still based on Madhavan (2000) methodology:

- Orders are assumed to be for one round lot;
- There are two types of traders: informed *(i)* and uninformed *(u)*. Let's denote Θ the trader's type ($\Theta = i \; or \; u$);
- A constant fraction (ω) of traders possess private information;
- The asset can take two value: high v^H or low v^L, with expected value equal to $\overline{v}_t$;
- The range of uncertainty is defined by: $\sigma = v^H - v^L$;
- For illustration ease, both states are equally likely at time t, meaning that $\overline{v}_t = \frac{(v^H+v^L)}{2}$.

Based on this set-up and the absence of other costs, a rationale market maker will quote bid and ask spread that are regret free ex post. So, the ask price will be the expected value of the security given that a purchase order has arrived (Madhavan, 2000).

$$p_t^{ask} = E[v_t|x_t = 1] = v^H \Pr[\Theta = i|x_t = 1] + \overline{v_t} \Pr[\Theta = u|x_t = 1] \qquad (9)$$

We note from this equation that the liquidity provider sets the prices based on the direction of the trade: an ask price for a buy order and a bid price for a sell order. This condition is known as the "ex-post rationality" (Glosten & Milgrom, 1985). Therefore, Madhavan (2000, p.216) states that "the set of public information includes all information at time t (including the knowledge of the trade itself)", and assuming symmetry, the bid-ask spread is:

$$p_t^{ask} - p_t^{bid} = \omega\sigma \qquad (10)$$

From 10, we see clearly that the spread is increasing with information asymmetry (the larger the proportion of informed traders, the larger the spread) and with uncertainty. The market maker needs to balance the reduction in loss from the informed trader with a wider spread and the profit reduction (opportunity cost) from trading with uniformed traders with reservation price inside the spread. Anyway, we observe that, in Glosten and Milgrom's model, spread will exist even if the dealer is risk neutral, behave competitively and without any other costs (Madhavan, 2000).

A second model, developed by Kyle (1985), is based on the assumption that there is one and only one informed trader in front of the noise traders. The model is auction-based, meaning that all traders place orders at the same time. The dealer then observes the order flow and clear the market at one price (Wuyts, 2007). Therefore, the model contrasts with the previous one in the sense that there is no bid-ask spread. Kyle (1985) showed that a rational expectations equilibrium exists and that market prices will ultimately incorporate all available information. According to Madhavan (2000, p.216), "with continuous order quantities taking any value over the real line and appropriate assumptions of normality, the Kyle model can be viewed as a linear regression". To understand Kyle's model, let introduce a new parameter: the net order imbalance in auction t, $q_t$and let remind that μ_{t-1} denote the dealer's asset expectation value in t-1. According to Kyle (1985), "the informed trader adopts a linear strategy so that q_t is a noisy signal of the true value". (in Madhavan, 2000, p.217). Therefore, the price of the asset can be expressed as:

$$p_t = \mu_{t-1} + \delta q_t \qquad (11)$$

Price is thus simply the sum of the dealer's previous belief and of an order-related component. In this model, the larger the quantity of the order, the larger the price impact on the order will be. However, Barclay and Warner (1993) have shown that larger orders are not necessarily related to informed traders in particular. Moreover, the model has other limitations. Firstly, only market orders are permitted while agents can condition their demand to price in real world markets; and secondly, the presence of only one informed traders while evidences have proven that it is more likely to have multiple informed traders (Cornell & Sirri, 1992).

Based on this observation, Holden and Subrahmanyam (1992) have developed a model by taking into account the presence of multiple informed traders competing in the market. They have found that competition leads to higher volume and more rapid information incorporation. Therefore, informed traders' profit are smaller and market more efficient.

Finally, an implicit assumption of information models is that dealers are uninformed. According to Madhavan (2000), this assumption has received attention in empirical studies that have confirmed that the hypothesis can be reasonably maintained. The attention is thereby concentrated on the learning process of the market makers. In fact, informed traders, on the contrary to liquidity traders, will generally trade on one side of the market. Market makers will thus be able to adapt their prices (after each trade) based on the size and direction of the trades. This issue has been discussed by Easley and O'Hara[16] (in Madhavan, 2000, p.218) who show that "the adjustment path of prices doesn't need to converge to the true price immediately since it is determined by the history of trades which reflects the actions of liquidity motivated traders as well".

iv. Order-driven Markets

Order-driven or limit-order markets are pure auction markets where traders interact directly with each other without the intermediacy of a market maker. Basically, with limit order, "an investor associates a price with every order such that the order will only be executed if the investor receives that price or better". (Madhavan, 2000, p.229). The trader, for example, specifies a quantity q he wants to buy only and only if the price of the security is equal or below a limit price L (a limit order). Thereby, a market order is simply a limit order where limit price L is the current price of the asset, p_t (or higher). Note that, in hybrid market, specialists directly compete with the limit order book to execute transactions. Given that the determinants of the liquidity in such a market are different than in dealer markets, this sub-section cannot be structured as the former one. However, in practice the bid-ask spread and its components remain the most studied liquidity related topic in order-driven markets.

a. Bid-ask spread

The first point of interest is the bid-ask spread in such a market. However, this question must be discussed in a different way in this context. On the one hand, traders providing liquidity are still expected to require compensation for handling costs, but on the other hand, inventory costs are handled differently because there is no obligation to take the opposite side of the transaction (Wuyts, 2007). Concerning the third component of bid-ask spread, Glosten (1994) shows that limit-order markets have positive bid-ask spread because of the probability of trading with informed traders. This is the basic trade-off identified by Madhavan (2000). He derives the expected profit of a limit order traders as the weighting average of the followings:

$$(p^{ask} + \delta - E[v|\Theta = u])\min\,[q^L, Q - q^{ask}] \tag{12}$$

$$-(E[v|Q; \Theta = i] - p^{aks} - \delta)\min\,[q^L, Q - q^{ask}] \tag{13}$$

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[16] Easly, D. & O'Hara, M. (1987). Price, trade size, and information in securities markets. *Journal Of Financial Economics,19(1)*, 69-90.

Where $q^L$is the quantity of a sell limit order at price $p^{aks} + \delta$, where δ is the minimum tick size; and Q is the quantity of the next market order. The term 12 is positive since the ask price exceeds the unconditional expectation of the security; on the other hand, the term 13 is negative because informed traders will trade only if $v > p^{ask} + \delta$ (Madhavan, 2000). The weights associated to each term are the probabilities that the trade is initiated by an informed or a uniformed trader; what vary given the order size and the state of the book. According to Madhavan (2000, p.229), "at a higher price, the probability of the limit order is executed by a uniformed trader is lower but the profits from executing against such a trader are higher". Handa, Schwartz and Tiwari[17] (in Wuyts, 2007) develop a model of an order driven market. In their model, market participants have different expectations of securities value and the bid-ask spread is a function of the different expectations and of adverse selection. Empirical studies confirm that the processing and asymmetric information costs are the most important components of the spread, while inventory costs are less important (see de Jong Nijman & Roell, 1995 and 1996; or Ahn, Cai, Hamao & Ho, 2002).

b. Choice between market and limit order

Further, an important point to focus on is why traders choose between market order and limit order. Traders can indeed choose either market order for immediacy either preferring limit order to obtain better transaction terms but with a delay and a risk of non-execution. Thus, there is a trade-off between the cost of delayed execution and the cost of immediacy, as suggested by Demsetz[18] in 1968 (in Foucauld, Kadan & Kandel, 2003). The study of this choice is particularly relevant because, in a limit order market, all dimensions of liquidity ultimately depend on the interaction between market orders and limit orders (Wuyts, 2007). Researchers have developed various models analyzing this choice by focusing on different determinants of liquidity. For example, Parlour (1998) studied order book influence; Foucault (1999) focused on volatility of the asset; Foucault, Kadan and Kandel (2003) have discussed the order arrival rate; and Rosu (2005) has analyzed the composition of traders. Let us discuss briefly their main findings in the next paragraphs.

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[17] Handa, P., Schwartz, R., & Tiwari, A. (2003). Quote setting and price formation in an order driven market. *Journal Of Financial Markets*, *6*(4), 461-489.

[18] Demsetz, H. (1968). The Cost of Transacting. *The Quarterly Journal Of Economics*, *82*(1), 33-53.

c. Order book

Parlour (1998) has developed a dynamic model of the limit order book in a one-tick market. He explains that:

> *A limit order is only executed when enough market orders arrive during the remainder of the day to execute all preceding orders in the book that have time priority. So, the endogenous probability of execution depends both on the state of the book when the trader submits his order, and how many markets orders he believes will arrive over the remainder of the day. Thus when a trader makes his decision he explicitly takes into account how his order affects the incentives of future traders to submit either market of limit order. (Palour, 1998, p.790).*

The model developed by Palour exhibits systematic patterns in liquidity due to this endogenous probability of execution. Indeed, traders will develop their trading strategy based on both sides of the book. As a conclusion, Palour shows that even with no asymmetric information the choice between market order and limit order depends on the state of the book and follows systematic patterns.

d. Volatility

Later, Foucault (1999) has developed a model based on the observation that previous dynamic models do not incorporate the risk for limit order traders of being "picked off" (executed at a loss when the limit order become mispriced due to new public information). He has developed a model in which the mix between market orders and limit orders can be characterized in equilibrium. He demonstrates that the volatility of the asset is a main determinant of the mix between market and limit orders. "When the asset volatility increases, the probability of being picked off and the losses, which ensue, are larger". (Foucault, 1999, p.101). He tests thus the assumption that the proportion of limit orders in the order flow is positively related to asset volatility. Then, he tests and proves the hypothesis that volatility is positively related to spread, and consequently that the proportion of limit orders is positively related to the size of the spread. His results show that "the small firms should have a larger proportion of limit orders, lower fill rates (the ratio of filled orders to total number of limit orders) and larger spreads than large firms, in limit order market". (Foucault, 1999, p.101). In short, higher volatility makes market order costlier and increases the likelihood of limit orders.

e. Traders' impatience

Foucault, Kadan and Kandel (2003) analyze how traders' impatience affect order choice in term of bid-ask spread dynamics and resiliency. At equilibrium, they argue that patient traders tend to place limit orders, while impatient ones place market orders. Their model suggests that order-driven markets will be more illiquid (larger spread and lack of resiliency[19]) when the proportion of impatient traders is larger. Alternatively, they show that "the resiliency of the limit order book increases in the proportion of patient traders and the waiting cost, while it decreases in the order arrival rate". (Wuyts, 2007, p.294). They prove that resiliency is maximal when traders have similar characteristics in term of waiting costs. In addition, they explain the following; "an increase in the proportion of patient traders reduces the frequency of market orders and thereby lengthens the expected time-to-execution of limit orders. Patient traders submit then more aggressive limit orders to reduce their waiting time". (Foucault, Kadan & Kandel, 2003, p.2). This explains the statement by which liquidity increases with the proportion of patient traders in the market.

Finally, Rosu (2005) studied - as Foucault, Kadan and Kandel (2003) - the arrival rate of agents and the proportion of patient traders in the market. His continuous time model of price formation proves the existence of an equilibrium in which the bid and ask prices depend only on the number of buy and sell orders in the book (which depends obviously on the arrival rate and the ratio of patient traders). According to Rosu (2005), impatient traders will always submit market orders while patient ones will submit limit order unless the limit order book is full. In that case, the patient trader will submit a market order or a "quick" limit order. This quick limit order is then immediately accepted by a trader who forms the other side of the book (Wuyts, 2007). If the limit order book is not full, the limit order will always be placed inside the bid-ask spread. Additionally, Rosu (2005) shows that the point at which the book is full coincides with the minimum spread, what proves there exists an optimal bid-ask spread. Further, he states that the bid and the ask prices both decrease after a market sell, with the bid decreasing more than the ask price. Rosu (2005) shows that this can result from an adjustment by limit order sellers. Indeed, after a market sell, limit order sellers observe a decrease in the

[19] Resiliency is measured by "the probability that the spread will reach its competitive level before the next transaction". (Foucault, Kadan, & Kandel, 2005, p.2).

bid price, resulting in a likely increase of the execution time. Therefore, they lower the ask price according to the new bid in order to adjust the execution time.

To sum up, we observe that liquidity is not driven by the same factors in dealer market and order driven markets. A major point to consider in limit order markets is the trade-off between submitting market order and limit order This trade-off directly influences the bid-ask spread. However, authors often link the determinants of the choice between limit and market order to the components of the bid-ask spread defined in quote markets.

v. The Importance of Market Structure

The importance of market structure has already been largely highlighted in the two previous subsections. Thereby, we have noticed that different components drive liquidity in dealer markets and in order driven markets. However, the dealer versus order driven markets is not the only distinction that exists in market structure. Indeed, as we mentioned earlier, markets can also be characterized through the distinction between continuous versus periodic auction systems, for example. Therefore, it is worth analyzing the impact of these structural differences on market liquidity. To go through this subject, let us organize our reflection based on the statement of Madhavan (2000, p.224) who argues that market architecture is “the set of rules governing the trading process, determined by choices regarding market type, price discovery process, order forms, protocols and transparency”.

To start, let us focus on the first point. Market type refers to the reliance to market makers, the degree of continuity and the degree of automation (Madhavan, 2000). Since we discussed the reliance to market makers already, we can concentrate on the two other points. According to Madhavan (2000), periodic system auction[20] is a particularly efficient system, among others in term of information aggregation. Indeed, this system is especially valuable when uncertainty about asset valuation is high. However, the demand for continuous market[21] is high despite the efficiency of call auction market. Next, the degree of automation of market have been largely studied due to the switch to electronic markets during the nineties. If some markets maintain a trading floor, most of them have today screen-based trading systems. Biais, Foucault and Salanie (1998) show that floor markets are the source of large spreads and

[20] **Periodic auction or call auction markets** are markets in which orders are batched for simultaneous exectution at points in time when the market is called (Vishwanath & Krishnamurti, 2009).

[21] **Continuous markets** are markets that allow trade to be made at any time during the trading day (Vishwanath & Krishnamurti, 2009).

inefficient risk sharing. Nevertheless, empirical evidences are less conclusive. Venkataraman[22] (in Wuyts, 2007) compared the NYSE (trading floor) and the Euronext Paris (electronic exchange), he proves that screen-based system offers low spread for liquid stock but that trading floor are more efficient for less liquid stock.

Second, the price discovery process refers to "the extent to which the market provides independent price discovery or uses prices determined in another market as the basis for transaction". (Madhavan, 2000, p.224). With respect to that, it is worth mentioning cross-listing stocks. Cross-listing stocks are securities traded simultaneously in different markets (primary and secondary markets or different stock exchanges, for example). Theory suggests that the higher volume market will enjoy reduced costs (assumption that costs are decreasing in volume), will attract further volume and will eventually consolidate into a single market (Madhavan, 2000). In addition, this phenomenon is strengthened by asymmetric information. Indeed, if markets are combined together, the proportion of informed traders will decrease, leading to prices that are more efficient with narrower spreads. Actually, this is also true in the case of symmetric information. In that case, price discovery will also be centralized in the primary market or the one with highest volume as shown by Hasbrouck (1995). Anyway, despite the fact that arguments are in favor of centralized markets, many markets remain fragmented (Madhavan, 2000).

Regarding the order forms, protocols and transparency, we have already implicitly discussed the importance of order forms in the previous subsection (market versus limit order) and we will devote the next subsection to transparency, a major concern in market microstructure. We will focus here on protocols and especially on a specific component; tick size. Numerous papers have investigated the tick size, which refers to the minimum price movement of a financial instrument and its impact on market quality. Most of them show that a reduction in tick size leads to a decrease of the spread and to a decrease of depth (see for example, Ahn, Cao & Choe, 1998; Griffiths & al., 1998; Goldstein & Kavajecz, 2000 or Chordia & Ball, 2001; all in Wuyts, 2007). It means that a tick size drop leads to both an improve (spread) and a damage (depth) in liquidity properties. It is important to note again that Bourghelle and

[22] Venkataraman, K. (2001). Automated Versus Floor Trading: An Analysis of Execution Costs on the Paris and New York Exchanges. *The Journal Of Finance*, *56*(4), 1445-1485.

Declerck[23] (in Wuyts, 2007) studied the introduction of the Euro in the Paris Bourse (and the associated tick size change) and showed that in this particular case, only the depth is significantly impacted while the spread remains unchanged.

As a conclusion, we understand that the components of market structure have large impact on market quality and liquidity. Analyzing the liquidity of a particular market implies then to understand all the steps and rules of the trading process.

vi. Transparency and Anonymity

According to O'Hara (1995, p.252), "market transparency refers to the ability of market participants to observe the information of the trading process". Despite the simplicity of the definition, the issue of transparency is extremely complex. First, it is worth noting that information refers to knowledge about prices, quotes, or volumes, the sources of order flow, and the identities of market participants (Madhavan, 2000). Further, it is common to divide transparency into pre- and post-trade transparency (Madhavan, 2000; Wuyts, 2007). According to Madhavan (2000, p.234),

> *pre-trade transparency refers to the wide dissemination of current bid and ask quotations, depths, and possibly also information about limit orders away from the best prices, as well as other pertinent trade related information such as the existence of large order imbalances. Post-trade transparency refers to the public and timely transmission of information on past trades, including execution time, volume, price, and possibly information about buyer and seller identifications.*

The level of transparency has important impacts: it influences the strategies of market participants and thus the market equilibrium (O'Hara, 1995). To understand its implications, it is first useful to compare it in quote- and order-driven markets in which transparency is different by nature. In the quote-driven market, dealers place the price before orders while in an order-driven market, orders are submitted and then prices are determined based on them (O'Hara, 1995). Order-driven markets can be further classified as continuous auction (traders submit orders for immediate execution), call market or batch trading system (orders accumulate and are cleared at periodic intervals). These systems differ by their degree of transparency. Therefore, according to Madhavan (1992), traders in a quote-driven or in a continuous order-driven system enjoy more transparency than traders do in a batch system. Moreover, auction markets offer more transparency than a dealer market. This is due to the

[23] Bourghelle, D. & Declerck, F. (2004). Why markets should not necessarily reduce the tick size. *Journal Of Banking & Finance*, *28*(2), 373-398.

fact that, in an auction market, the limit order book can be scanned by traders and offers then more information than a dealer system through which only the quotes for a certain size are given (Wuyts, 2007).

Furthermore, because traders' strategy is modified, we understand easily that transparency also has an important impact on liquidity. According to Pagano and Roell (1996), it is widely held that greater transparency leads to greater market liquidity by reducing the opportunity of informed traders for taking advantage of less informed ones. Actually, it has been showed that transparency impacts differently transaction costs for informed and uninformed traders. With respect to this distinction between informed and uninformed traders, Pagano and Roell (1993) analyze how transparency affects the distribution of gains among traders. For the purpose of this paper, we won't go into details but only try to get this assumption and the link with liquidity beside their work. Pagano and Roell (1993) divide the market in four categories: batch markets, dealer markets, continuous markets and transparent markets. Under the assumption that traders act identically in all market structures, they show first that the expected trading costs of uniformed traders in the transparent market are always less than or equal to their expected trading costs in the dealer market. This can be explained by the fact that it is more difficult for the informed traders to "hide" information in the transparent market and thus his profit will be smaller (O'Hara, 1995). On the contrary, uniformed traders will enjoy greater profit. In continuous markets, they show that trading cost will lie between those of the dealer and transparent markets. It means that uniformed traders do on average at least as well than trading in the dealer market but could do better by trading in a transparent market. In any case, the intuition below their research is that greater transparency leads to lower transaction cost for uniformed traders and thus to greater liquidity. In a later paper, Pagano and Roell (1996) confirmed this intuition by studying limit-order markets and by showing that more pre-trade transparency increases liquidity. In effect, the implicit bid-ask spread is narrower since noise traders can protect themselves against informed traders. However, we keep in mind that the study of transparency is a very complex topic that relies on restrictive assumptions.

The last point is the issue of anonymity[24] which is related to the concept of transparency (Wuyts, 2007). Benveniste, Marcus and Wilhelm (1992) find that providing information about

[24] The degree to which the identity of market participant is revealed.

the identity of liquidity demanders in general increases the bid-ask spread. However, Foucault, Moinas and Theissen (2007) find that, in an order-driven market, revealing the identity of the liquidity suppliers can reduce the bid-ask spread and improve depth.

Section 3: Liquidity Measures

This subsection aims at presenting the different proxies commonly used in the literature to quantify liquidity. Our goal here is not to provide an exhaustive list of proxies but to focus on the most used and studied ones. In order to do so, we structure the following section according to the data used to construct the measures: transaction costs; volume or price. Let us keep in mind that liquidity measures are only static "proxies" and that none of them can capture all the dimensions of market liquidity. Therefore, when studying liquidity, it is important to combine multiple measures; to choose them with respect to the feature we want to examine and to keep critical thinking.

i. Transaction Costs-based Measures

Transaction costs-based measures refer to bid-ask spread and its variants. Although very simple, the bid-ask spread is one of the most commonly used liquidity proxy documented in the literature.

- **Absolute spread**

The simplest one, the absolute spread (or quoted spread) is computed as the difference between the lowest ask and the highest bid price (Sarr and Lybek, 2002):

$$S_t = P_t^A - P_t^B \tag{14}$$

- **Relative spread**

The spread can also be measured as a percentage spread (or relative spread) what allows taking into account that a given spread would be less costly the higher the price of the asset; and thus liquidity comparison of multiple stocks (Gabrielsen, Marzo & Zagaglia, 2011). In this case we have:

$$RS_t = \frac{(P_t^A - P_t^B)}{(\frac{P_t^A + P_t^B}{2})} \tag{15}$$

In 15, the relative spread is computed by dividing the absolute spread by the mid-price. However some authors prefer dividing it by the last traded price P_t (e.g. Fleming & Remolona, 1999 in Gabrielsen, Marzo & Zagaglia, 2011). This version of the relative spread allows taking moving markets into account since P_t could be the ask price in an upward moving market or the bid price in a downward moving market. However, in order to be relevant this last measure requires to know the last traded price before P_t^A and P_t^B are quoted but it cannot have occurred to long before the measure of the absolute bid-ask spread. Note again that both absolute and relative measures may be logarithmized to improve their distributional properties (Gabrielsen, Marzo & Zagaglia, 2011).

- **Realized spread**

Next, if there are multiple dealers with multiple bid and ask prices, and particularly if they are not obligated to trade at the quote price, it can be more informative to ignore the outliers. In that case, the spread is sometimes calculated based on the average of the execution prices for a given period. Therefore, the spread is called the "realized spread" (Sarr & Lybek, 2002).

- **Effective spread**

Further, the effective spread is another concept computed as follows:

$$ES_t = |P_t - \left(\frac{P_t^A + P_t^B}{2}\right)| \tag{16}$$

Where P_t is the last traded price before time t and $\left(\frac{P_A + P_B}{2}\right) = P_t^M$ is the mid price. If the effective spread is smaller than half the absolute spread, this reflects trading within the quotes. Again, this measure can be computed in relative term by dividing it by the last traded price or by the mid-price (Gabrielsen, Marzo & Zagaglia, 2011).

- **Roll's measure of spread**

Finally, note that the data necessary to compute the measure are not always observable in all market (Hibbert, Kirchner, Kretzschmar & McNeil, 2009). In such cases, the Roll measure can be used to approximate the spread[25]. This measure, exposed above, is computed as twice the square root of the negative covariance between subsequent prices changes. The Roll

[25] The Roll's measure could be classified in the « Price-based measures » but, due to its meaning we prefered sorting it with the « Transaction costs-based measures ».

measure is thus cheap to compute as it only requires daily price data. Moreover, it could be a better proxy for liquidity than the actual bid-ask spread since transactions are often done within the spread (Roll, 1984). However, according to Roll (1984) the measure is only valid if two assumptions are hold: (1) the market in which the asset is traded is efficient in terms of information and; (2) the probability distribution of price changes is stationary. These strong assumptions have led to downward bias in the Roll's measure of the spread, leading to extensive research on the subject. Huang and Stoll (1997) propose a general approach for the components of the spread. They find that the spread is mainly driven by a large order-handling cost component, and small but significant adverse selection and inventory cost component; and that the components depend on trade size. Moreover, Wuyts (2007) shows that the relative weights of each component in the spread differ with the type of market: dealer-driven or order-driven. In a dealer market, all components are present since inventory cost is unimportant in order-driven market. Adverse selection costs and order handling costs are significant but their weight and relation to trade size are subject to debate since controversy results have been found (de Jong Nijman & Roell, 1996; Ahn, Cai, Hamao & Ho, 2002; Huang & Stoll, 1997; all in Wuyts, 2007). Numerous studies (not developed in this paper) aim to distinguish and measure the components of the spread.

ii. Volume-based Measures

Volume-based measures are the indices proposed in the earliest stage of market microstructure literature. Practically, volume-based measures can be calculated as a volume or quantity of share per time unit. Thus, they are usually used to evaluate the depth dimension of liquidity (von Wyss, 2004). However, they also emphasis the relationship between price and quantity of an asset. In other words, these measures evaluate the degree of price impact of a transaction of a specific size (or breath) (Gabrielsen, Marzo & Zagaglia, 2011).

Many volume-based proxies emerge in the literature. The most common are trading volume and turnover. Further, more sophisticated measures have been investigated, such as the Hui and Heubel ratio, the depth, the conventional liquidity ratio or the Amihud's illiquidity measure.

- **Trading volume**

Trading volume is used to verify the existence of numerous market participants and transactions of a particular asset and is incorporated in many liquidity studies. The trading volume per time interval is simply computed as follows (von Wyss, 2004):

$$Q_t = \sum_{i=1}^{N_t} q_i \tag{17}$$

Where N_t is the number of trades between *t-1* and *t*; and q_i is the number of shares of transaction *i.* Nevertheless, according to Gabrielsen, Marzo and Zagaglia (2011), trading volume can be an inappropriate liquidity measure. This would be mainly due to the double counting of transaction since a transaction on the buy side can also be recorded as a transaction on the sell side. Despite this weakness, trading volume remains a key determinant for the pricing structure of assets, as shown by Blume, Easly and O'Hara (1994) for example. Thanks to the wide availability of data, it is a preliminary step in the study of liquidity (Gabrielsen, Marzo & Zagaglia, 2011).

- **Turnover**

The trading volume "can be given more meaning by relating it to the outstanding volume of the asset being considered." (Sarr & Lybek, 2002, p.12). Then, we obtain the turnover rate (or relative turnover), which is computed by dividing the turnover (equation 18) by the total volume of the asset available for trade (Hibbert, Kirchner, Kretzschmar & McNeil, 2009).

$$V_t = \sum_{i=1}^{N_t} p_i . q_i \tag{18}$$

Where p_i denotes the price of trade *i.* Afterwards, the turnover rate that allows greater comparability between assets, is computed as follows:

$$Tn_t = \frac{\sum_{i=1}^{N_t} p_i . q_i}{S_t . P_t} \tag{19}$$

Where S_t is the free float of the asset and P_t is the average price of the asset over the period (t-1) to t. This index is usually computed for a single time period (a day, a week, a month etc.). However, it is used to compute the ratio as an average over a period specified in advance (Gabrielsen, Marzo & Zagaglia, 2011).

- **Hui and Heubel ratio**

Hui and Heubel (1984) developed an additional index to measure liquidity of individual financial asset with a focus on its breath component. As a measure for single asset, it cannot be directly applied for the maker as a whole. Practically, "this index constructs a metric between the largest price change divided by the ratio of traded volume of market capitalization." (Gabrielsen, Marzo & Zagaglia, 2011, p.8).

$$L_{HH_i} = \frac{(P_{\max;i} - P_{\min;i})/P_{\min;i}}{V_i/(S_i.\overline{P_i})} \tag{20}$$

Where $P_{\max;i}$ is the highest daily price over a determined period and $P_{\min;i}$ is the lowest value over the same horizon; V_i is the total volume of the asset *i* traded over the period; S_i is the free float of the asset and $\overline{P_i}$ is the average closing price. In term of interpretation, we would say that the market has more breath when L_{HH} is low, meaning that the market is more resilient (Sarr & Lybek , 2002).

Hui and Heubel liquidity measure (L_{HH}) is usually calculated as an average of the 5-days periods in the sample in order to smooth variability. According to the literature, this time period is a weakness given that asset prices can adapt very quickly to liquidity failure; what leads to incapacity of detecting market anomalies. However, in order to avoid this problem, the ratio could be computed on daily data to capture short-term price movements (Sarr & Lybek, 2002). Another weakness is the availability of high quality data. Indeed, in a dealer market, reliable price data could not be available. In that case, bid and ask price can be used as proxies of prices. However, since bid and ask prices are generally less volatile than actual price, the index could not be able to detect anomalies in liquidity (Gabrielsen, Marzo & Zagaglia, 2011).

- **Depth**

As simple that trading volume, the market depth can be used as liquidity proxy. On the contrary to trading volume that represents the traded volume of a specific stock, depth corresponds to the sum of the best bid and ask quantity in the order book at time t (von Wyss, 2004).

$$D_t = q_t^A + q_t^B \tag{21}$$

Depth may be divided by two and be used as an average depth of the best bid and ask depth. We can also use the log(depth) to improve the statistical properties of the measure. Depth can finally be calculated in currency term in order to make the comparison of different stocks possible. Further, the use of depth present weakness as well. In effect, large orders could not be executed at best bid or ask price but influence liquidity anyway (von Wyss, 2004).

- **Conventional liquidity ratio**

The conventional liquidity ratio (or simply liquidity ratio) provides a measure for how much traded volume is necessary to induce a one-percent price (Gabrielsen, Marzo & Zagaglia, 2011).

$$LR_{i\,;\,t} = \frac{\sum_{t=1}^{T} P_{i\,;\,t} . V_{i\,;\,t}}{\sum_{t=1}^{T} |P_{i\,;t} - P_{i\,;t-1}|} \tag{22}$$

Where $P_{i\,;\,t}$ is the price of asset i on time t ; $V_{i\,;t}$ is the volume traded; and $|PC_{i\,;t}|$ is the absolute percentage price change over a given period of time (arbitrary chosen). Usually, the ratio is computed using a period of one month. Then the numerator represents the total traded volume over four weeks and the denominator is the absolute value of (the sum of) the daily percentage price changes of the stock over the month. Therefore, the higher the liquidity ratio, the higher the liquidity of the asset, which means that large volume of trades have little influence on price (Gabrielsen, Marzo & Zagaglia, 2011).

- **Amihud's illiquidity measure**

Amihud (2002) introduced a new liquidity measure to investigate the influence of market condition on stock returns (Gabrielsen, Marzo & Zagaglia, 2011). Its index - the illiquidity measure or Amihud's illiquidity measure - is used to measure the impact of market illiquidity on stock returns. Thanks to it, Amihud (2002) shows that illiquidity has a significant impact on price returns for NYSE stocks over the period 1964-1997. The measure is "the average ratio of absolute stock return to dollar volume, which is easily obtained from daily stock data for long time series in most stock markets". (Amihud, 2002, p.2).

$$ILLIQ_{i\,;\,T} = \frac{1}{D_T} \sum_{t=1}^{D_T} \frac{|R_{t\,;T}^{i}|}{V_{t\,;T}^{i}} \tag{23}$$

Where D_T is the number of daily data available; $R^i_{t\,;T}$ is the return on day t of year T; and $V^i_{t\,;T}$ is the daily volume. Therefore, we see from the formula that the day-t price impact of one currency unit of trades is given by $\frac{|R^i_{t\,;T}|}{V^i_{t\,;T}}$ (Hibbert, Kirchner, Kretzschmar & McNeil, 2009). This ratio is thus mainly useful in regression model to estimate the compensation in return for asset illiquidity.

iii. Price-based Measures

Price based measures allow to derive liquidity proxies directly and only from price behavior. In this category, we find two different types of measure: classical indices such as the variance ratio and the Marsh and Rock ratio; and econometric methods such as event studies and autoregressive process (Gabrielsen, Marzo & Zagaglia, 2011).

- **Variance ratio**

The variance ratio or Market-Efficiency Coefficient (MEC) is one of the most widely-used liquidity measure in the literature. The index measures “the impact of execution costs on price volatility over short time horizon” (Gabrielsen, Marzo & Zagaglia, 2011, p.14). Or, as Sarr and Lybek (2002, p.14) state, “the MEC exploits the fact that price movements are more continuous in liquid markets, even if new information is affecting equilibrium prices”.

The intuition behind the ratio is the following: if execution costs are high, asset markets are characterized by price volatility higher than the theoretical volatility of equilibrium prices. Therefore, a more liquid market implies a smaller variance of price around the equilibrium price. In other word, the difference between the equilibrium price and the transaction price is smaller in liquid markets (Gabrielsen, Marzo & Zagaglia, 2011). The ratio is based on a comparison of short-term and long-term volatility.

$$VR_i = \frac{var(R_{i\,;T})}{T.var(Z_{i\,;T})} \tag{23}$$

Where $var(R_{i\,;T})$ is the long-term variance; $var(Z_{i\,;T})$ is the short-term variance; and T is the number of sub-periods into which longer period of time is divided. When the variance ratio for asset i is lower than 1 ($VR_i < 1$), it suggests that the market for asset i is illiquid. A ratio closer but below one indicates a more resilient market, with short-term returns (volatility) equals to long-term equilibrium returns (Gabrielsen, Marzo & Zagaglia, 2011; Sarr & Lybek, 2002). Factors that enhance short-term volatility are numerous: price rounding's, spreads or inaccurate price discovery among others. On the other hand, some factors reduce short-term market volatility such as market maker intervention or sequential information arrival, leading to MEC higher than one (Sarr & Lybek, 2002). The time intervals used to compute the ratio are chosen arbitrary. Hasbrouck and Schwartz (1988) use for example the ratios two-days/ half-hour; one-day/one-hour; and two-day/one-day variance. This analysis is useful to distinguish the different information content of short-term and longer-term variance. Nevertheless, this arbitrary choice is pointed out as a weakness of the measure in the literature. The intervals chosen have indeed an important impact on the value of the ratio. Moreover, the variance ratio presents a second and important drawback: it relies on the notion of equilibrium price that are unobservable in reality. However, thanks to its computation ease and the fact that is takes into account real trading activity (and thus transactions inside or outside the bid-ask spread; contrarily to certain volume-based measure); the variance ratio remains a widely-used and informative liquidity measure.

- **Marsh and Rock Ratio**

Marsh and Rock (1986) (in Gabrielsen, Marzo & Zagaglia, 2011) propose a liquidity measure that assumes that price changes are independent from trade size, except for large traded blocks. The proposed index considers the relation between the percentage price change and the absolute number of transactions:

$$MR_i = \frac{1}{M^i} \sum_{m=1}^{M^i} \left| \frac{P_{i;m} - P_{i;m-1}}{P_{i;m-1}} \right| . 100 \tag{24}$$

The main difference with volume-based measure is that the scaling factor is the number of transaction and not the trading volume. "This represents the idea that the liquidity of an asset is better represented by the price effects of transactions, rather by the impact of volume". (Gabrielsen, Marzo & Zagaglia, 2011).

Again, the main issue with this index is the arbitrariness involved in its formulation; especially for the time period. It is well obvious that the results provided by the index are different for short or long-term time horizon. According to Gabrielsen, Marzo and Zagaglia (2011), it is reasonable to adopt the ratio for short studied periods. The exact meaning of short period is however not defined. Finally, contrarily to most volume-based measures, the measure is useable for both dealer and auction markets.

- **Econometric methods**

Beside the various simple ratios presented so far, more complex econometric methods can be used to study market liquidity. However, these technics are less commonly used because of their computational burden. This is the reason why, in this sub-section, we have chosen to only present shortly two of them: the autoregressive process and the event study.

Autoregressive process, and specifically autoregressive moving average (ARMA) model of volume traded, are used to separate the impact of anticipated trading volumes and unanticipated ones. The ARMA model is then used to forecast trading volume. The volumes that deviate from the forecast are considered as not anticipated and are associated with new information flowing to the market. This distinction is used the explain dealer's spreads. Other (more sophisticated) models can be developed to capture the volatility related to the time necessary for market participants to agree on new equilibrium price (autoregressive conditional heteroskedasticity and generalized autoregressive conditional heteroskedasticity models) (Sarr & Lybek, 2002).

Finally, event study is a useful tool to investigate liquidity around a certain event; for example, a new information issuance or a shock in the market. Event studies are based on the observation of returns and volumes around the event, which can provide insights on liquidity. However, it is worth keeping in mind that "it is difficult to provide a widely accepted interpretation of changes in liquidity by considering only the observed pattern of asset returns and volumes exchanged" (Gabrielsen, Marzo & Zagaglia, 2011, p.16). As a consequence, this tool is mainly valuable to complement the information provided by the ratios presented here above.

Chapter 3 – Chinese Financial Markets Description

Even if Chinese financial markets appear today as modern and as some of the most important stock exchanges in the world in term of market capitalization and transaction volumes; they still present some unique specificities. Therefore, getting to know these specificities is crucial in order to understand this paper. This chapter aims to present some relevant points for our analysis by describing the main characteristics of Chinese markets.

Section 1: Origins and reforms of Chinese Financial Markets

i. Introduction

Modern Chinese financial markets find their origins in the early 1980's, when Chinese government initiated a number of policies to reform the economy (Kam Hong, 2003). Privatization and reorganization of state-owned companies were critical points at this time. The first step of the process resulted in markets still largely controlled by the state where the capital structure of the companies was mostly owned by the state or by legal person (other state owned companies), both non-tradable. Consequently, less than one third of the shares of the companies were tradable. According to Aharony, Lee and Wong (2000), the Chinese government first ran an experiment with a stock market on a small scale with domestic investors only. China established Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) in 1990 and 1991 respectively. They are still the two stock exchanges of Mainland China[26]. In addition to this two market places, we find the Hong Kong Stock Exchange (HKEX).

Chinese markets were segmented into A-shares (Renminbi-denominated shares), B-shares (US dollar- and Hong Kong dollar-denominated shares) and H-shares (shares of Chinese mainland corporates traded in Hong Kong Stock exchange). A-shares were only open to local investors while B- and H-shares were open to foreign investors too. Chinese government used B-share to expand its markets to foreign investors and finally was ready to list some of its best SOEs[27] as H-share using the HKEX, outside the Chinese government jurisdiction (Aharony, Lee & Wong, 2000). The process was totally opposed to mature market economy since the

[26] Mainland China, Chinese Mainland or mainland refer to areas under the jurisdiction of the People's Republic of China and exclude the Special Administrative regions of Honk Kong and Macau.
[27] State owned enterprises

decision to go public was at government's hand and not at company's hand. Furthermore, another system applied before 2001 differs from mature open markets in that the aggregate amount of new shares was determined by the State Planning Committee, the People's Bank of China and the China Securities Regulatory Committee (CSRC) (Kam Hong, 2003).

ii. Reforms

In 2001, China became a member of the World Trade Association (WTO). A year later, it opened its domestic market (A-share) to foreign Qualified Foreign Institutional Investors, continuing its market opening (Yao, 2013). In 2003, the chairman of China Securities Regulatory Commission acknowledged that the compartmentalized share structure of Chinese companies was an issue. Finally, in 2005, Chinese government initiated a process to reform the capital structure of A-share issuers to make it entirely tradable (a significant step forward compared to the previous situation); a program issued by the CSRC and named "*Regulation of A-Shares Structure Reform of Listed Companies"*. According to Yao (1998), the basic capital structure for an A-share company in China prior to 2005 was the following:

- The State shares and State-owned legal person shares, which composed two-thirds of the total equity of a listed A-share issuer;
- The employees' shares;
- And the public shares (less than one third of the total shares of a listed issuer).

Both State/State-owned and employee shares were non-tradable. The reform stated the process by which: "all non-tradable A-shares of existing listed issuers shall be converted into tradable ones; and all A-shares to be issued by newly listed IPO issuers shall henceforward be uniformly tradable" (CSRC, 2005). Furthermore, the state decided to lift its ban on margin trading and short selling in A-shares (Yao, 2013).

Original purpose of B-share market was to attract foreign investors to invest their freely convertible currencies in China when the country had large shortage in foreign currencies (Yao, 2013). In order to strengthen this position, the B-share market was opened to individual Chinese investors in 2001 (whom could trade with their legal foreign currency account) but remained forbidden to Chinese Legal person. Nevertheless, this reform did not appear to be as effective as forecasted. The B-share market remained illiquid and stagnant. According to Yao (2013), various studies have been lead to explain the poor performance of B-share market. These studies reveal that "B-share issuers are generally concentrated in the traditional and cyclical industries; and that many of A-share issuers are leaders in their industries while most of B-share issuers were transformed though administrative means from SOE's to become State-controlled B-share issuers" (Yao, 2013). Therefore, B-share market was avoided by foreign investors whereas they were indented to be its major investor force. Ultimately, the CSRC eased China-incorporated firms quoted on B-share market to be transfer to Hong Kong Exchange (much more liquid, mature market) as H-share in 2013. H-shares' face value and transactions are denominated in HK-dollar while B-shares' are and traded in US-dollar (on SSE) or HK-dollar (on SZSE). Furthermore, H-share companies are constraint to the Hong Kong stock exchange's regulatory requirements.

Section 2: Share classes

This section aims to provide a clear overview of today different kinds of shares that Chinese companies can issue. A distinction is made between companies incorporated inside or outside China Mainland. This section is based on a Deutsche Bank paper (2014).

i. Companies incorporated inside the mainland: A-, B- and H-shares

A-share: Chinese companies incorporated and traded inside the China mainland on SSE and SZSE in Renminbi. These companies are generally state-owned or state-controlled.

B-share: Chinese companies incorporated and traded inside the China mainland on SSE and SZSE but denominated in US-dollar (on SSE) and HK-dollar (on SZSE). These companies are generally state-owned or state-controlled.

H-share: Chinese companies incorporated in the China mainland but traded on HKEX in HK-dollar. These companies are generally state-owned or state-controlled.

ii. Companies incorporated outside the Mainland: Red chips and P chips

Red chips: companies incorporated outside the Mainland and generally controlled by Chinese government entities (HKEX.com, 2015). Red chips are listed on HKEX in HK-dollar.

P-chips: companies incorporated outside the Mainland and run by private Chinese individual investors. They are listed on HKEX and denominated in HK-dollar. P-chips are also called Mainland Private Enterprises.

In addition, some companies issue shares in the United-States (on NYSE), London (on LSE) and Singapore (on SGX) stock exchanges. They are called **N-shares**, **L-shares** and **S-shares** respectively. These companies are most often incorporated outside the mainland and are generally controlled by private investors.

iii. Access to investors

Both local and foreign investors access to stocks differs with the class of share and the nature of the investor (individual or institutional). Historically, the domestic Chinese market (the A-share market) was the less accessible to foreign investors. Until 2002, the A-share market was closed to foreign investors due to Chinese willingness to control its markets. Nevertheless, China has softened its regulation since 2002 by creating the system of QFII. It allows foreign licensed investors to trade A-shares on SSE and SKSE (Deutsche Bank, 2014). Moreover, in 2012, the thresholds to be recognized as QFII[28] has been lowered and a derivative form of the concept as appeared as the Renminbi QFII or RQFII (Yao, 2013). Furthermore, A-share market is open to both retail (individual) and institutional Chinese investors. In addition, we must mention the Foreign Strategic Investors (FSIs) whom were allowed to trade on A-share market since 2006 (CSRC, 2005). This measure was taken in order to bring foreign advanced management skills, technology and fund, and to improve the corporate governance of listed companies in China. These investors can only acquire their A-shares in private offering (Yao, 2013). Finally, Shanghai-Hong Kong Stock Connect Program has been launched in 2014 and grants now access to A-shares to foreign investors via HKEx (see details in section 3, iii).

The B-share market was opened to all foreign investors (only) for a long when CSRC opened it to local individual investors in 2001, whom are now the largest investors on this market. It remains closed to Chinese institutional investors (Yao, 2013). According to general opinion, B-share market is nevertheless declining and could merge with A-share market in near future (Chen, 2011) or could see its listed stocks switch to H-shares (Yao, 2013).

Finally, the Chinese stocks listed on HKEX (H-shares, P-chips and Red chips) and on other stock exchanges (N-shares, L-shares and S-shares) are open to all investors (foreign or local; individual or institutional).

[28] QFII's are Qualified Foreign Institutional Investors as defined by the CSRC. See conditions in appendix 1.

	Market	Currency	# of stocks[29]	Open to[30]	Short selling	Margin trading
A-shares	SSE SZSE	RMB RMB	1114 468	Lid, List QFII's	Authorized Banned for QFIIS	Authorized Banned for QFIIS
B-shares	SSE SZSE	US-dollar HK-dollar	53 51	Fid, Fist Lid	Banned	Banned
H-shares	HKEX	HK-dollar	202	All	Authorized	Authorized
Red chips	HKEX	HK-dollar	133	All	Authorized	Authorized
P-chips	HKEX	HK-dollar	541	All	Authorized	Authorized
N-, L-, S-shares	NYSE, LSE, SGX	US-dollar, Pounds, SGD	/	All	Authorized	Authorized

Table 1 – Share classes recap table

Section 3: Mainland Stock Exchanges and Honk Kong Stock Exchange

i. Differences

The Mainland and Hong-Kong entities differ to a large extend. The 2015 Ranking of Economic Freedom (The Heritage Foundation & The Wall Street Journal, 2015) that ranks countries with regard to the degree of freedom of their economy illustrates this well. The ranking gives a score out of a 100 and evaluates the degree of market freedom, among others factors. For this particular criterion, Hong-Kong received a score of 90 and is described as follows:

> *Hong Kong has a 0 percent average tariff rate and remains one of the world's most open economies for international trade and investment. The highly developed and prudently regulated financial system offers a wide range of innovative financing options. The banking sector is dynamic and resilient. The large and growing financial exposure to the mainland continues to deepen.*

[29] Sources: HKEX 2014 report, CSRC 2014 report, SSE 2014 fact book and SZSE 2014 fact book.
[30] Lid = local individual investors; List = local institutional investors; Fid = foreign individual investors; Fist = foreign institutional investors.

On the other hand, China Mainland only receives the score of 43/100 and is described in these words:

> *China's average tariff rate is 4.1 percent. Export taxes, subsidies to state-owned enterprises, anti-dumping barriers, and other measures restrict trade. The government screens foreign investment and still tightly controls the financial system. State-owned enterprises benefit from greater access to capital and lower financing costs, but small and medium-sized companies continue to suffer from the lack of access to credit.*

The historical political differences before the re-unification of the two areas can explain this large gap between China and Hong-Kong. Thereby, it's still different regulatory boards that regulate the China Mainland stock exchanges and the Hong Kong Stock Exchange. SSE and SZSE are under the jurisdiction of the China Securities Regulatory Commission while the Hong Kong Stock Exchange Regulatory Board and more specifically by the Securities and Future Commission (SFC) governs the HKSE. According to the HKEX, the two main differences between Mainland markets and Honk Kong exchange are:

- firstly, the HKEX is more international and has more institutional investors;

- and secondly, the HKEX offers greater product choices.

ii. Stock Exchanges' Structure

The Hong Kong stock market consists in two separate boards: The Main Board (MB) and the Growth Enterprise Market (GEM). Because of its listing requirements, the Main Board is designed for companies with track of certain minimum profit, revenue, operating cash flow and market capitalization level while Growth Enterprise Market facilitates fund raising by companies that do not fulfill the MB's requirements but that have growth potential and a certain level of operating cash flow (PWC, 2014).

Shanghai Stock Exchange consists only in a main board while Shenzhen Stock Exchange is composed of the Main Board, the Small and Medium Enterprise board, the ChiNext and the Lefu boards. The SME and the ChiNext boards both facilitate fund-raising of small and medium enterprises with less strict listing requirements. Concerning the Lefu board, it is a SZSE brand for listed funds; we will not pay special attention to that market (SZSE.cn, 2015).

Regarding trading mechanism, Hong Kong Stock Exchange has a continuous order-driven system with a break at noon[31]. Shanghai Stock Exchange has a call auction at the opening and continuous order-driven trading after with a one-and-half hour lunch break[32] (Guo & Tian, 2005; SSE.com, 2016). Hong Kong and Shanghai stock exchanges mainly differ thus by the presence of a call auction to determine the opening price before the opening of continuous trading. Further, both differ from most traditional markets that use hybrid structure by relying on market makers and limit-order-book.

iii. Shanghai-Honk Kong Stock Connect Program

"Shanghai-Hong Kong Stock Connect" (denominated here-after "SSE-HK Stock Connect", "SSE-HK Connect Program", "Connect Program" or simply "the program") also often called "The Through Train" is defined as follows by the Hong Kong Exchanges and Clearing limited and the Shanghai Stock Exchange and China Depository and Clearing Corp. Limited (2016, p.1):

> *Shanghai-Hong Kong Stock Connect is a securities trading and clearing links programmed developed by the entities sub-mentioned, aiming to achieve a breakthrough in mutual market access between the Mainland and Hong Kong.*

Announced on April 10, 2014 and launched on November 17, 2014, the program is seen by observers as an innovative mutual market access scheme that represents an historical development of Chinese financial markets (BNP Paribas, 2014). In effect, the program has opened Chinese market to foreign investors at a level never seen before. So far, foreign investors were only allowed to invest in mainland-listed stocks via QFII or RQFII (or in B-shares) which were only available to large institutional investor pre-approved by the Chinese authorities (Deloitte, 2014). Of course, as a mutual program, it offers the possibility for mainland investors to trade stocks listed in Hong Kong. This possibility is called the Southbound direction while the Northbound direction refers to Hong Kong investors trading stocks listed in Shanghai. This second direction is obviously the one we are focusing on.

According to Asifma and Thomson Reuters (2014), Stock Connect is a transformational development for China's capital markets. It develops and matures the financial industry and open new volumes of international investments into the SSE. It also leads to an increased

[31] HKEX trading hours are as follows: 9:30 to 12:00 – Continuous auction/morning session; 13:00 to 16:00 – Continuous trading/afternoon session (HKEX.com, 2016).

[32] SSE trading hours are as follows: 9:15 to 9:25 – Call auction; 9:30 to 11:30 - Continuous trading/morning session; 13:00 to 15:00 – Continuous trading/afternoon session (SSE.com, 2016).

integration of Chinese capital markets in the global landscape, in particular by increasing the Renminbi quantity in use by foreign investors.

Besides the numerous challenges involved for market participants (order execution, tax issues…), the main interest of the program (for the purpose of this paper) is the new openness of the Shanghai A-shares market to foreign investor, including retail investors and hedge funds. Thanks to the program, any investor with minimum account balance of 500.000 RMB can access A-shares listed in Shanghai via the HKEx. This represents a potential to attract massive incremental investment flows from investors willing to invest in China. This new flows bring a substantial increase in liquidity to Shanghai stock market (Asifma & Thomson Reuters, 2014).

Concerning regulations and rules applied to the program, the main remarkable feature is the volume quota. Northbound trades are subject to a daily quota of 13 billion RMB and an aggregate quota of 300 billion RMB. The quotas apply on a net buy basis, meaning that investors always have the authorization to sell stocks (SSE & HKEx Regulators, 2016). The second important rule is the eligibility of stocks to be included in the program. Regarding the Northbound, only A-shares are included in the program. All constituents of SSE 180 index and SSE 380 index are included, along with all shares both listed on SSE (as A-shares) and HKEx (as H-shares) except if the share is not traded in RMB or is under “risk alert”. The stocks included in the program receive regular updates regarding the respect of various conditions (see appendix 2 for more details). On July first, the program contained 568 stocks out of 1149 A-shares listed on the SSE (SSE.com, 2016). Finally, in term of trading regulations, investors are required to follow SSE’s trading schedule and only limit orders are accepted (SSE & HKEx Regulators, 2016)[33].

As a final observation, it should be noted that if the start of the program has been astonishing (with quota attained in a few hours), the results for 2015 have been a bit under expectation with only 40% of the total quota achieved. Investors claim now openness to Shenzhen Stock Exchange where more small and middle caps are traded (Yiu, 2016).

[33] Other regulations such as foreign ownership limits, circuit breaker, and short selling or fees policy are available in the appendix 2.

Section 4: Investors' Profile

i. Investors' Structure

Investors' structure in Mainland Chinese markets differs from classical markets such as US markets. Indeed, individual investors are much more numerous and active in China than in most of other markets. According to Deutsche Bank (2014), individual investors hold 26% of the total (A-share) market capitalization and account for 78% of daily trading volume. Following to the individual investors' behavior, Chinese markets are more volatile. The 200-trading-day volatility of Shanghai Composite Index is 18% (annualized standard deviation of the relative price change), which is about 1,5 times the volatility of S&P 500 (Deutsche Bank, 2014). Nevertheless, this proportion of individual investors is nothing comparable to the one experimented in the early 2000's when 99% of the investors in A-share markets (both in Shanghai and Shenzhen) were individuals (Ng & Wu, 2007). However, this specificity makes it mandatory to study deeper the trading behavior of financial actors in China; and especially in Mainland since the market structure of HKEX appear to be more classical and mature.

ii. Individual and Institutional Investors' Trading Behavior

Ng and Wu (2007) have conducted a study on the trading behavior of institutions and individuals in Chinese equity markets, delivering their main finding as follows. The authors considered the institutional investors and four groups of individual investors with respect to their trade values. They first analyzed the impact of past returns on investors' behavior: they have proven that both positive and negative past returns play a significant role in investor decisions, but their role varies across different investor categories and different trading-horizons. They show first that institutions tend to be momentum investors, while individuals tend to be contrarian investors. Further, they found that institutions act as momentum[34] traders when they buy and sell stocks. This is consistent with previous researches of Grinblatt, Titman and Wermers (1995) and Nofsinger and Sias (1999). Second, they demonstrate that the three lower groups of individual investors act as contrarian[35] investors when they buy stocks, but conversely they tend to hold on to stocks with past poor performance. Previous studies on less sophisticated individual investors confirm those findings. Among others,

[34] "Momentum strategy involves finding the stocks that are the strongest, and are the likeliest to trade higher" (Light, 2012).

[35] Contrarian trading involves investing in the stocks that are performing poorly and then selling them when they are performing better.

Odean (1998) showed that individual investors have a strong preference to realize winning investments rather than losing ones and tend to hold losing investment too long. Third, Ng and Wu (2007) show that the fourth group of individual investors (with the largest trade value) tends to behave rather as institutions when they buy and act rather like smaller individuals when they sell.

Further, Ng and Wu (2007) investigate the trading behavior in Large and Small stocks. Their results show corroborating evidence that institutions tend to be momentum investors and their momentum investing is stronger in small than large stocks. Institutions are more likely to buy small stocks with strong past return performance and sell those with weak past return performance. However, they find no past-return effect on institutions buying of large stocks, but strong effects on their selling of large stocks. In addition, they demonstrate that the three lowest individual investors are strongly influenced by past returns for large stocks rather than small ones (both for buy and sell orders). Another finding shows that those investors tend to hold on to losing small stocks for a longer period than they do to losing large stocks. There are two interpretations for this result. Firstly, small individual investors are more willing to cut losses on large stocks than small ones. Secondly, it is too costly for them to support losses on large stocks. Finally, the study shows that the largest individual investors behave conversely. They are less inclined to buy small stocks while more inclined to buy large ones with past strong performance. They also tend to sell both large and small stocks when prior days' performance is poor.

In conclusion, institutions and individuals differ in their trading behavior with respect to both the past stock performance and stock size. It is interesting to note that individual investors do not all behave the same way, and that largest ones tend to behave in a more sophisticated fashion. Therefore, the specific structure of Chinese investors with large dominance of individuals in daily trading volume makes their behaviors particularly significant toward market movement and we must consider it.

Chapter 4 – Research Questions and Hypotheses

Since 2014, the Shanghai - Hong-Kong Connect has been allowing to foreign investors a much easier access to A-shares quoted in Shanghai. This facilitated access has been impacting prices, volumes and - we can expect - liquidity. However, probably because of the program's youngness, no study has treated this subject to our knowledge. Therefore, our goal in the empirical analysis will be to study liquidity patterns of stocks in- and out-the-program in order to compare these patterns and to determine if liquidity and its patterns are different for stocks included in the program.

This question is of interest when it comes to have a deeper understanding of the impact of a greater opening of Chinese financial markets to foreign investors. Indeed, Chinese markets remain less accessible than most other modern markets to international investors. Also, if its opening increases, it could have impacts on its behavior in term of volatility or liquidity among others. Because liquidity is the lifeblood of financial markets, it is worthwhile analyzing this particular feature.

We will focus in this paper on the intraday pattern of liquidity and to a smaller extent on day-of-the-week effect. Guo and Tian (2005) have already studied behavior of liquidity pattern in the Shanghai Stock Exchange over the 2000-2002 period. They found that the 5-minutes bid-ask spreads display a L-shaped pattern during the day and that the depths show an inverted L-shaped pattern. Moreover, they found that the bid-ask spread pattern has a positive relation with the volatility and a negative relation with stock prices and trading volume; while the depth pattern has a negative relationship with volatility and price but a positive relationship with trading volume. Other authors have studied the same phenomenon on other stock exchanges. For example, Köksal (2012) studied the liquidity pattern of the Istanbul Stock Exchange and found a L-shaped pattern of the bid-ask spread but a U-shaped pattern of the returns, number of trades and volumes. Krishnan and Mishra (2013) showed that many liquidity proxies have a U-shaped patter on the National Exchange in India.

In the first part of this study, we will compute and compare liquidity intraday pattern of two samples of stocks: one portfolio composed of "in-the-program" stocks and one portfolio of "out-the-program" stocks. In addition, we will be able to compare average liquidity proxies over the same period. It could have been interesting to study the liquidly patterns of stocks included in the program before and after the launch of the program, however due to nonavailability of data, this analysis is not possible. This preliminary analysis leads us to our first research question:

Sub-Question 1: Are liquidity proxies of stocks included in the program different from the ones of stocks that are not part of the program?

Given the general observations of the SSE regulators (improvement in price and volume), we can expect better liquidity proxies for the stocks included in the program. Our first hypothesis is thus the following:

Hypothesis 1: Liquidity proxies of "in-the-program" stocks are better than the ones of "out-the-program" stocks.

Further, we expect to observe intraday liquidity patterns similar to the ones described above. However, these patterns could exhibit larger variation during the day due to higher trading activity. Any case, we will compare those patterns carefully. In order to do so, we ask the following question:

Sub-Question 2: Are liquidity patterns of stocks included in the program different from the ones of stocks that are not part of the program?

This question is difficult to answer. On the one hand, we can expect similar patterns given that studies tend to show that very different markets exhibit similar patterns. On the other hand, the SSE-HK Connect program gives such a different access to the stocks it includes that we could expect at least some slight differences. Our second hypothesis is as follows:

Hypothesis 2: Stocks in-the-program and out-the-program both exhibit liquidity intraday patterns consistent with previous researches (L-shaped spread, U-shaped volume Etc.).

Further, we will explore the relationship between liquidity and trading price, level of risk and trading activity with the goal of answering the following question:

Sub-question 3: What are the determinants of intraday liquidity patterns?

In this second part of the study, we will test the next hypotheses for the full sample and for both in- and out-the-program samples, using the same methodology. Therefore, we will be able to observe if both samples deliver the same conclusions.

Empirical researches have commonly studied these relationships (Guo & Tian, 2005; Köksal, 2012). Demsetz[36], Tinic[37] ,Benston and Hagerman[38] and Stoll [39] (all in Guo & Tian, 2005) have shown the existence of an inverse relationship between spread and stocks price. According to Guo and Tian (2005, p.15), this relationship is explained "by the existence of fixed costs in the order processing component of the spread. If order-processing costs constitute a relatively fixed dollar amount, then higher priced stocks will produce lower proportional spreads". Therefore, we take the following hypothesis:

Hypothesis 3: There is an inverse relationship between stock price and spread.

The level of risk of an asset has been shown as an important determinant of spread. Because traders are risk adverse, they will associate higher spread to riskier asset since higher risk can lead to potential loss (Guo & Tian, 2005; Köksal, 2012). According to Guo and Tian (2005), the positive relationship between spread and level of risk can also be linked to the fact that greater price volatility implies larger holding costs for specialists. Therefore, we formulate our next hypothesis as follows:

Hypothesis 4: There is a positive relationship between return volatility (level of risk) and spread.

In addition, we will test the relationship between trading activity and spread. Higher trading activity can be associated either with lower spread because of the economies of scale in trading cost, either with higher spread because higher activity might be a signal of informed trading (McInish & Wood, 1992[40] – in Köksal, 2012). With respect to this second possibility, some authors have used trading activity as a proxy for flow of information coming to the market (Guo & Tian, 2005). Which effect dominate the other is still an open question. Guo and Tian (2005) take the hypothesis that the second effect exceed the former one, as found by McInish and Wood (1992) (in Köksal, 2012). As far as we are concerned and based on previous empirical evidences, we prefer the following hypothesis:

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[36] Demsetz, H. (1968). The Cost of Transacting. *The Quarterly Journal Of Economics*, *82*(1), 33.
[37] Tinic, S. (1972). The Economics of Liquidity Services. *The Quarterly Journal Of Economics*, *86*(1), 79.
[38] Benston, G. & Hagerman, R. (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal Of Financial Economics*, *1*(4), 353-364.
[39] Stoll, H. (1978). The Pricing of Security Dealer Services: An Empirical Study of Nasdaq Stocks. *The Journal Of Finance*, *33*(4), 1153.
[40] McInish, T. & Wood, R. (1992). An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks. *The Journal Of Finance*, *47*(2), 753.

Hypothesis 5: There is an inverse relationship between trading activity and spread.

Finally, we will test the effect of the inclusion in the Stock Connect Program and formulate the last hypothesis:

Hypothesis 6: The Stock Connect Program has a positive impact on liquidity measures by spread and depth.

Chapter 5 – Data and Methodology

Section 1: Data

We have construct two samples of 52 stocks (one sample of "in-the-program" stocks and one sample of "out-the-program" stocks) and studied them on two periods.

i. Stocks' Selection

Our goal is to analyze the impact of the SSE-HK Exchange program in term of liquidity. In order to do so, we have first constructed two samples of A-Shares: the first one contains stocks part of the program, the second one is composed of stocks not part of the program.

In order to isolate the impact of the program, we tried to make samples as comparable as possible. To this end, we have divided the population of A-Shares traded on the Shanghai Stock Exchange into four sub-samples, according to the market capitalization of the companies. We are basing our clustering on quartiles of the full population. In doing so, we obtain four groups with the following bounds:

Market Capitalization (in CNY)

> 16,717 billion	Between 8,516 billion and 16,714 billion	Between 4,997 billion and 8,516 billion	< 4,997 billion
Group 1	**Group 2**	**Group 3**	**Group 4**

Table 2 – Sample clustering

Then, we have operated a distinction between the stocks part and not-part of the program. Finally, we have randomly selected 26 stocks in each group of market capitalization: 13 stocks in the program and 13 stocks out the program. Thus, we obtain two sub-samples of 52 stocks well diversified in term of market capitalization (list in Appendix 3).

ii. Period Choice

We have determined our sample periods on two criteria: return and volatility. Because our goal is to isolate the effect of the SSE-HK Connect Program on market liquidity, we have been willing to select a period of "normal volatility and return". To do so, we have collected the daily price of the Shanghai Stock Exchange Composite Index[41] over a 180 days' period, between September 22, 2015 and June 20, 2016. Note that the limited availability of historical data for intraday data did not allow us to work on an older period.

Based on this data set, we have computed the daily returns of the index, the 20-days return and the volatility (standard deviation) on the 20-days' periods. After that, we have been able to construct confidence intervals on the returns and on the standard deviation of the 20-days periods.

From the daily returns, we have obtained the following intervals: daily return $\in [-3{,}55\,\% \,; 3{,}48\%]$ and 20-Days Std. Dev $\in [0{,}43\% \,; 2{,}93\%]$. We also obtained an average return over the 20-days periods of -1%. Knowing that we have determined a period of daily returns and standard deviation included in these bounds. Therefore, our 20-(trading) days "normal" sample is March 31, 2016 to April 28, 2016. This period has a standard deviation of 0,81%, average daily returns of -0,81% and a total return of -1%. One has to note that the period studied to choose our samples is characterized by a bearish market with a total return of -9,24% and a relatively low volatility (std. dev. of 1,76%).

In addition, we have chosen a 20-days period of abnormal return and standard deviation. This period is from December 28, 2015 to January 27, 2016. The period is characterized by -19% total return and 2,81% standard deviation which is much higher than the averages over the 180-days period.

iii. Data Collection and Clearing

Knowing the composition of our samples and our periods, we have collected the intraday data useful for our analysis. We have extracted (from the Bloomberg Database) for each stocks, for each trading day of the period, on a minute-by-minute basis, the following information: highest, lowest and close bid and ask prices; the close traded prices; and the ask, bid and traded volume. In addition, we have extracted the outstanding number of shares and the free float rate for each stock, on a daily basis for the three studied periods.

We have then cleared our database to make it workable for our analysis. Firstly, we have only conserved the data for the continuous trading hours: from 09:30 to 15:00. In practice, we have deleted the data lines for all timeslots before 09:30 and from 15:00. In addition, we have

[41] Considered as a good proxy for the Shanghai A-Share market as a whole.

deleted all data between 11:30 and 13:00 (which corresponds to lunch break). Because our data are extracted with GTM time, trading session will be further denoted from 03:30 to 09:30 (or 02:30 to 08:30 in period 2), with lunchtime between 05:30 and 07:00 (or 04:30 to 06:00 in period 2). Doing so, we have obtained 240 quotations for each trading day and 4800 data lines for each period.

Section 2: Methodology

i. Descriptive Analysis

The goal of the descriptive analysis is to determine the liquidity patterns of the Shanghai Stock Exchange Market during the day and to make a comparison of the liquidity of the stocks part/not part of the SSE-HK connect program.

To do so, we have selected a sample of liquidity measures applicable to high frequency data and applied them to our sample at minute interval through the day. For the morning session, the first interval is thus from 09:30 to 09:31 and the last from 11:29 to 11:30 (last quote used is 11:29); and for the afternoon session, the first interval is from 13:00 to 13:01 and last interval from 14:59 to 15:00 (last quote used is thus 14:59).

The liquidity proxies selected are the absolute bid ask-spread, the relative bid-ask spread, the effective bid-ask spread, the Roll's measure of spread, the trading volume, the depth and the turnover ratio. The spread measures are computed using the last bid and ask prices of the minute intervals. It appears that different views emerge in the literature concerning the data to use. Some authors prefer lowest ask and highest bid while others prefer best bid and best ask, or again other choose last bid and last ask. Guo and Tian (2005) use this last choice and it appears to be the most available. Moreover, we have noted that using lowest ask and highest bid induces abnormal results.

We have computed the absolute bid ask-spread as $S_t = P_t^A - P_t^B$ for each interval of the day, for each day of the sample, for each stock. We have then computed the average spread by minute for the 4800 intervals of our dataset for each group. In addition, we have computed the daily average spread over the 240 data of each day, again for each group. Doing so allows us to compare our different groups. Finally, we have calculated the "minute average spread" over our 20-days sample. Therefore, we have obtained the average absolute bid-ask spread during the day on a minute-by-minute basis and plot it. We have repeated the process for each group and for the full sample which constitutes our market average bid-ask spread. We process the same way for the relative bid-ask spread using the formula $\frac{(P_t^A - P_t^B)}{(\frac{P_t^A + P_t^B}{2})}$; and for the effective bid ask spread computed as $|P_t - \left(\frac{P_t^A + P_t^B}{2}\right)|$. It should be noted that we have excluded the values of our analysis for the interval with no ask or bid quote.

Concerning the Roll's measure of spread, we have first computed the minute return as $\frac{P_t - P_{t-1}}{P_{t-1}}$ for each interval of our sample. Then, we have computed the time series covariance between R_t and R_{t-1} using the data of our 52 stocks. Finally, we have computed the Roll's measure using the formula: $2.\sqrt{-Cov(R_t; R_{t-1})}$ for each minute interval. For positive value of the covariance, we have set the Roll's measure to zero, as it is the most common way to deal with this issue according to Corwin (2014).

After that, we have computed trading volume by minute for each stock. From these values, we have computed total group volumes (as the sum of the stock volumes) and the average group volume per minute for each minute of our sample. Additionally, we determine the minute-average total volume during the day over the 20-days period and plotted it to visualize the daily volume pattern. Finally, we have computed the daily volumes as the sum of the minute-volumes and the average daily volumes. As the spread analysis, we have processed this computation for each group and for the 52-stocks sample. In addition, we have applied the same methodology to depth and "dollar depth" respectively computed as the sum of bid and ask volume, and the sum of the value of bid volume and the value of ask volume.

Finally, we have computed the turnover ratio over the total period to give us another perspective of liquidity. To do so, we have first determined the number of shares available for trade by multiplying the outstanding shares by the free float rate. Then, we have calculated the average daily price of each stock. After that, we have obtained the turnover for each stock for each day as the sum of the minute turnovers. Therefore, we have the turnover rate by dividing theses turnovers by the product of the average daily price and the number of shares available for trade. We have thus finally obtained the turnover rate for each stock for each day of the sample period and average market turnover as the average of all the individual stocks' turnovers.

Based on these result, we are able to compare the liquidity of stocks in- and out-the program. Firstly, we have done a graphical analysis of the pattern of absolute/relative/effective spread and volume/depth during the day. Second, we are comparing this figure to research significant differences. Finally, we have researched correlations between our different measures.

ii. Regression Analysis

Our main purpose here is to test hypothesis 3 to 5 and to verify the robustness of liquidity patterns investigated in the descriptive analysis. In order to do so, we have used a linear regression to explain the 10-minutes average spread (relative spread) and 10-minutes average depth. We obtain 24 intervals per day.

The three first explanatory variables find their foundation in hypothesis 3 to 5: price, volatility and trading activity. The price is the 10-minutes average price to which we apply the logarithmic transformation to prevent from non-normality and/or heteroscedasticity problems. Then, we have used 10-minutes standard deviation of return as a proxy for volatility (log(10-minutes volatility)). Finally, trading activity is approximated by trading volume (log(10-minutes average trading volume)).

After that, we have included dummy variables to model day-of-the-week effect and time-of-the-day effect. Doing so, we have created respectively 4 and 23 dummy variables. These variables allow us to confirm the robustness of the patterns observed in the descriptive analysis.

In addition, given the construction method of our data set, we have included dummy variables for the market capitalization groups. Indeed, thanks to that, it is easy to verify if stocks with higher market capitalization have higher or lower spread and depth.

Finally, we have added a dummy variable to represent the inclusion in the Stock Connect Program. It allows us to test and quantity the impact of the program in term of liquidity (hypothesis 6).

As a consequence, our model is as follows[42]:

[42] The model is also estimated for Log(depth) as explained variable.

$$
\begin{aligned}
Log(Spread_{i,t}) = \ & \beta_0 + \beta_1 \log\left(Price_{i,t}\right) + \beta_2 \log\left(Volatility_{i,t}\right) + \beta_3 \log\left(Trading\ volume_{i,t}\right) \\
& + \sum_{h=1}^{3} \delta_h Market\ Cap_i + \sum_{j=1}^{4} \alpha_j Day_{i,t} + \sum_{k=1}^{23} \gamma_k\, Time_{i,t} + \beta_4 Dummy\ Program_i \\
& + \varepsilon_{i,t}
\end{aligned} \tag{25}
$$

Spread, price and trading volume refer to 10-minute average values. Volatility is computed as the standard deviation of the ten last returns of the interval. It should also be noted that we do not include a dummy variable for the group 3 of market capitalization, for Wednesday and for the interval 11:30-11:40 to avoid perfect multicollinearity.

We have verified hypothesis 3 to 5 by testing the significance of coefficient β_1 to β_3. Day-of-the-week effect is checked out by testing the significance of the α_j and time effect by testing the significance of the γ_k . Finally, the effect of market capitalization group and inclusion in the program is verified by testing the significance of δ_h and β_4 respectively.

Lastly, we estimate the model above - and the same model with depth as explained variable - with ordinary least squared method.

Chapter 6 – Results

Section 1: Descriptive Analysis

In this first section, we will successively analyze our results for in-the-program and out-the-program stocks. After that, we will compare the liquidity of the two groups based on these preliminary results and try to understand where patterns come from. It should be noted that we analyze the first period in this chapter. If no mention is made of a difference, the reader can conclude that the results are consistent with the second period – almost all results are similar in period 1 and 2. The full results for the second period are available in the appendix 4.

i. In-the-program Sample

The bid-ask spread analysis reveals slightly different – though close - results from those of Guo and Tian (2005) with an average relative spread of 0,16% over the 4800 data sample against a 0,18% spread for Guo and Tian (2005). Interestingly, we can notice different spread values between the groups. Group 4 in particular exhibits higher spread though the analysis of period 2 does not confirm it. Deeper study of the data does not reveal the presence of outlier in this group. Actually, a majority of stocks in this group show higher relative spread compared to the groups of higher market capitalization.

	Group1	**Group 2**	**Group 3**	**Group 4**	**Average**
Thursday 31/03/16	0,17%	0,10%	0,12%	0,27%	0,17%
Friday 1/04/16	0,17%	0,12%	0,13%	0,31%	0,18%
Tuesday 5/04/16	0,17%	0,10%	0,12%	0,27%	0,17%
Wednesday 6/04/16	0,17%	0,10%	0,11%	0,26%	0,16%
Thursday 7/04/16	0,17%	0,10%	0,12%	0,29%	0,17%
Friday 8/04/16	0,17%	0,11%	0,13%	0,29%	0,18%
Monday 11/04/16	0,13%	0,09%	0,11%	0,24%	0,14%
Tuesday 12/04/16	0,14%	0,11%	0,13%	0,27%	0,16%
Wednesday 13/04/16	0,15%	0,10%	0,11%	0,25%	0,15%
Thursday 14/04/16	0,15%	0,10%	0,11%	0,25%	0,15%
Friday 15/04/16	0,15%	0,10%	0,12%	0,25%	0,15%
Monday 18/04/16	0,15%	0,10%	0,12%	0,28%	0,16%
Tuesday 19/04/16	0,16%	0,10%	0,12%	0,27%	0,16%
Wednesday 20/04/16	0,16%	0,11%	0,14%	0,39%	0,20%
Thursday 21/04/16	0,16%	0,11%	0,13%	0,31%	0,18%
Friday 22/04/16	0,17%	0,12%	0,14%	0,32%	0,19%
Monday 25/04/16	0,18%	0,12%	0,13%	0,30%	0,18%
Tuesday 26/04/16	0,17%	0,11%	0,13%	0,27%	0,17%
Wednesday 27/04/16	0,16%	0,10%	0,13%	0,26%	0,16%
Thursday 28/04/16	0,17%	0,12%	0,14%	0,31%	0,18%
Average	**0,16%**	**0,10%**	**0,12%**	**0,27%**	**0,16%**

Table 3 – Average Relative spread of in-the-program sample (period 1)

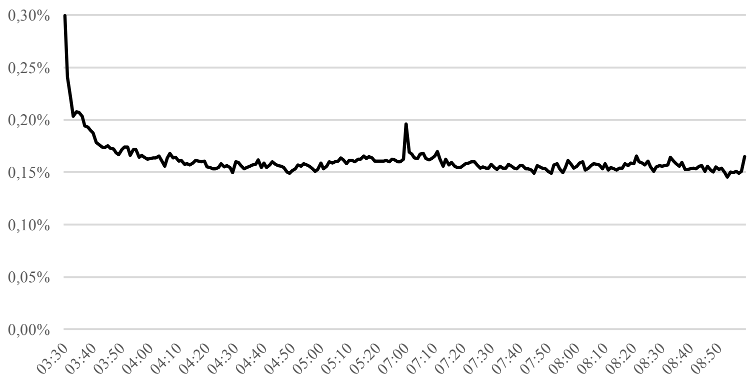
The table above gives us the average relative spread per day between the 31/03/2016 and the 28/04/2016 for in-the-program sample. The group spreads are computed as an average of all stock of the group, global averages are a mean of the daily average spread of the four groups.

The day-of-the-week effect shown by various former studies does not clearly appear here. The size of our sample can be in cause. However, the higher Monday's spreads[43] are visible in three out of the four weeks studied. According to Guo and Tian, higher Monday's spreads are logical result since non-trading period (the weekend) allows for building-up and accumulating new information, which will reflect on the prices on the first trading day of the week. Traders would thus reduce their trading activity on Monday due to uncertainty and risk of encounter informed traders.

The slightly increase in spread in the end of the week is also consistent with Guo and Tian (2005) but more difficult to explain by market microstructure. Inventory management should indeed lead to a narrowing of the spread at the end of transaction period and not to a widening.

Moreover, regarding depth, our results are not consistent with Guo and Tian (2005) in term of day-of-the-week effect. Indeed, we should observe lower depth on Monday to be coherent with the microstructure view of lower liquidity after non-trading period. However, we can argue that the size of our sample is too small to study in deep liquidity pattern through days of the week.

Figure 2 – Average Spread per minute during the day for in-the-program sample



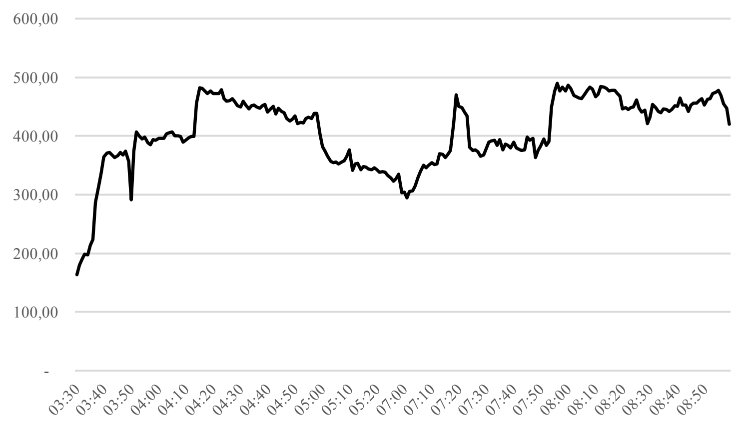
The figure 2 displays the evolution of average spread during the day. It is computed as the average spread of the whole sample of in-the-program stocks on a minute-per-minute basis. In other words, it exhibits the average pattern of spread during the day, over the period 31/03/2016 – 28/04/2016.

On the other hand, liquidity patterns during the day are easier to observe. As we can see on the graph and as expected, the spread follows an L-shaped pattern during the day. Spread is

[43] Tuesday 05/04 is to be considered as Monday given that is the first trading day of that week.

highest at the opening of the continuous trading session, just after the call auction, and declines quickly during the ten first minutes of trading to reach average values. Just after the lunch break, quotations resume with substantially higher spreads and declines steadily in the next intervals. In period 2, this phenomenon is present but in lower magnitude. Finally, we note an increase at the end of the trading session. Spread patterns in period 2 are basically the same but more volatile.

Figure 3 – Total depth per minute during the day for in-the-program sample

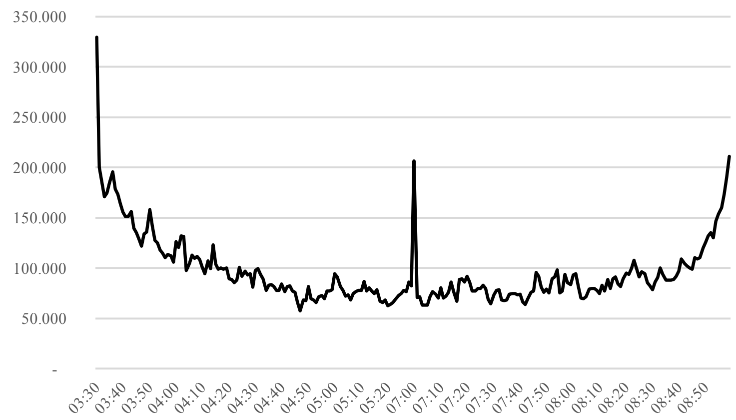


The figure 3 displays the evolution of depth during the day. It is computed as the total depth of the whole sample (of in-the-program stocks) on a minute-per-minute basis. In other words, it exhibits the average pattern of depth during the day over the period 31/03/2016 – 28/04/2016.

The figure 3 exhibits the evolution of depth during the day. We notice that depth is the lowest (164 M) at the opening of the trading session and then increases to reach average values (around 404M) after 10 minutes. We note that depth is characterized with high volatility. In any case, it is possible to distinguish its pattern, which is consistent with previous findings of Guo and Tian (2005). Beside the low opening level, we notice a decrease in the last intervals before lunch break. After the break, depth starts again at a lower level (304M) and recovers quickly to come back to average values. The pattern of the depth of period 2 confirms these findings, in a less obvious way.

In addition, it is interesting to compare depth with trading volume. The figure 4 exhibits a U-shaped pattern of trading volume. This pattern is consistent with the findings of Köksal (2012). Trading volume opens at the highest volume (probably because of the clearing of the call auction process) and then decreases to reach a lowest volume a few minutes before lunch break. Trading volume then recovers slightly in the last intervals of the morning session. After lunch, the volume reaches a peak in the first minute of the afternoon session, before coming back to average values. Finally, trading volume increases roughly in the last intervals of the day to finish at its second highest level.

Figure 4 – Average volume per minute during the day for in-the-program sample



The figure 4 displays the evolution of trading volume during the day. It is computed as the average trading volume of the whole sample (of in-the-program stocks) on a minute-per-minute basis. In other words, it exhibits the average pattern of trading volume during the day over the period 31/03/2016 – 28/04/2016.

As expected, correlations are negative between relative spread and depth but positive between volume and spread (table 4), which is confirm by period 2. Those two correlations are significant at a 99% confidence level. On the other hand, volume and depth do not exhibit a significant correlation. The negative relationship between depth and spread is consistent with Guo and Tian (2005) and Köksal (2012) findings. It gives us evidence that traders use both spread and depth to carry out their strategies. Wider spreads come with lower depth and vice versa. The relation with trading volume is more questionable and more difficult to explain.

		Relative Spread	**Volume**
Volume	Correlation	0,380	
	P-value	0,000	-
	N	4800	
Depth	Correlation	-0,347	0,017
	P-value	0,000	0,237
	N	4800	4800

Table 4 – Correlations between liquidity measures of in-the-program sample

The table above display correlations between relative spread, volume and depth. Each variable is computed on the 4800-minutes intervals of period 1, using the 52 stocks of the in-the-program sample.

Finally, let us note that other measures such as effective spread or dollar depth exhibit the same pattern (see appendix 4). Also, the computation of the Roll's measure of spread shows an underestimation of the spread with a value of 0,09%, consistent with the literature. Furthermore, Roll's measure of spread and true relative spread show a correlation of 0,192 significant at a 99% confidence level.

ii. Out-the-program Sample

The bid-ask spread analysis of the out-the-program sample reveals almost identical average values compared to the findings of Guo and Tian (2005) with an average relative spread of 0,171% versus 0,177%. Group 1 and 2 have identical average spread (0,12%) while group 3 and 4 exhibit higher spreads. In particular, group 4 presents again the highest average spread (confirmed by period 2).

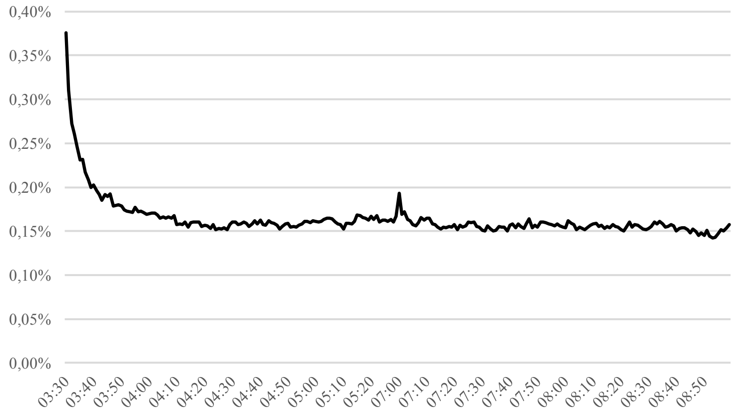
	Group1	Group 2	Group 3	Group 4	Average
Thursday 31/03/16	0,12%	0,13%	0,14%	0,28%	0,17%
Friday 1/04/16	0,13%	0,13%	0,15%	0,34%	0,19%
Tuesday 5/04/16	0,12%	0,13%	0,13%	0,30%	0,17%
Wednesday 6/04/16	0,12%	0,02%	0,13%	0,29%	0,17%
Thursday 7/04/16	0,12%	0,13%	0,13%	0,30%	0,17%
Friday 8/04/16	0,13%	0,13%	0,15%	0,32%	0,18%
Monday 11/04/16	0,11%	0,09%	0,14%	0,25%	0,15%
Tuesday 12/04/16	0,11%	0,13%	0,15%	0,29%	0,17%
Wednesday 13/04/16	0,11%	0,11%	0,13%	0,23%	0,14%
Thursday 14/04/16	0,12%	0,12%	0,14%	0,23%	0,15%
Friday 15/04/16	0,11%	0,12%	0,14%	0,24%	0,15%
Monday 18/04/16	0,13%	0,13%	0,14%	0,27%	0,17%
Tuesday 19/04/16	0,12%	0,12%	0,14%	0,24%	0,15%
Wednesday 20/04/16	0,14%	0,14%	0,16%	0,41%	0,21%
Thursday 21/04/16	0,13%	0,12%	0,15%	0,31%	0,18%
Friday 22/04/16	0,13%	0,15%	0,16%	0,34%	0,20%
Monday 25/04/16	0,13%	0,14%	0,15%	0,33%	0,19%
Tuesday 26/04/16	0,12%	0,14%	0,14%	0,31%	0,18%
Wednesday 27/04/16	0,12%	0,13%	0,14%	0,28%	0,17%
Thursday 28/04/16	0,13%	0,14%	0,15%	0,35%	0,19%
Average	**0,12%**	**0,12%**	**0,14%**	**0,28%**	**0,17%**

Table 5 – Average Relative spread of out-the-program sample (period 1)

The table above gives us the average relative spread per day between 31/03/2016 and 28/04/2016 for out-the-program sample. The group spreads are computed as an average of all stock of the group, global averages are a mean of the four groups' daily average spread.

Again, day-of-the-week effect does not clearly appear here but it is easy to guess it. Higher Monday's spreads are visible in three out of the four weeks studied. Obviously, the same explanation can explain this day's influence. We note that three out four times, Wednesday is the day-of-the-week with the lowest spread, consistent with Guo and Tian (2005) results. However, we remain aware that the limited size of our sample does not allow us to provide significant results regarding day-of-the-week effect but only give us an overview that seems to confirm previous works.

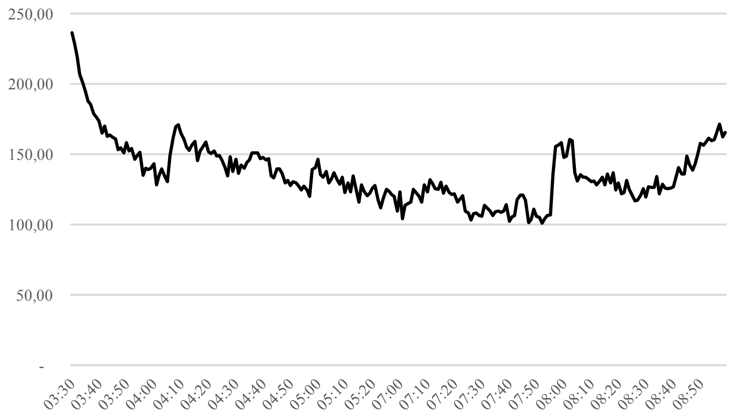
Figure 5 – Average spread per minute during the day for out-the-program sample



The figure 5 displays the evolution of average spread during the day. It is computed as the average spread of the whole sample (of out-the-program stocks) on a minute-per-minute basis. In other words, it exhibits the average pattern of spread during the day, over the period 31/03/2016 – 28/04/2016.

The figure 5 represents the relative bid-ask spread during the day. Again, we find the L-shaped consistent with the literature. We also recognize highest value after lunch break and slight increase at the end of the trading session.

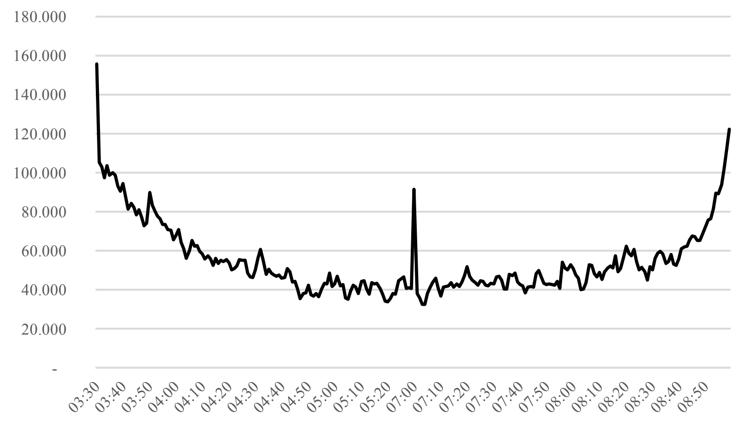
Figure 6 – Total depth per minute during the day for out-the-program sample



The figure 6 displays the evolution of total depth during the day. It is computed as the total depth of the whole sample (of out-the-program stocks) on a minute-per-minute basis. In other words, it exhibits the average pattern of depth during the day, over the period 31/03/2016 – 28/04/2016.

Out-the-program total depth exhibits a particular pattern, which is in-between the L-shaped and U-shaped pattern. Total depth is the highest at the start of the trading session and then decreases to reach its average values and fluctuates during the day with a relatively high volatility. Moreover, depth appears to increase in the last intervals of the day. This pattern is surprising and not consistent with Guo and Tian (2005) findings. However, Köksal (2012) and Tissaoui (2012) have found that many proxies, including depth can follow a U-shaped profile. Further, we can argue that the non-smooth profile of the curve is due to the relatively limited size of our dataset. Period 2 analysis reveals the same pattern, even if it is more volatile and thus less perceptible.

Figure 7 – Average volume per minute during the day for out-the-program sample



The figure 7 displays the evolution of trading volume during the day. It is computed as the average trading volume of the whole sample (of out-the-program stocks) on a minute-per-minute basis. In other words, it exhibits the average pattern of trading volume during the day over the period 31/03/2016 – 28/04/2016.

On the other hand, average trading volume exhibits a clear U-shaped pattern, consistent with previous findings. Again, we observe three remarkably high values: at the opening of the morning session, at opening of the afternoon session and at the closing of the session. We note here a volume pattern closer to the depth pattern, even if depth takes longer to decrease at the opening, does not show a peak after lunch time and does not inflate as much as volume at the closing.

		Relative Spread	Volume
	Correlation	0,388	
Volume	P-value	0,000	-
	N	4800	
	Correlation	0,114	0,130
Depth	P-value	0,000	0,000
	N	4800	4800

Table 6 – Correlations between liquidity measures of out-the-program sample

The table above display correlations between relative spread, volume and depth. Each variable is computed on the 4800-minutes intervals of period 1, using the 52 stocks of the out-the-program sample.

We see from the table 6 that significant relationships exist between relative spread and depth, relative spread and volume and between volume and depth. The first relationship is the most surprising since we would have expected a negative one[44]. In this case, a wider spread is associated with a higher depth. In other words, a weakening in one liquidity factor comes with the improvement of another liquidity factor. Nevertheless, we note that though it is a significant observation, this relationship is still rather small with a correlation coefficient of 0,114.

[44] Which is indeed negative for period 2.

Finally, we remark that other liquidity proxies such as effective spread or dollar depth demonstrate patterns similar to the ones shown here. Also, Roll's measure underestimates the relative spread with a value of 0,09% over the total sample. The measure shows a correlation of 0,266 with true value of spread at a 99% confidence level.

iii. In- and out-the Program Sample Comparison and In-depth Analysis

We observe form table 7 than except for the first group, in-the-program stocks have lower spread than out-the-program ones. This is consistent with what we expect: better liquidity for stocks part of the program. Nevertheless, this difference is rather small and other factors than the program could explain them, such as stocks characteristics (level of risk, expected return etc.). Further, it is interesting to note that both in- and out-the program groups 4 exhibit the highest relative spread (confirmed by period 2). Also, we observe that relative spread tends to increase in smaller market capitalization groups.

	Group 1	**Group 2**	**Group 3**	**Group 4**	**Average**
In-the-program	0,16%	0,10%	0,12%	0,27%	0,16%
Out-the-program	0,12%	0,12%	0,14%	0,28%	0,17%

Table 7 – Average relative spread in- and out-the-program

The table above display average relative spread for the period 1, for each group of in- and out-the-program samples (and global average). It allows a group-per-group comparison of average relative spread over the period.

Regarding depth, we see from table 8 that the in-the-program sample exhibits a much higher average minute depth over the studied period. However, group-by-group analysis differs slightly for in- and out-the program sample. On the one hand, in- and out-the-program groups 1 have the highest depth. On the other hand, hierarchy of depth differs in the three remaining groups.

	Group 1	**Group 2**	**Group 3**	**Group 4**	**Average**
In-the-program	19.327.731	673.927	667.612	3.475.219	6.036.122
Out-the-program	8.107.819	2.356.013	858.931	227.209	2.887.493

Table 8 – Average depth in- and out-the-program

The table above display average depth for the period 1, for each group of in- and out-the-program samples (and global average). It allows a group-per-group comparison of depth over the period.

These early comparisons seem to confirm better liquidity for stocks that are part of the program, which is confirmed by an average daily turnover rate of 14% for in-the-program sample against 6% for out-the-program sample. However, we cannot confirm that those differences in spread and depth are statistically significant. Indeed, comparing average of time series does not allow us the use of classical statistic tests (student test, anova etc.). Therefore, we will focus further on the interpretation of graphical results.

Figure 8 displays the evolutions of in- and out-the-program relative spreads during the day. We clearly observe the same L-shaped pattern for both in- and out-the program samples. Interestingly and consistently with table 7, we note a higher initial spread at the start of the morning session for out-the-program sample. Then, the narrowing of the spread is quicker for in-the-program stocks. In-the-program stocks seem to reach their average spread values as soon as 3:40 while out-the-program attain those values around ten minutes later. Later, the pattern is strongly similar, with an increase in same magnitude just after the lunch break and a slight inflation at the end of the trading day. Although in-the-program spread curve seems to evolve in a less smooth manner, the figure does not confirm this feeling. Indeed, in-the-program minute spread has a standard deviation of 0,03% over the total period against 0,04% for out-the-program one. However, beginning-of-the-day values that are much higher for out-the-program sample and that act as outliers (and inflate the standard deviation) can probably explained this higher volatility.

Figure 8 – Comparison of relative spread behavior (in- versus out-the-program)

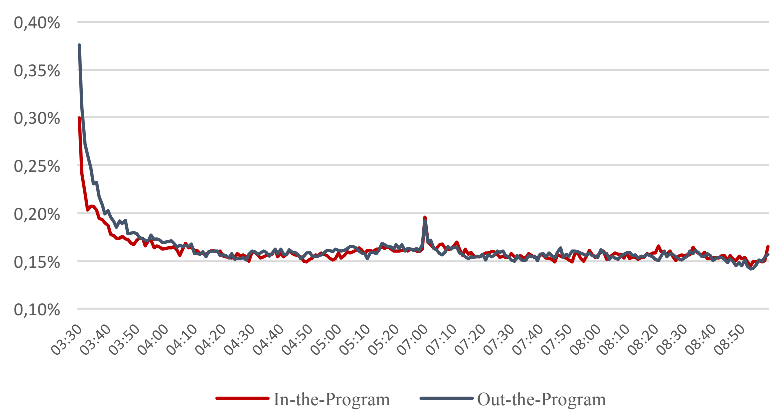
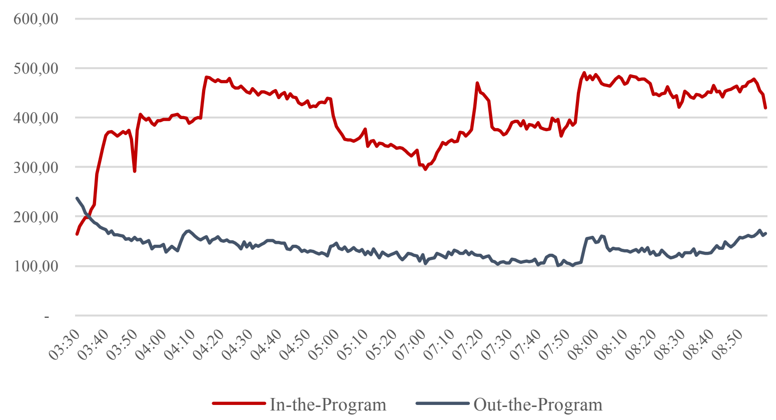


Figure 8 displays relative spread behaviors of in- and out-the-program samples. Relative spreads are computed as above, as minute average spread using the 52 stocks of each sample. Thus, we obtain average minute spread over the period for each group.

Next, figure 9 illustrates the depth of in- and out-the-program samples. We observe two very different patterns. In-the-program sample shows L-shaped curve over the day consistent with Guo and Tian (2005) while out-the-program sample exhibits a U-shaped pattern consistent with Tissaoui (2012). The two patterns differ in multiple points. Firstly, the depth starts at its highest level for out-the-program stocks while it starts at its lowest for in-the-program ones.

Then, in the first interval of the day, the depth increases for in-the-program stocks but decreases for out-the-program sample. Moreover, this increase/decrease has significantly different magnitude (much higher for in-the-program sample). After that, the depth navigates around its average values for both in- and out-the-program sample, but with a higher volatility for in-the-program sample (standard deviation of 1.190.000 versus 423.200 during the day). Additionally, in-the-program sample shows a lunch break effect similar to the one observable at session start. On the contrary, the break does not seem to influence significantly the out-the-program stocks' depth. Also, we observe a decrease in depth in the last intervals of the day for in-the-program stocks, while out-the-program sample's depth inflates slightly. Finally, correlations between the depth and the spread show different results: in-the-programs stocks demonstrates significant negative correlation between the two proxies (correlation coefficient: -0,347), while out-the-program sample's depth and spread correlate significantly (correlation coefficient: 0,114).

Figure 9 – Comparison of depth behavior (in- versus out-the-program)



The figure 9 display depth behaviors of in- and out-the-program samples. Depth are computed as above, as minute average depth using the 52 stocks of each sample. Thus, we obtain average minute depth over the period for each group.

To finish the comparison, let us note that Roll's measure of spread both underestimates relative spread of in-the-program and out-the-program samples. However, spreads of out-the-program stock are more correlated with Roll's measure (correlation coefficient: 0,266 versus 0,192). Moreover, both in- and out-the-program samples' relative spreads correlate negatively with returns, respectively with correlation coefficients of 0,060 and 0,056 (significant at 99% confidence level). Finally, as we have observed here-above, trading volumes exhibits strong U-shaped patterns for the two samples.

At this stage, we can already draw some conclusions. Firstly, in-the-program sample seems to enjoy slightly better liquidity than out-the-program one according to the liquidity proxies studied (spread, depth, trading volume, turnover) which confirms our first hypothesis.

However, none can conclude that the SSE-HK Stock Connect program is the only source of better liquidity. Indeed, the stocks included or not can differ by other characteristics. Secondly, both samples exhibit L-shaped spread pattern during the day but show strongly different patterns of depth. The question that arises is what explains the patterns present in the Shanghai Stock Exchange?

First of all, it should be reminded that the non-constancy of bid-ask spread during the day and across day of the week is in conflict with market efficiency hypothesis (Guo & Tian, 2005; Tissaoui, 2012). This fact must be a motivation for regulator to understand better the causes of the patterns. Then, let us recall that the structure of the order-driven Shanghai A-share market allows us to isolate easier the effects acting on liquidity proxies than other more sophisticated markets. Finally, in order to explore this question, we should keep in mind that, as we have stated in the literature, three main drivers affect liquidity: order processing cost (or handling cost), inventory costs, and asymmetric information cost.

The first cost is based on the hypothesis that liquidity demand elasticity changes during the day and that, market makers act to exploit these differentials (Guo & Tian, 2005) and to compensate for providing liquidity. However, this theory widely rests on the monopolist market maker hypothesis and is thus not applicable to the Shanghai order driven market. The theories regulating the second cost, the inventory cost, state that trader act in order to attain and maintain a desired level of inventory. The change of spread and depth in the last intervals of the day is consistent with this theory since traders are expected to quote bid and ask price in order to optimize their inventory level. According to Guo and Tian (2005), this adjustment should lead to a widening spread and lowering depth at the closing. This is consistent with our results for in-the-program stocks but only partially consistent for the out-the-program sample. Nevertheless, those results are not completely incompatible. Indeed, Tissaoui (2012) explains the U-shaped of depth (of out-the-program sample) in the same way; he states that the increase in depth at the end of the trading session is attributed to inventory strategy. As far as we are concerned, we argue that the main interest of the patterns, more than their form, is the presence of seasonality. For both in- and out-the-program samples, we observe that opening and closing are source of abnormal trading behaviors. The question is “why those trading behaviors are different for sample in- and out-the program?”. We could argue that the investor profiles differ with the sample, given that in-the-program sample is much more accessible to foreign investors. In any case, this result could be the source of further exploration.

The theories regulating the third cost, the, asymmetric information cost, are based on the existence of non-public information (adverse selection problem). Thus, traders quote their bid and ask price to protect themselves against the risk of trading with an informed trader. According to Guo and Tian (2005) and Tissaoui (2012), we can expect lower liquidity after period of non-trading due to the accumulation of non-public information. Uninformed traders are less willing to trade after this period due to the higher probability of meeting an informed trader. This is consistent with spread curves for in- and out-the-program stocks and for depth for in-the program sample. However, this is not consistent with out-the-program sample's depth curve. Given the lack of monitoring of the release of public information and private information by regulators (Guo & Tian, 2005), call auction and early trading (ndlr. at the opening of the trading day) is not attractive to uninformed traders, what explains higher spread and lower depth.

As a conclusion to the descriptive analysis, we hold the presence of clear intraday pattern in liquidity proxies. For in-the-program sample, adverse selection problem and inventory management can explain these patterns (for spread and depth). For out-the-program sample, adverse selection problem and inventory management can explain the pattern in spread while asymmetric information problem cannot explain depth pattern but well inventory management strategies. Beside this difference, we note that the sample included in the SSE-HK Connect program exhibits better liquidity proxies. When gathered together, these findings bring us to wonder why these differences exist. Our first guess is the greater openness of in-the-program stocks to foreign investors. However, the subject requires further research.

Section 2: Regression Analysis

The present section aims at formally confirming the intraday spread/depth pattern found in the descriptive analysis, at testing the hypothesis three to six and at further investigating the impact of the inclusion in the Stock Connect Program.

Firstly, table 9 provides descriptive results for the variables of interest for the full sample.

	10-min Average Spread	10-min Average Depth	10-min Average Price	10-min. Return Volatility	10-min Average Volume
Max	2,2410%	1.923.931.301	98,29	0,0307	6.709.710
Min	0,0040%	3063	0,07	0,00	6,30
Mean	0,1728%	4.352.266	14,52	0,0018	86.186
Standard deviation	0,0012	32.578.835	12,51	0,0012	176.666
Median	0,0014	403.274	10,57	0,0015	39.816

Table 9 – Descriptive statistics of quantitative variables of the regression model

The above table provides descriptive statistics of the quantitative variables used in the regression model, derived from the analysis of all stocks (in- and out-the-program) over period 1. This represents 46,495 observations.

Based on a total of 46.495 observations, we observe large magnitude between minimum and maximum values which can be expected for such cross-sectional data. Average trading volume of 86.186 and average share price of 14,52RMB suggest that typical trading behaviors consist of relatively large volume of low-priced stocks. Average value of spread (0,1728%) is very close to the one found by Guo and Tian (2005) (0,1739%). However, the depth appears to be much larger with a mean value of 4.352.266 against 266.057. This can be attributed to the continuous development of the Shanghai Stock Exchange since their study or simply to our samples.

	10-min Average Spread	10-min Average Depth	10-min Average Price	10-min- Average Volatility
10-min Average Spread	-			
10-min Average Depth	-	-		
10-min Average Price	-0,339***	-0,106***	-	
10-min- Average Volatility	0,366***	0,009***	-0,036***	-
10-min Average Volume	0,083***	0,259***	-0,177***	0,315***

Table 10 – Correlations between quantitative variables of the regression model

The above table provides correlations between the quantitative variables included in the regression model. Coefficients of correlation are computed from all stocks data over period 1, what represents 46,495 observations. Note that *** means correlation significant at 99% confidence level.

Correlation results exhibit positive linear relationship between spread, volatility and volume but a negative one between price and spread. The depth, on the other hand, also positively correlates with volatility and volume but is negatively associated with price. These results are fully in line with Guo and Tian (2005). Correlations between the independent variables are relatively small with a maximum correlation coefficient of 0,315 between volume and volatility. These low correlations suggest that we should not face co-linearity troubles.

According to Guo and Tian (2005), the negative relationship between spread and price can be explained by the existence of fixed cost in the order-processing component of the spread. The authors explain, "If the order-processing costs constitute a relatively fixed dollar amount, then higher price stocks will produce lower proportional spreads". (Guo & Tian, 2005, p.15). Then, the positive relationship with volatility is usually associated to inventory cost component. It makes sense since higher volatility represents higher inventory management risks. Therefore, market participants require higher compensation in the form of wider spread (Guo & Tian, 2005). Lastly, we note that the positive correlation between spread and volume is not consistent with hypothesis 5.

i. Spread Analysis

We can now address the heart of this section; the regression results. We have proceeded to six regression analyses. Three of them aim to explain the spread behavior while the other three study depth. In order to ease the reading, we present here in details the results for the spread analysis and only briefly discuss the result for the depth analysis in the next sub-section. Both results are consistent and confirm our previous findings.

We regress spread against the independent variables for in-the-program sample, out-the-program sample and the full sample. This allows us to compare the two samples and to identify prospective inconsistency. We use the ordinary least squared method to estimate the parameters of the model. The graphical analysis confirms that using a Log-Log model allows us to avoid non-normality and heteroscedasticity problem. However, it is important to keep in mind the implications of a Log-Log model in terms of interpretation. We have verified multicollinearity using the VIF coefficients, and autocorrelation with Durbin-Watson procedure. We did not face multicollinearity problem but well (positive) autocorrelation in all our regressions. Autocorrelation means that our estimators are unbiased but possibly not efficient. In other words, their variances are not minimal and the student tests could be inflated, what can lead to false positive [45] (Stanford.edu, 2015). However, for the purpose of this paper and according to previous researches on this particular topic (Guo and Tian, 2005; Köksal, 2012), we are assuming that we can deal with autocorrelation.

Regressions of in- and out-the-sample relative spread provide consistent results, which are consistent with full sample results as well. Therefore, we will base our analysis on the full sample regression. Actually, we have included an additional dummy variable in this model compared to the two first one: the variable “in-the-program”. This variable takes the value 1 if the stock is included in the Stock Connect Program and 0 otherwise. This should provide additional evidence of the effect of the Stock Connect Program in term of liquidity.

The results of the regression of the (log) relative bid-ask spread (equation 25) against the explanatory and dummy variables are presented in table 11 (page 72).

Based on 43.378 observations, the model exhibits a F-statistic (for the joint hypothesis that all estimators are equal to 0) of 4.180,612 which allows us to reject the null hypothesis of equality and conclude to the significance of the model. In addition, the (adjusted) R^2 of the regression is equal to 0,766.

We first note that hypothesis 3 to 5 are confirmed with significant coefficients for price (negative relationship), volatility (positive relationship) and volume (negative relationship). In other words, relative spread decreases when price and volume increase but inflates when volatility is higher. This is consistent with previous findings (Guo & Tian, 2005; Köksal, 2012; Tissaoui, 2012) and sustains the market microstructure theory. The positive coefficient of volatility shows that the difference of spread across stocks can explain their different levels of risk. This is consistent with market microstructure theory; a higher level of risk implies a higher inventory management and adverse selection risks. Therefore, market participants require higher compensation for providing liquidity under the form of wider spread. Regarding trading volume, it is not surprising that higher volumes are associated with lower spread. Indeed, higher volumes are expected to put downward pressure on order processing costs (Guo & Tian, 2005). Finally, we have already explained here above the logic behind the

[45] Incorrect reject of the null hypothesis that the estimator equals to zero.

negative coefficient of price. As a part of transaction cost is fixed, higher prices imply lower relative costs and then lower spreads.

Independent Variables	**Coefficients**	**t-statistic**
Intercept	-0,935***	-60,590
Log(10_min_Price)	-0,523***	-207,002
Log(10_min_Volatility)	0,404***	128,734
Log(10_min_Volume)	-0,067***	-38,022
Monday	0,004**	2,073
Tuesday	0,003*	1,730
Thursday	0,003	1,377
Friday	0,006***	3,288
03:30 to 03:40	0,032***	7,285
03:40 to 03:50	0,015***	3,577
03:50 to 04:00	0,011***	2,639
04:00 to 04:10	0,011**	2,504
04:10 to 04:20	0,006	1,403
04:20 to 04:30	0,003	0,755
04:30 to 04:40	0,007*	1,677
04:40 to 04:50	0,010**	2,259
04:50 to 05:00	0,007*	1,744
05:00 to 05:10	0,013***	3,069
05:10 to 05:20	0,013***	2,938
05:20 to 05:30	0,014***	3,293
07:00 to 07:10	0,021***	4,833
07:10 to 07:20	0,008*	1,890
07:20 to 07:30	0,006	1,313
07:40 to 07:50	0,005	1,231
07:50 to 08:00	-0,005	-1,193
08:00 to 08:10	0,005	1,123
08:10 to 08:20	0,005	1,275
08:20 to 08:30	-0,002	-0,477
08:30 to 08:40	-0,003	-0,719
08:40 to 08:50	-0,003	-0,639
08:50 to 09:00	-0,043***	-10,009
In-the-Program	-0,008***	-5,943
Group_1	0,014***	7,534
Group_2	-0,010***	-5,755
Group_4	0,335***	189,030

Table 11 – Regression Results

The table above provides the results of the regression of the (log) relative bid-ask spread against the explanatory and dummy variables (equation: $Log(Spread_{i,t}) = \beta_0 + \beta_1 \log(Price_{i,t}) + \beta_2 \log(Volatility_{i,t}) + \beta_3 \log(Trading\ volume_{i,t}) + \sum_{h=1}^{3} \delta_h Market\ Cap_i + \sum_{j=1}^{4} \alpha_j Day_{i,t} + \sum_{k=1}^{23} \gamma_k\ Time_{i,t} + \beta_4 Dummy\ Program_i + \varepsilon_{i,t})$ Note that *** means significant at a 99% confidence level; ** 95% confidence level and * 90% confidence level).

Then, the coefficients for day-of-the-week dummies tend to confirm the intuition discussed in the descriptive analysis. Indeed, Monday dummy variable shows a significant coefficient of 0,004, higher and more significant than other day of the week expect Friday; what is also consistent with previous findings.

Further, higher and more significant coefficients for beginning of the day intervals confirm intraday L-shaped pattern. The coefficient is the highest for the first interval and then decreases from 3:40 to 4:30. After that, it fluctuates during the day. The coefficients for interval just before (05:20 to 05:30) and just after (07:00 to 07:10) are significant and higher than other intervals, which confirms again the results showed in the descriptive analysis. According to Guo and Tian (2005), it is possible that dummy variables capture a time-of-the-day preference for trading which could be explained by structural change in the trading process across the day.

The significance of dummies for time-of-the-day and day-of-the-week demonstrates that spread behaviour cannot be solely explained by variation in price, volatility and volume. Moreover, the fact that the spread pattern is quite similar to the one of multi-dealers' system (Chan & al., 1995; in Guo & Tian, 2005) demonstrates that specific market characteristics (designated dealer, pure auction system etc.) do not explain spread behaviours.

Additionally, dummies for the inclusion in one or another group of market capitalization show significant coefficients. They seem to confirm our previous findings with a higher coefficient for group 4 (of smallest market capitalization). This is an interesting finding; it tends to show that the relative spread of A-shares relates to the market capitalization.

Finally, yet importantly, the coefficient for "in-the-program" dummy variable exhibits a significant negative value. This demonstrates that the inclusion in the program lead to smaller spreads and hence, higher liquidity. Even through it is still difficult to attributes the better liquidity solely to the inclusion in the program, we can consider this finding as an additional evidence that it has positive impact on liquidity.

ii. Depth Analysis

Finally, a few words about depth[46]. We find significant negative coefficient for both price and volatility, and positive one with volume. This is consistent with what has been exposed before (ndlr. higher volatility leads to higher risk and turns into narrower depth/wider spread; higher volumes put downward pressure on order processing costs and lead to higher depth/narrower spread). This demonstrates that each dimension magnifies the effect of the other one such that when the spread is wider, the depth is narrower, and vice versa. This suggests that both spread and depth are used interchangeably to measure and define liquidity. However, we note one confusing result; it is the negative sign of price coefficient for both spread and depth. This result is consistent with Guo and Tian (2005) who have not investigated it further. As far as we are concerned, we simply remark that if the negative relationship between spread and trading price makes sense from the microstructure of the market point of view, the one with depth is more ambiguous and difficult to explain.

Regarding the time-of-the-day and day-of-the-week effect, the results confirm the existence of both significant inter-day and intraday patterns. In addition, the dummy variables for the inclusion in the program and belonging to a market capitalization group confirm our previous findings. Indeed, we have further evidence that depth is higher for stocks included in the program, and the belonging to a group of small market capitalization negatively influences it.

Lastly, we have estimated the regression model of the depth for in-the-program and out-the-program sample in order to compare the patterns exhibited in the descriptive analysis. The two samples show very similar results regarding coefficient estimators of price, volatility and volume. However, the coefficients for dummies of time variables are different in large magnitude, which can be the sign of different trading behaviours for stocks in- and out-the-program.

[46] Comprehensive results can be found in appendix 4.D.i; .iv and .v.

Chapter 7 – Conclusion

Main Results

This thesis aims to provide a thorough study of the impact of the Shanghai-Hong Kong Stock Connect Program on Shanghai A-shares in term of liquidity. Our analysis reveals that stocks included in the program exhibit better liquidity proxies.

In addition, we have observed clear L-shaped patterns for spread for both in- and out-the-program samples. Those patterns are in conflict with the market efficiency hypothesis and suggest adverse selection problem. Indeed, we expect lower liquidity after periods of non-trading that allow accumulation of non-public information – and so higher spread at the start of the trading session. Moreover, the inventory management strategies used by market participants to attain a desired level of inventory can explain spread patterns, especially at the closing of the session.

Patterns of depth are more questionable. In practice, we have observed inverted L-shaped patterns for in-the-program stocks but U-shaped patterns for out-the-program sample, which the two periods have confirmed. We argue that inventory management strategies can explain both of those patterns, while asymmetric information cost can also explain the depth of in-the-program sample. This difference would lead us to suggest that trading behavior of investors trading stocks that are included in the program versus the behavior of the investors whose stocks are not in the program are different. This could be due to the higher proportion of international investors trading in-the-program stocks.

As the final note on liquidity patterns, we have observed U-shaped patterns of trading volume for both samples, which is consistent with inventory management theory and the characteristics of the market - call auction at the opening.

Subsequently, the regression analysis has confirmed the significance of time-of-the-day effect as well as the impact of price, return volatility and trading volume on spread and depth. In addition, we have demonstrated the implication of the impact of the market capitalization and of the inclusion in the program. As expected, spread is negatively impacted by price and volume while it is positively related to volatility. The depth, on the other hand, is negatively impacted by price and volatility but positively by volume. Spread relationships make sense from a microstructure point of view:

- Higher prices produce lower proportional spreads, as order-processing costs are a relatively fixed dollar amount.
- Higher level of risk implies higher inventory management risk and adverse selection problem leading investors to require wider spread.
- Higher volume leads to lower spread as high volume put downward pressure on order processing costs.

Depth relationships can be explained similarly aside for price, as its negative coefficient is more ambiguous. However, the study shows that depth and spread are used interchangeably to measure and define market liquidity by market participants.

Moreover, the significances of time-of-day effect demonstrates that spread and depth cannot be solely explained by price, volatility and volume and proves thus the presence of seasonality in trading behaviors. The significantly different coefficients of time-of-the-day effect between in- and out-the-program samples provide further evidence of difference in trading behaviors.

Finally, the regression model has demonstrated that being part of the program seems to influence liquidity positively, as well as being part of a group of higher market capitalization. The greater availability of those stocks would be an intuitive explanation.

Finally, the reader should note that all our results are consistent with the existing recent literature (among others Guo and Tian, 2005; Köksal, 2012; Tissaoui, 2012) and reinforce it. Specifically, those findings indicate that liquidity patterns cannot be solely attributed to specialists or market maker's activity[47] as the Shanghai Stock Exchange is a purely order driven market.

Implications of the Results

We distinguish two major types of implications we would like to draw the reader's attention to: the implications for the investors and the implications for regulators.

Firstly, investors should be aware of the liquidity patterns and of the determinants of liquidity. Indeed, illiquidity represents a cost that needs to be taken into account in investment strategies. So, being mindful of the evolution of spread during the week and over the day can

[47] this was suggested by former researches such as McInish and Wood (1992) or Brockman and Chung (1998) for example.

lead to smartest transaction timing, in order to minimize the illiquidity costs. Also, having highlighted L-shaped intraday patterns indicates a non-respect of the market efficiency hypothesis and the likely presence of informed traders. Investors should be aware of this matter of fact when making investment decision since CAPM and other factors models require the market efficiency hypothesis (Fox, 2009). Further, our results suggest that investors looking for highly liquid (a-share) stocks should prefer high market capitalization stocks and stocks included in the Stock Connect Program. Moreover, investors must be aware that measuring liquidity solely via spread or depth is not enough. Indeed, our results confirm that both dimensions play a role in determining stock liquidity and must be analyzed simultaneously.

For regulators, our findings are relevant from two points of view. The first one is related to the improved liquidity provided by the inclusion in a mutual stock exchange program such as the one studied. Indeed, we have noted that being part of the program seems to be a source of liquidity. Therefore, having a greater access to stocks improves their liquidity. This implication is in line with previous literature and with the link often made between market liquidity and the degree to which the market is open. The second implication for regulators is related to the presence of pattern in spread and depth. As previously mentioned, those patterns indicate adverse selection problems. These problems imply a need of improvement in information release and monitoring. The development of Chinese financial markets requires such improvements to keep attracting foreign investors.

Limitations of the Research

Before ending this thesis with some suggestions for future research, we would like to point out three limitations to the study we performed.

The first limitation arises from our dataset, which is limited to two periods of twenty days and which studies a bearish market. Indeed, the limited availability of intraday data has limited us in our choice of period so that all the available data were part of a decreasing market. If we do not argue that this matter of facts has an important consequence on our results, the reader should be aware of it. Also, the constraints of working with high frequency data have lead us to limit our sample to twenty days. This represents a pretty short period of time. However, our results are consistent with the existing literature and the use of two distinct periods allows us to mitigate this limitation. Still regarding the data, the reader should keep in mind that we studied only 104 A-shares while more than 1000 stocks of this type are traded in Shanghai.

Secondly, we need to remember that we faced positive autocorrelation in the data of the regression model. As we have stated previously, autocorrelation means that the estimators are unbiased but not efficient. In other words, we could have failed to reject the null hypothesis that their values equal to zero because of overestimated variance. Thus, the problem is that we could have concluded to the significance of some estimators that are not actually significant. However, since the goal of our model is not prediction, we state that we can deal with it, especially because our results are consistent with the pattern analysis and with the former literature.

Finally, the reader should be aware that our study does not provide any certitude that the stocks included in the Shanghai-Hong Kong Stock Connect Program are more liquid solely because of the program. Indeed, nothing allows us to affirm that stocks were not already more liquid before the launch of the program. Such a study would be worthwhile but was unfortunately not possible given the limited access we had to intraday data. Therefore, we can suggest that stocks included in the program exhibits a better liquidity but we cannot affirm that the program is the source of this liquidity, although the greater availability[48] provided by the program is an intuitive explanation.

Suggestions for Future Research

Finally, we would like to mention three suggestions for future research that we believe are worth investigating.

Firstly, we remain interrogative regarding the difference of pattern of depth between in- and out-the-program samples – inverted L-shaped versus U-shaped. If both patterns have been already met in the literature on order-driven markets and can be explained by market microstructure, we are astonished to meet such differences on the same market. It seems to indicate that investors trading stocks included in the program have completely different trading behaviors in term of depth compared to the ones trading stocks not part of the program. A first step would be to check the robustness of those patterns on a much longer period of time and with a larger number of stocks. If they are confirmed, it would be of

[48] Leading to greater trading volumes and putting thus downward pressure on processing costs.

interest to investigate the source of the differences in trading behavior. This could suggest that a greater opening to foreign investors lead to a modification in liquidity patterns (at least in term of depth).

A second suggestion for future research is to confirm the impact of the Shanghai-Hong Kong Stock Connect Program. As we stated, we are limited to the availability of our data. However, the study of a longer timeframe covering a period before and a period after the launch of the program would give us tangible evidence of the impact of the program. A suggestion would be to use the data from stocks added recently to the program[49], proving the positive impact of mutual programs such as this one would be worthwhile for regulators and stock exchanges around the world. Especially for the less developed ones that face lack of liquidity.

Finally, a third suggestion would be to investigate the southbound trading (i.e. from Shanghai to Hong Kong). Given that Hong Kong Stock Exchange was already much more open to foreign investors than the Shanghai Stock Exchange, we would expect smaller impact on Hong Kong stocks included in the program. However, it is worth reminding that the program also allows Chinese investors to trade abroad more easily. Therefore, such a study could contribute in highlighting the impact of trading behavior of Chinese investors.

[49] A-shares are frequently added to the program when meeting the requirements described in chapter 3 and detailed in appendix 2.

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