行政院國家科學委員會專題研究計畫 期末報告

日本股票市場投資專家對於預期決策過程的實證分析(第 2 年)

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中 文 摘 要 ： 我這次要申請三年的 NSC 研究計畫經費，主要目的為完成以下兩計畫。第一個計畫是使用由 QUICK 公司，一家日經集團的日本股市資料顧問公司，所提供的 TOPIX 指數（月資料）實證股票專家如何使用這些資料預期日本股市。而在第二個計畫中，我們使用 QUICK 調查資料庫結合對日本股票市場的期望假說進行股價預測。希望這兩個計畫產生的結果，研究如何優化這些股價預期資訊以提供更好的日本總體經濟政策。具體來說，我們希望實證這些資料是否能成為預期未來 GDP 和通貨膨脹率的領先指標，並驗證這些對於股價預期和預期假說的時間序列資料，適不適合做為日本官方的總體經濟領先指標，提供日本總體經濟政策制定者更好的指標。

這兩個計畫為何能提供政策制定者達到更好的日本金融政策管理目標？有兩個原因，其一，不穩定的股價走勢對於公司和金融機構的金融活動有顯著影響，而貨幣政策制定者能不能分析造成不穩定的原因而提供一個相對穩定的金融環境就相當重要。自 1990 年起，因為對於國際金融市場的開放，金融市場交易員人數有戲劇性的上升趨勢，因此，這些投資人的預期通常與資產價格合併。所以這些金融市場政策制定者能不能瞭解投資者的投資機制就是相當重要的議題。

其二，, Mankiw, Reis, and Wolfers (2003)曾提出’disagreement may be a key to macroeconomic dynamics’，同時很多近期以代理人基為主的模型亦顯現出異質期望對觀察現實情形還是無法像傳統的資本資產定價模型在效率市場和預期假說下提供較好的解釋力，像是股票報酬的肥尾分配和零和交易量現象。先前的研究告訴我們如果能釐清如何決定異質期望，將有助於我們瞭解金融市場的現況甚至預期未來。因此，為了達到更好的政策管理，第二個計畫的研究結果將提供釐清預期異質性的方法。

這個研究計劃案是我提供其他亞洲國家總體經濟政策建議的第一步，在未來，我希望獲得專家對亞洲其他國家，像是台灣，中國，南韓，新加坡等經濟預期走勢的調查資料。我會分析對這些不同的市場所產生的不同預期過程和這些調查資料如何成為有效資訊來幫助預期未來總體經濟情勢和如何制定更好的總體經濟政策。並能藉由反應這些市場參與者的行為，為這些國家提供更好的總體經濟建議。

中文關鍵詞： agent-based，股價資料，問卷調查，異質期望，政策管理

英 文 摘 要 ：

英文關鍵詞：

Final Report:

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Project title: Empirical analyses on the expectation formation process of Japanese stock market professionals

Project number: 100-2410-H-004-079-MY2

First of all, I would like to emphasize that I am grateful to NSC for having provided me funds to attend an international conference, hire research assistants, buy research-related stuffs. I believe that all opportunities that NSC provided to me have helped me greatly improve my papers. In my NSC research project, I proposed two research ideas. The first project provides evidence on the determinants of the professionals' expectations in Japanese stock market by using a monthly forecast micro survey dataset on the TOPIX distributed by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group. In the second research project, I document the determinants of the expectation heterogeneity of stock price forecasters on the Japanese Nikkei Stock Average by using the QUICK survey data.

Due to the big support from NSC, the first one was published to *Journal of Economic Dynamics and Control, (SSCI: Impact factor 1.117)* titled: "Strategy switching in the Japanese stock market."

"Strategy switching in the Japanese stock market," *Journal of Economic Dynamics and Control* 37, 2010-2022.

In addition, this research paper was selected as Best paper prize for junior researchers, Association of Behavioral Economics and Finance Annual Conference, 2011,

http://www.iser.osaka-u.ac.jp/abef/event/20111210/syourei_award_5th.pdf.

The second one has been completed and published to: *Pacific-Basin Finance Journal* 20, 723-744 *(SSCI),* titled: "Belief changes and expectation heterogeneity in buy- and sell-side professionals in the Japanese stock market" The contents of these papers are pretty much the same as I proposed in my NSC project.

The first paper, titled: "Strategy switching in the Japanese stock market" is summarized as follows:

Unstable stock price movements have a significant impact on the economic activities of firms and financial institutions. Practitioners attempt to determine the sources of the unstable price movements for better risk management in financial markets. It is also important that monetary policymakers clarify the cause of the instability and provide stable environments for financial market participants. As found in the laboratory works by Hommes, Sonnemans, Tuinstra, and van de Velden (2005, 2008), expectations or beliefs about future states of financial markets crucially influence the trading decisions by investors in financial markets, and the aggregated behavior of the investors determines the actual realization of economic variables. The results of the laboratory works suggest that expectations feedback mechanism plays an important role in financial markets for determining the market outcomes. Thus, improved explanations of investors' expectation formation processes can facilitate a better understanding of the sources of risk in financial markets. This paper provides empirical evidence for understanding the determinant of expectations using a monthly forecast survey dataset on the TOPIX distributed by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group.[1]

We empirically demonstrate that professionals involved in the Japanese stock market utilize either fundamental or technical trading strategies in their expectation formation processes and that they switch between fundamental and technical trading strategies over time. We then interpret our result by discussing that the strategy switching would be key to understanding the persistent deviations of the stock index price from the fundamental value, which is a stylized fact of stock markets.[2]

Our conclusions are consistent with what several agent-based models predict and are presented as follows. Recent agent-based theoretical models successfully explain the cause of the price deviations from the fundamental price, which is still not adequately explained by traditional asset-pricing models using efficient market and rational expectation hypotheses.[3] Many agent-based theoretical models assume that agents' expectations are formed from combining several investment strategies. The price deviations from the fundamental value are explained in an environment in which agents switch the level of dependence on the strategies over time. Standard agent-based models, popularly exemplified by a model created by Brock and Hommes (1998), assume that agents combine fundamental and trend-following strategies in their forecasting. Investors using the fundamental strategy expect future prices to hover around the fundamental or intrinsic value of the asset, which is often measured by a firm's earnings or dividends. The trend-following strategy states that investors expect future price movements persistent with the past price trend. Thus, they will buy shares in response to the recent upward price movements, and sell them for the downward price changes in the past. The models demonstrate that when most agents select the trend-following strategy, the stock price tends to deviate from the fundamental value, which explains such phenomena as bubbles and crashes. Conversely, when most agents adopt the fundamental strategy, the market stabilizes, pushing the market price back towards the fundamental price and leading the market to be informationally efficient. Standard agent-based theoretical models demonstrate that investors utilize the two strategies over time interchangeably; this "strategy switching" is a major factor in explaining the unstable price movements of financial assets.[4]

[1] TOPIX is a Japanese stock market index and is computed and published by the Tokyo Stock Exchange. It consists of 1,669 firms listed in the first section of the Tokyo Stock Exchange, and the market value of the index is 197.4 trillion yen as of February 1, 2011. The unit of the TOPIX is the "point."

[2] See, for example, Shiller (1981).

[3] Agent-based models also replicate volatility clustering, fat tails of return distribution, nonzero volume, autocorrelations of volume, and positive, contemporary cross-correlations between the volume and the squared returns. See, for example, LeBaron, Arthur, and Palmer (1999). Hommes (2006) and LeBaron (2006) survey the literature on agent-based computational finance and explain its usefulness in generating financial market phenomena.

[4] Kirman (1991), Lux and Marchesi (1999, 2000), and Gaunersdorfer, Hommes, and Wagner (2008) also explain the strategic interactions and volatility. In addition, Chiarella, Iori, and Perelló (2009) and Farmer and

Our paper provides empirical evidence on strategy switching in Japanese stock markets and argues whether strategy switching can explain persistent price deviations from economic fundamentals.

We explore the strategy switching in the Japanese stock markets by sorting forecasters into buy-side and sell-side professionals. Buy-side professionals are those who work for investment institutions, such as mutual funds, pension funds, and insurance firms, which purchase securities on their own account. Sell-side professionals work for companies that sell investment services to asset management firms, or buy-side professionals, and provide research, including recommendations to their clients. [5] Rather than measuring the characteristics of the average forecasts across survey respondents as in previous studies on expectation formations, such as those of Branch (2004), Brown and Cliff (2004, 2005), Lux (2009, 2010), and Verma, Baklaci, and Soydemir (2008), this paper identifies empirically the strategy switching of buy-side and sell-side professionals.

This paper has the following four significant contributions to the literature. First, this paper empirically validates the strategy switching, which is an important contribution of several agent-based models to the literature for understanding empirical features in financial markets. Some laboratory experiments with human subjects, such as those of Hommes, Sonnemans, Tunstra, and van de Velden (2008) and Heemeijer, Hommes, Sonnemans, and Tuinstra (2009), support this important observation in theoretical agent-based stock markets. In the literature on foreign exchange markets, Frankel and Froot (1990), Westerhoff and Reitz (2003), and Gilli and Winker (2003) provide evidence being consistent with strategy switching. The literature in foreign exchange not only demonstrates that professionals typically combine technical trading and fundamentals but also indicates that they switch between them. This phenomenon is modeled in Frankel and Froot (1990), and the justification for this approach is based, for example, on Frankel and Froot (1987), showing that professionals rely on regressive expectation formation (fundamentals) and extrapolative expectation formation (chartist), and that weights change. This becomes explicit in Menkhoff, Rebitzky, and Schröder (2009) and Jongen, Verschoor, Wolff, and Zwinkels (2012), who demonstrate that chartists and fundamentalists change forecasting behavior over time, depending on earlier trends and the degree of fundamental misalignment. An empirical study by Boswijk, Hommes, and Manzan (2007) confirms this phenomenon in the US stock market. In the literature on inflation expectations, Branch (2004) and Pfajfar and Santoro (2010), using a survey on inflation expectations, provide empirical evidence that agents switch prediction regimes. Although we have seen theoretical and laboratory works as well as conventional empirical evidence, direct evidence is still required to empirically support strategy switching in the Japanese stock market.

Second, we empirically identify the types of professionals, which are buy-side and sell-side professionals, who actually switch strategies. Previous theoretical research on agent-based models concludes that investors switch their strategies and their behaviors are key in explaining several empirical features in stock markets. Nonetheless, those papers identify neither the specific type of financial institutions to which those agents belong nor their respective business categories.

Joshi (2002) demonstrate that trend-following strategies amplify noise and cause stylized phenomena in financial markets, such as excess and clustered volatility.

[5] For more information on the various activities in which buy-side and sell-side professionals engage, see Groysberg, Healy, and Chapman (2008) and Busse, Green, and Jegadeesh (2012).

Third, we empirically analyze the behavior of both buy-side and sell-side professionals, and show that both types of professionals behave similarly. Several papers, such as Clement (1999) and Hong and Kubik (2003), investigate the behavior of sell-side investors from a cross-sectional viewpoint, but focus exclusively on the sell-side professionals. Accordingly to Groysberg, Healy, and Chapman (2008), this is due to a lack of data on buy-side professionals. Within the relatively limited amount of research conducted on buy-side professionals, Cowen, Groysberg, and Healy (2006) and Groysberg, Healy, and Chapman (2008) examine the forecasts made by both buy-side and sell-side professionals, but show different behavior of these two groups.

Fourth, we validate the strategy switching in the Japanese stock market on a monthly frequency. Boswijk, Hommes, and Manzan (2007) find strategy-switching behavior on a yearly frequency. It still remains unknown, however, with what specific frequency stock investors actually change their strategies.

Boswijk, Hommes, and Manzan (2007) provide evidence of strategy switching in US stock market. They create an estimation using Brock and Hommes's (1998) type of agent-based model on regime switching. They use the yearly S&P 500 and the corresponding earning data from 1871–2003, emphasizing the amplification mechanism, e.g. bubbles are triggered by shocks to economic fundamentals which are then amplified by trend-following behavior.

Our paper differs from that of Boswijk, Hommes, and Manzan (2007) as follows: first, we characterize expectation formations of the buy-side and sell-side professionals. Thus, we demonstrate the mechanisms of strategy switching by different types of professionals. Second, Boswijk, Hommes, and Manzan (2007) assume an agent-based model in estimating regime switching, such that the market is in equilibrium, on average. As indicated in the following section, we follow the approach of Boswijk, Hommes, and Manzan (2007) to derive a fundamental price, which is estimated based on the Gordon growth model, and construct a fundamental strategy. However, our estimation equation is not an equilibrium pricing equation; instead, it utilizes forecast survey data from stock market professionals to investigate strategy switching. Thus, compared to Boswijk, Hommes, and Manzan (2007), we make fewer assumptions while validating the phenomenon.

The second research project, titled: "Belief changes and expectation heterogeneity in buy- and sell-side professionals in the Japanese stock market" is summarized as follows.

In contrast with common assumptions about traditional rational representative agents, several papers investigate survey data regarding professional forecasts of such macroeconomic series as inflation and GDP, as well as such financial series as stock prices and foreign exchange rates, and find expectations to be heterogeneous.[6] While Mankiw, Reis, and Wolfers (2003) suggest that "disagreement may be a key to macroeconomic dynamics" (p. 242), several recent agent-based models demonstrate that heterogeneity drives observed features in real stock markets that have not yet been sufficiently explained by traditional

[6] For example, Allen and Taylor (1990), Ito (1990), and Frankel and Froot (1990) identify expectation heterogeneity in foreign exchange markets, while Mankiw, Reis, and Wolfers (2003) and Capistran and Timmermann (2009) find heterogeneity in inflation expectations. Meanwhile, Patton and Timmermann (2010) demonstrate expectation heterogeneity for GDP growth and inflation.

asset-pricing models under efficient market and rational expectation hypotheses, such as clustered volatility and fat tails of the return distribution.[7] Thus, providing better explanations of the factors determining the differences in expectations can facilitate a better understanding of risk management and option pricing in financial markets. While several studies have examined the determinants of expectation heterogeneity in inflation, GDP, or foreign exchange rates, recent empirical research has faced the challenge of explaining the expectation heterogeneity that exists among stock market professionals. Utilizing a panel dataset of monthly surveys of market professionals regarding TOPIX forecasts, conducted by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group, this paper empirically examines the determinants of expectation heterogeneity or "dispersion" in the Japanese stock market.

The academic literature offers three possible sources of expectation heterogeneity.[8] One explanation revolves around the idea that forecasters share the same information-processing technology but have access to different sets of information about the current state of the economy (see, for example, Carroll, 2003; Kyle, 1985; Lucas, 1973; Mankiw and Reis, 2002). The second source of expectation heterogeneity offered in the literature indicates that agents who share the same information about the current state of the economy interpret it differently (see, for example, Laster, Bennett, and Geoum, 1999; Patton and Timmermann, 2010). A third possibility presented is that the forecast dispersion arises as a result of the existence of fundamentally different types of agents in the market (for example, in the noise-traders and rational-arbitrageurs model presented by De Long, Shleifer, Summers, and Waldmann, 1990 and a series of fundamentalists and chartists models).[9] Due to the difference in types, the third strand of opinion in the literature contends that agents not only observe different information, but also have different ways of interpreting the same information. Thus, an implication of the third explanation of the source of expectation heterogeneity in the literature overlaps with the first and second explanations. We investigate whether or not this third assertion in the literature can be empirically validated in the Japanese stock market. In particular, we explore the reason that professionals' expectations are heterogeneous by disaggregating the forecasts in our sample offered by professionals into those of fundamentally different types, namely, into buy- and sell-side professionals.

Buy-side professionals are those who work for investing institutions, such as mutual funds, pension funds, and insurance firms, which purchase securities on their own account. Buy-side analysts research and make recommendations to their own institutions' investors regarding purchasing securities. Such buy-side recommendations are usually not available to the public. Meanwhile, sell-side professionals work for companies that sell investment services to investors, that is to say, the buy-side professionals, and provide recommendations to the public. Sell-side analysts work for brokerage firms; their research is used to promote

[7] For example, Hommes (2006) and LeBaron (2006) survey the literature on agent-based computational finance and explain the importance of heterogeneity in generating financial market phenomena.
[8] We refer to Frijns, Lehnert, and Zwinkels (2010) with regard to categorizing the literature into three strands.
[9] See, for example, Hommes (2006) and LeBaron (2006), who survey papers on agent-based computational finance. Boswijk, Hommes, and Manzan (2007), Branch (2004), Frankel and Froot (1990), Menkhoff, Rebitzky, and Schröder (2009), and Reitz, Stadtmann, and Taylor (2009) empirically demonstrate that the existence of fundamentalists and chartists in the same market generates the forecast dispersion.

securities to buy-side investors.[10] We demonstrate that our results are consistent with the explanations offered by the third strand of the literature in the manner outlined below.

We first present evidence that buy-side and sell-side professionals utilize different information in order to make their forecasts. Meanwhile, they often interpret the same information differently, resulting in varied expectations. Secondly, we demonstrate that certain forms of information exchange take place between buy-side and sell-side professionals that contributes to the heterogeneity in expectations. More precisely, we show that buy-side professionals refer to sell-side professionals' evaluation of the market, particularly when the sell-side professionals share opinions resembling those of the buy-side professionals. In contrast, buy-side professionals do not take this action when attempting to relate foreign exchange rates to future stock prices. On the other hand, sell-side professionals seek to share market views similar to those of their customers, that is to say, to the views of buy-side professionals. Our results imply that expectation heterogeneity can be attributed to the fact that buy-side and sell-side professionals with different business goals interact with one another and differ with regard to the contents of the information accessed as well as their interpretations of the same information in their forecasts. Thus, we conclude that the existence of fundamentally different types of professionals within the same market is an important factor involved in generating the dispersion.

In addition, we demonstrate the robustness of our results after controlling for important events in the Japanese economy during our sample periods, such as the Lehman shock, the Bear Stearns shock, the Resona shock, the merger of the Mitsubishi Tokyo Financial Group and UFJ Holdings, the quantitative easing monetary policy, the settlement of the account in each fiscal year, and the January effect.

This paper makes the following six contributions. First, we empirically explain the determinants of the expectation dispersion among Japanese stock market professionals. While several papers investigate the sources of the dispersion in expectations of exchange rates, inflation, GDP, and unemployment, they do not specifically explore the expectations of Japanese stock market professionals.[11] Second, we demonstrate the causes of the forecast dispersion related to the stock index by examining professionals' opinions regarding the various macroeconomic, political, and psychological factors that influence future stock prices. The QUICK corporation asks respondents to select the factors that influence future stock prices from the following choices: "Business conditions," "Interest rates," "Foreign exchange rates," "Politics and diplomacy," "Internal factors and market psychology in stock markets," and "Stock and bond markets abroad." These macroeconomic, political, and psychological factors are among the most likely candidates with which to explain stock index price forecasts. Our panel dataset enables us to directly relate professionals' ideas about these factors to the expectation dispersion. This approach differs from those presented in previous papers, such as that of Lamont (2002), in which the expectation dispersion is explained by investigating the forecasters' age and reputation.

[10] For more information on the different activities in which buy-side and sell-side professionals engage, see Groysberg, Healy, and Chapman (2008) and Busse, Green, and Jegadeesh (forthcoming).
[11] See, for example, Menkhoff, Rebitzky, and Schröder (2009) and Reitz, Stadtmann, and Taylor (2009) for heterogeneity in exchange rate expectations; Mankiw, Reis, and Wolfers (2003) and Capistran and Timmermann (2009) for heterogeneity in inflation; Patton and Timmermann (2008) and Döpke and Fritsche (2006) for heterogeneity in both GDP and inflation; and Lamont (2002) for the heterogeneity in GDP, inflation, and unemployment.

Third, we empirically analyze both buy-side and sell-side professionals’ dispersions of the stock index forecasts. While several papers investigate the behavior of sell-side investors from a cross-sectional viewpoint, their efforts focus exclusively on sell-side professionals.[12] According to Groysberg, Healy, and Chapman (2008), this action is due to the lack of data on buy-side professionals. Among the relatively limited amount of research conducted on buy-side professionals, Cowen, Groysberg, and Healy (2006) and Groysberg, Healy, and Chapman (2008) examine the forecasts made by both buy-side and sell-side professionals, but focus on individual stocks and do not characterize the forecast dispersion of buy-side and sell-side professionals.

Fourth, we empirically identify the types of professionals who actually drive the forecast dispersion. We demonstrate that buy-side and sell-side professionals significantly impact the dispersion. The third strand of literature mentioned above poses the idea that the existence of different types of professionals within the same market, such as noise traders and rational arbitrageurs in the noise-trader model and fundamentalists and chartists in agent-based models, contributes to the forecast dispersion. Nonetheless, those papers identify neither the type of financial institutions to which noise traders, rational arbitrageurs, fundamentalists, and chartists specifically belong nor their respective business categories.

Fifth, we demonstrate that a form of information exchange between buy-side and sell-side professionals exists that determines the forecast dispersion. The research of sell-side professionals is usually available to the public, whereas that of buy-side professionals is conducted exclusively for buy-side firms’ portfolio managers (Cheng, Liu, and Qian, 2006). However, it is not empirically validated as to whether or not they utilize each other’s analyses in making their forecasts. Even if they do, the information from sell-side professionals used by buy-side professionals and the information from buy-side professionals that sell-side professionals utilize in making their forecasts remains unknown.[13]

Sixth, in addition to analyzing the relationship between professionals’ behavior and the expectation dispersion, we examine the impacts of important economic and financial events upon the dispersion. These events include the global financial crises, the nationalization of Resona Bank, and the merger of the Mitsubishi Tokyo Financial Group and UFJ Holdings, each of which have given rise to important structural changes in Japanese financial markets. Such an approach can be taken with our dataset, as our sample covers the past 10 years in which these events have taken place.

[12] See, for example, Clement (1999) and Hong and Kubik (2003).

[13] Busse, Green, and Jegadeesh (forthcoming) find sell-side analysts’ recommendations to be informative to buy-side professionals but do not find the reverse to be true.

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Report on using traveling fund from NSC

I have used the NSC traveling fund for having attended the annual meeting of Japanese Finance Association (日本ファイナンス学会）at Tokyo, Japan from June 1 and 2, 2013.

The annual meeting of Japanese Finance Association (日本ファイナンス学会）is a great and actually prestigious conference in the field of Finance in Japan. This conference normally invites great professors in relevant fields, and they are also editors for excellent international journals. This year Professor Tarun Chordina at Emory University and a Managing Editor of Journal of Financial Markets was invited for the keynote speech. This conference is organized by many well-known finance professors in Japan. Usually, more than 50 people attend this conference. The conference brings together researchers and practitioners from diverse fields in Finance for understanding emergent and collective phenomena in finance, and to discuss on effectiveness and limitations of economic models and methods in Economics and Finance. Since I am doing research about computational finance, it is a really good conference to attend and a great opportunity for improve the quality of my papers. I have presented my paper, titled "Empirical analysis of non-execution and picking-off risks on the Tokyo Stock Exchange." I actually had many opportunities to talk with many professors in my field. Discussions with such professors further improved my paper.

After attending this conference and the discussions with others, my paper has been improved a lot and actually been submitted to Review of Financial Studies for a publication.

I learned a lot by having attended these conferences. I really feel that I am grateful to the NSC for funding me to attend the conference and talk with many researchers in my fields. I believe the things I learned there have made my research ideas much better.

In the following, I attach the invitation email for the annual meeting of the Japanese Finance Association (日本ファイナンス学会）, and I attach the paper I presented there.

Invitation email for the annual meeting of the Japanese Finance Association (日本ファイナンス学会）:

-----Original message-----

From:Nippon Finance Association <honbu@nfa-net.jp>

To:1319 平山健二郎 <hiraken@kwansei.ac.jp>,yoichi.otsubo@uni.lu,nisaka@sophia.ac.jp,serita@db3.so-net.ne.jp,ryuichi@nccu.edu.tw,2959 森保　洋 <moriyasu@nagasaki-u.ac.jp>,1953 神楽岡　優昌 <kagraoka@cc.musashi.ac.jp>,t-tkng@cc.musashi.ac.jp,m_suzuki@cc.musashi.ac.jp

Date:Mon, 25 Mar 2013 19:01:19 +0900

Subject:第 21 回大会プログラム確定のご案内

「マーケットマイクロストラクチャー」セッション関係者　各位

日本ファイナンス学会

第 21 回大会プログラム委員会

委員長　神楽岡 優昌

拝啓 時下ますますご清祥のこととお喜び申し上げます.

さて，プログラム委員会では６月１日(土)，２日(日)に開催される日本ファイナンス学会第 21 回大会のプログラムの調整をしてまいりました．今般，採択論文を中心に，討論者，司会者のスケジュール調整を経て、プログラムが確定いたしましたので，貴台の関係するセッションについて，以下のとおり，お知らせする次第です.

なお，下記におきまして，お名前，所属などの情報に誤りがあった場合，また，ご質問・ご不明な点等ございましたら，プログラム委員，もしくは事務局までお問合せいただければ幸いです.

6 月 1 日(土)13：30〜15：30　マーケットマイクロストラクチャー <会場Ｂ>

司会：平山健二郎（関西学院大学） hiraken@kwansei.ac.jp

13：30〜14：10　International Cross-listing and Price Discovery under

Trading Concentration in the Domestic Market: Evidence from Japanese Shares

報告者：大坪陽一（Luxembourg School of Finance, University of Luxembourg）

yoichi.otsubo@uni.lu

討論者：井坂 直人（上智大学） nisaka@sophia.ac.jp

14：10〜14：50　Long-run effects of minimum trading unit reductions on stock prices

報告者：井坂 直人（上智大学） nisaka@sophia.ac.jp

討論者：芹田 敏夫（青山学院大学） serita@db3.so-net.ne.jp

14：50〜15：30　Empirical analysis of non-execution and picking-off risks on the Tokyo Stock Exchange

報告者：山本竜市（台湾国立政治大学） ryuichi@nccu.edu.tw

討論者：森保 洋（長崎大学） moriyasu@nagasaki-u.ac.jp

報告者の方へ

貴台論文は採択されております．添付の「大会報告要領」を必ずご覧いただき，内容をよくご確認ください．とくに，予稿集原稿の締め切り（4 月 14 日(日)）を遵守し，それまでに司会と討論者の方に予稿集原稿をご送付いただきますよう，よろしくお願い申し上げます．

司会者・討論者の方へ

このたびはご快諾いただきまして誠にありがとうございます．ご担当していただく報告論文は，予稿集原稿締め切りの後で送付されることになっております．報告論文の配布の準備ができ次第，ご案内を差し上げます．

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阿部　茂

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The paper is attached in the following.

Empirical analysis of non-execution and picking-off risks on the Tokyo Stock Exchange

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This version: April 2013

Abstract

This paper investigates how the state of the order-book economy influences non-execution and picking-off risks. We utilize data from the limit order book and transactions in individual stocks on the Tokyo Stock Exchange. We demonstrate that, on the one hand, the risk of non-execution increases, while the risk of being picked off, on the other hand, decreases when: 1) the depth on the incoming investor's side becomes thicker, 2) the bid-ask spread becomes narrower, 3) volatility declines, and 4) the depth on the opposite side to the incoming investor becomes thicker. In addition, we report asymmetric determinants of non-execution and picking-off risks between buy and sell limit orders, as well as among our sample firms. We interpret the asymmetry to be attributed to differences in transaction volume and order book thickness between buy and sell sides of the order book as well as among the firms. More transactions lead to higher quote competitions among limit order traders, increasing the thickness of the order book inside of the spread. It then decreases the rate of executions and of being picked off for limit orders existing outside of the spread. Our results suggest that real-time information on order book and transactions is highly valuable to stock investors, who trade individual securities and

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manage a portfolio of individual stocks, such as ETFs. Our findings assist real stock investors in reducing the monitoring cost, making more profitable order choices among market and limit orders and exposing/hiding/canceling/revising limit orders, and understanding the price formation process in an order-driven market. They are crucial for investors for better risk management in actual stock markets.

JEL classification: G11
Keywords: Limit order market; Non-execution risk; Picking-off risk; Investment decisions; Market microstructure

1. Introduction

Electronic trading systems have been proliferated to modern stock exchanges for trading equity securities. They offer an automatic clearing mechanism by which investors place either market or limit orders. Market orders are executed immediately at the best available prices. Limit orders are transacted only when an individual hits the orders, in accordance with a pre-specified number of shares at the limit price at which they are willing to trade. Thus, in contrast with trading according to market orders, limit order traders can avoid the cost of a bid-ask spread by placing the orders at favorable limit prices, but they face the risks of non-execution and of being picked off. On the one hand, the risk of non-execution arises precisely because limit orders are executed solely when someone hits the limit orders, and the order of execution is determined by price and time priority rules. Limit orders have a higher price priority to be executed if placed at prices closer to the best quotes. Orders that were submitted at the same prices but that were placed prior to the incoming limit order trader have a higher time priority to be traded than the order by the incoming trader. Thus, the time and price priority rules may cause limit orders to fail the executions.

On the other hand, a limit order trader faces the picking-off risk as the market price may cross his/her limit price. If a limit order is posted to the order book and the order is not cancelled, someone can “pick off” his/her order and make money, resulting in a loss for the limit order trader. For example, suppose that a trader places a limit buy order at the best bid, and the order is not cancelled, even though the best ask is expected to fall below his/her limit price due to a drop in the asset's intrinsic value. Other investors can make money by picking off the limit order at the best bid (selling the shares to limit order traders at his/her limit price) and then buying shares at the best ask, which is lower than the price at which the shares were sold. The limit order trader incurs a loss because the price at which he/she bought the shares is higher than the market price at which investors can actually buy the shares. Therefore, due to the risks of non-execution and of being picked off, optimal order choices between market and limit orders involve quantitative evaluation of these two risks.

The present paper makes a unique contribution to the field of market microstructure by quantifying the determinants of both the risks of non-execution and of being picked off. Our study provides important insights into the following three issues. First, several theoretical and empirical studies examine traders' order choice between market and limit orders that involves trade-off between immediate execution and favorable transaction price.[1] Since non-execution and picking-off risks significantly influence traders' order choice between market and limit orders, an econometric analysis to quantify these two risks also offers a better understanding of dynamic order-submission strategies that actual stock investors use. Second, when stock investors attempt to reduce the risks of non-execution and of being picked off, they must monitor the market closely and revise or cancel the orders if necessary. However, they may reduce the monitoring cost, if they have certain ideas regarding determinations of the risks. Thus, our investigation assists real stock investors by contributing to better risk management. Third, as the optimal choice of strategies constitutes traders' fundamental decision problem, the study in the present paper offers additional insight into the price formation process and how order-driven markets work.

We conduct this analysis by utilizing an order book and transaction data on individual stocks listed on the Nikkei 225 from September 1, 2006 to August 31, 2007, distributed by Nikkei Media Marketing, Inc., an information vendor in the Nikkei Group. We demonstrate that, on the one hand, the risk of non-execution increases, while the risk of being picked off, on the other hand, decreases when: 1) the depth on the incoming investor's side becomes thicker, 2) the bid-ask spread becomes narrower, 3) volatility decreases, and 4) the depth on the opposite side to the incoming investor becomes thicker. In addition, we report asymmetric determinations of non-execution and picking-off risks between buy and sell limit orders, as well as among our sample firms. We interpret the asymmetry to be attributed to differences in transaction volume and order book thickness. For example, more transactions on the sell side of the order book for certain stocks lead to higher quote competition among limit order traders on the sell side, increasing the thickness of the order book inside of the spread. It then decreases the rate of executions and of being picked off for limit orders on the sell side existing outside of the spread. Our results are robust for a different one-year period, covering from September 1, 2005 to August 31, 2006, in which volatility is higher, possibly adding extra risk to dynamic strategies, implying a higher risk

[1] With regard to theoretical studies of order choice, Parlour (1998) constructs a one-tick model showing that order aggressiveness depends on the market depth of the order book. For empirical studies, see, for example, Aitken, Almeida, Harris, and McInish (2007); Beber and Caglio (2005); Biais, Hillion, and Spatt (1995); Duong, Kalev, and Krishnamurti (2009); Griffiths, Smith, Turnbull, and White (2000); Hall and Hautsch (2006); Handa, Schwartz, and Tiwari (2003); Ranaldo (2004); and Wald and Horrigan (2005).

premium. Our findings suggest that real-time information on order book and transactions is highly valuable to stock investors, and will assist investors in making profitable order choices about placing a limit or a market order.

Although our most significant contribution is that we measure both non-execution and picking-off risks and analyze their determinants on the Tokyo Stock Exchange, this paper makes another significant contribution with our size-stratified analyses of the Tokyo Stock Exchange. We relate the non-execution and picking-off risks to the states of the order book and transactions over individual stocks, which have not been sufficiently examined in past empirical studies. Duong, Kalev, and Krishnamurti (2009) empirically explore the determinants of the order choice between market and limit orders by institutional and individual traders on the Australian Stock Exchange. They imply that picking-off activity by institutional investors tends to be prevalent and that the risk is thus exacerbated in large-sized stocks in comparison with mid- and small-cap stocks. In addition, since the number of transactions is usually lower for mid- and small-cap stocks than for large stocks, the non-execution risk may be larger for mid- and small-sized stocks than for large stocks. Liu (2009) theoretically and empirically analyzes the determinants of order cancellation/revision. By utilizing the dataset on the Australian Stock Exchange, Liu (2009) shows that non-execution and picking-off risks increase order cancellation/revision for actively traded stocks, and that there are more order cancellations/revisions for larger stocks. Thus, the results suggest that both the non-execution and the picking-off risks increase for larger stocks. However, direct evidence, which demonstrates empirical determinants of the non-execution and the picking-off risks using the order book and transaction data for individual stocks on the Tokyo Stock Exchange, is still lacking. Moreover, our approach investigating the two risks for individual stocks assists certain types of traders by contributing to better risk management. The traders include not only day traders trading individual securities, but investors managing a portfolio of individual stocks as well, such as those managing ETFs (Exchange Traded Funds), whose trading volumes have recently expanded rapidly.

Our study is related to those estimating cancellation probability and execution times of a limit order, as order cancellation/revision is driven by an increase in the costs associated with non-execution and the picking-off risks that a limit order becomes out-the-money. Ellul, Holden, Jain, and Jennings (2007) and Yeo (2005) find that over one-third of all limit orders are cancelled on the NYSE. Hasbrouck and Saar (2009) provide evidence on INET indicating that approximately 93% of all limit orders are ultimately cancelled, while 36.69% are cancelled within two seconds of submission. Boehmer, Saar, and Yu (2005) and Hasbrouck and Saar (2009) compute the cancellation probability of a limit order, while Cho and Nelling (2000) and Lo, MacKinlay, and Zhang (2002) estimate limit-order execution times. Certain studies, such as, those conducted by Chakrabarty, Han, Tyurin, and Zheng (2006) and Hasbrouck and Saar (2009), estimate a competing risk model of cancellation and execution times. However, each of the previous studies fails to compute probabilities of both non-executions and of being picked or to determine their determinants. Detecting the determination of each of the two risks should be a prerequisite to understanding why limit order traders cancel and/revise their orders.

Our paper is also related to the literature on the optimal choice between hiding and disclosing limit orders.[2] Traders face a trade-off between gaining and losing time priority based on their choice as to whether to expose or hide their orders at a particular limit price. Traders gain time priority for exposed orders and lose it for hidden orders. The decision depends on the risks of non-execution and of being picked off. If both risks are small, traders prefer to disclose their orders and gain time priority for their orders to be filled. Therefore, our empirical investigation of the two risks offers insight into traders' choices related to hiding and exposing their orders in the order book.

The remainder of this paper is organized as follows. Section 2 introduces our dataset and defines the risks of non-execution and of being picked off in detail. The section also reports summary statistics of the two risks. Section 3 presents our testing hypotheses, while Section 4 conducts empirical analyses. Section 5 offers concluding remarks.

2. Dataset and definitions of non-execution and picking-off risks

2.1. Data

We utilize the dataset provided by Nikkei Media Marketing, Inc, which contains the following information: 1) transaction prices; 2) whether trades occur at the best bid or ask (from

[2] See, for example, Bessembinder, Panayides, and Venkataraman (2009) for the empirical relation between hidden orders and execution probability in Euronext-Paris stocks. De Winne and D’Hondt (2007) empirically find widespread usage of hidden orders on Euronext Paris, and examine the trader's choice between hidden and usual limit orders. Pardo and Pascual (2005) find higher frequent usage of undisclosed limit orders on the Spanish Stock Exchange as liquidity suppliers are likely to trade with informed traders.

which the direction of trades can be determined);[3] 3) whether the prices are determined in the opening or closing sessions; 4) order-book information, such as five-limit orders from the best quotes with the depth available at these limit prices; and 5) time stamps every one minute. Our sample covers a one-year period, specifically from September 1, 2006 to August 31, 2007, for all 225 individual Nikkei stocks listed on August 31, 2007. The entire period includes 247 trading days (82 and 165 trading days in 2006 and 2007, respectively). We select the individual stocks that were listed on the Nikkei 225 on August 31, 2007, the last day of our sample, but exclude any stocks that were ever delisted from Nikkei 225 stocks during our sample periods. In addition, we exclude any stock whose trades were ever suspended for particular days during our sample periods.[4] As a result, 207 stocks remain in our sample.

This paper sorts the firms in our sample into quartiles according to market capitalization at the end of our sample period in order to present size-stratified results. The lowest quartile (the group with the smallest size) in our sample contains 51 firms, whose market capitalizations range from ¥17.4 billion (Clarion Co., Ltd.) to ¥203.7 billion (Denki Kagaku Kogyo K.K.). The second quartile includes the next-smallest group, comprising 52 stocks, according to market capitalization, ranging from ¥206.1 billion (Fuji Electric Holdings Co., Ltd.) to ¥444.0 billion (Shionogi & Co., Ltd.). The third quartile group consists of the next 52 stocks in size, ranging from ¥453.0 billion (Mitsubishi Motors Corp.) to ¥1181.9 billion (Resona Holdings, Inc.). The members of the largest market capitalization group (the last 52 firms) range from ¥1,205.3 billion (Asahi Glass Co., Ltd.) to ¥14,642.1 billion (Toyota Motor Corp.).

The Tokyo Stock Exchange switches execution systems between the continuous double auction, which is used after the opening session and prior to the closing session, and the call auction system, which is used during opening and closing sessions. This paper only uses the sample during the period of continuous double auction. Table 1 presents summary statistics of the limit order book and transactions during our sample period. We report the main sample statistics summarized according to firm capital size. In addition to the means of the relevant series, we also report the medians underlined in the table, as cross section mean does not reflect the central tendency of some series due to the fact that certain stocks have very large values for

[3] In our sample, all trades occur at the best prices for all stocks.

[4] Tokio Marine Holdings, Inc. is the only stock in our sample for which transactions were suspended on certain days. These transactions were suspended from September 26 to September 29, 2006 due to a stock split.

certain statistics, causing the cross section standard deviation to be very large.

Large trading volumes in shares and values for buy and sell transactions indicate that stocks listed on Nikkei 225 are active, as most of the Nikkei 225 stocks in our sample represent large firms among the approximately 3000 firms in the Japanese stock market. The market is very liquid, as the spread in tick and the relative spread are both very small, indicative of very low transaction costs. Small volatility and mid-quote returns also suggest a liquid stock market. Volume in value, depths in value, and mid-quotes are higher for larger stocks than smaller ones, simply because share prices tend to be higher for larger stocks.

Some statistics demonstrate certain differences across firm groups in our sample firms, although the differences are not very large. For example, transaction volumes in shares are smaller for the smallest group than for the other groups. The mean of buy transaction volumes is 4828 shares for the smallest group, while the means for 2nd, 3rd, and 4th quartile groups are 6027, 5577, and 5864 shares, respectively. For the sell transaction volumes, the smallest firm group has a mean of 4502, and the 2nd, 3rd, and 4th quartile groups have 5379, 5025, and 5011 shares of the means, respectively. These results indicate that on average the larger stocks are more actively traded than the stocks of the smallest group.

In addition to transaction volumes, depths in shares are usually smaller for the smallest-sized group than for the other groups. For example, the median of the buy depth is 14,102 shares for the smallest firms, and 19,623, 18,978, and 42,850 for the second, third, and the largest-sized groups, respectively. This tendency is also observed for the depth in shares on the sell side of the book. The results indicate that the larger the size of the stocks, the more actively limit order traders place limit orders. Given the fact that investors trade the larger stocks more actively, the results related to depths implies that investors in the Japanese stock market compete with one another using their quotes and attempt to place their orders inside of and/or at the quotes so as to result in greater chances of execution.

The previous empirical studies, such as those conducted by Duong, Kalev, and Krishnamurti (2009) and Liu (2009), imply that the risks of non-execution and of being picked off differ depending on the size of the firm. They suggest that both the non-execution and the picking-off risks are exacerbated for larger stocks. We observe that the larger stocks tend to have greater transaction volumes in shares and depths in shares than the smallest firms. Thus, the previous studies imply that the differences in transaction volumes in shares and depths in shares may result in different degrees of non-execution and of picking-off risks across our firm size groups.

In addition to the differences among firms, we observe certain differences between the buy and sell sides of the order book economy. For example, buy volumes in shares are larger than sell volumes for all of the firm size groups. The mean of buy volume in shares is 4828 and of sell volume is 4502 for the smallest stocks. In addition, sell depth in shares tends to be greater than the buy depth for our sample firms. For example, the median of the buy depth is 14,102 and that of the sell depth is 16,246 for the smallest group. This result implies more active trading as well as higher quote competitions among limit traders on the sell side of the order book than on the buy side. In addition, previous studies conducted by Duong, Kalev, and Krishnamurti (2009) and Liu (2009) imply that the difference between buy and sell sides of the order book may also cause asymmetric degrees of non-execution and of picking-off risks between buy and sell limit orders. We will confirm the asymmetry across our sample firms, as well as between buy and sell limit orders in the next section.

Table 1: Summary statistics of limit order book and transactions.

The numbers without parentheses and underlines are the mean of the series within size groups, while the numbers with underlines are the median. The numbers in parentheses are standard deviations of the series within size groups. Transaction volume and volume in value refer to the number of shares and its value in Yen traded. Depth and depth in value are the number of shares and its value in Yen available at the best quotes. Mid-quote is presented in Yen. Mid-quote returns x 100000 is the percentage change in mid-quote times 100000. Actual spread in tick is the difference between the prevailing best ask and bid prices divided by average minimum tick sizes, which is calculated by referring the average mid-quote over our sample periods to the minimum tick size table in the Tokyo Stock Exchange. The relative spread is computed by dividing the actual spread by the mid-quote and multiplying this by 100. Volatility is the standard deviation of the last 20 recorded transaction price returns. The sample spans from September 1, 2006 to August 31, 2007 for 207 Nikkei 225 individual stocks listed on August 31, 2007.

	Buy transaction volume	Buy transaction volume in value	Buy depth	Buy depth in value	Sell transaction volume	Sell transaction volume in value	Sell depth	Sell depth in value	Mid-quote	Mid-quote returns x 100000	Actual spread in tick	Relative spread	volatility
1st quartile (smallest group)	4828	2812101	200268	50786604	4502	2638538	74379	24812928	845	-0.02	1.40	0.24	0.0013
	(3527)	(1063457)	(1115751)	(233123203)	(3180)	(979945)	(221305)	(47909228)	(734)	(0.05)	(0.63)	(0.13)	(0.0007)
	3484	2699989	14102	11622836	3336	2570199	16246	12921342	671	-0.03	1.23	0.20	0.0011
2nd quartile	6027	4635603	62999	35460339	5379	4201709	67708	39224837	9326	-0.004	1.73	0.19	0.0011
	(5206)	(1590784)	(123967)	(28934608)	(4383)	(1375220)	(130649)	(31600246)	(58341)	(0.04)	(1.19)	(0.08)	(0.0005)
	4028	4207072	19623	27105235	3731	3767469	25170	31036432	904	-0.012	1.22	0.17	0.0010
3rd quartile	5577	6958220	92807	71895847	5025	6330090	96117	79691064	29392	0.006	1.68	0.16	0.0010
	(4884)	(2568183)	(335707)	(100878509)	(4300)	(2319543)	(305888)	(118223728)	(114857)	(0.04)	(1.21)	(0.08)	(0.0005)
	3886	6661748	18978	45253053	3673	5902064	20434	49548086	1469	0.001	1.21	0.13	0.0008
4th quartile (largest group)	5864	14134693	65976	585084015	5011	12263378	74131	609326047	152317	0.01	2.58	0.21	0.0014
	(7575)	(6591010)	(86098)	(1730174087)	(6159)	(5940014)	(96402)	(1732789350)	(362191)	(0.02)	(2.57)	(0.16)	(0.0011)
	3756	12602349	42850	172615737	3410	10565826	48242	186429125	3209	0.01	1.28	0.18	0.0011

2.2. Timings of execution and being picked off

Throughout the paper, we compute the risks of non-execution and of being picked off for limit orders posted by an investor *at the best prices*. The following illustrates the timings of order execution and being picked off in order. First, we determine the timing of order execution as follows. We utilize the fact that in our sample, all trades were conducted at the best prices, and determine the execution time. On the one hand, we first compute the number of shares existing at the requested price when the trader places a limit order at the best quote. We refer to this amount as the *target amount*. We then look at the actual transaction record and determine the execution when the number of shares traded at his/her requested price have reached the target amount since the order was placed. The order fails to be executed if the trades do not exceed the target amount during the pre-specified order lives. On the other hand, the execution time of the limit order is also recorded when any trade occurs at a limit price outside of the requested price. Since all trades are conducted at the best prices in our sample, if trades occur outside of the limit price, the limit orders before the trader should have been executed or cancelled at his/her requested price, and his/her limit order should be executed as well. We consider our order size to be small enough that our investors do not influence the transaction records of our dataset.

A time priority rule is incorporated in order to determine our execution time. The determination differs from that utilized in previous studies. Lo, MacKinlay, and Zhang (2002) define the lower-bound execution time when the transaction occurs at the limit price at which a trader has placed his/her limit order. Handa and Schwartz (1996) determine the execution time when a transaction is observed at the limit price or lower (higher) after posting a limit buy (sell) order. However, the actual execution time could be later if some limit orders were placed at the same limit price prior to the incoming limit order trader. The hypothetical determination of the execution time presumes that there are no other limit orders with the same limit price in front of his/her order, and the limit order is placed at the top of the queue.

This paper computes the rates of being picked off from the actual transaction and order book records. A limit order submitted at the best price is picked off whenever the best quote crosses the limit price that he/she specified. For example, we say that a limit buy order faces the picking-off risk when the best ask falls below his/her limit price, since somebody will sell shares to him/her and buy them at a lower price. Our approach differs from those in previous studies. Hollifield, Miller, and Sandas (2004) impose weak functional form restrictions on the execution likelihood and the cost of being picked off and define them based on the difference between the limit price and the theoretical true asset value at the prevailing period. Fong and Liu (2010) compute the costs by comparing the pre-specified limit price with the closing price of the day. But even if the closing price lies inside of the spread, the orders may have been picked off before the closing price is revealed, if the price crosses the best price before the market closes.

2.3. Summary statistics of rates of non-execution and of being picked off

Table 2 presents summary statistics of the risks of non-execution and of being picked off. The risks are associated with limit orders placed at the best quotes. We compute rates of non-execution and picking-off for different order lives of 1-, 5-, 15-, and 30-minute intervals. The means of the probabilities and the standard deviations across the firms are reported. The buy orders are separated from the sell orders. Table 2 illustrates the following five features. First, execution likelihoods are usually higher for buy orders than for sell orders for given time intervals when the limit order is placed at the best prices. It indicates that the average time for a limit buy order to be transacted is shorter than that for a sell order. Second, buy limit orders usually face slightly higher picking-off risk than do sell orders for given time intervals. Our first two results are related to the fact presented in Table 1 that depth on the sell side is thicker than that on the buy side. Table 1 reveals that transactions are more active on the sell side of the book than on the buy side, leading to a higher possibility of execution on the sell side than on the buy side, if no limit orders are posted inside of the best quotes. However, our first two results imply that the higher trading activity on the sell side induces higher quote competition among limit order traders than the buy side, and the effect from the quote competition is greater than the effect from transaction volumes. Thus, after our limit order trader places an order at the best price, more limit orders are entered into the market and the orders are posted within the best price. However, it increases the non-execution probability but decreases the risk of being picked off for our limit order trader placing the orders at the previous best prices. The first two results imply that trading activity and order book depths are key factors in explaining the two risks as well as the asymmetry of the two risks between buy and sell limit orders. We will investigate this issue further in the next section.

Third, it is unclear whether the non-execution and picking-off risks have monotonic relations with the size of the firms. In the previous section, we observed in Table 1 that transaction volume and depths are larger for 2nd, 3rd, and 4th size groups than the smallest group. Large transaction volumes indicate that more market orders are hitting the limit orders, causing an increase rates of execution and of being picked off. Larger depths imply greater quote competition among limit order traders, causing limit orders placed at the previous best quotes to be more likely to remain unfilled and thus not to be picked off. If the effect from transaction volume is stronger than that from depths, the larger size groups would have higher rates of executions and of being picked off. On the other hand, the larger size groups would have lower execution and picking-off probabilities, if the effect from the depths is stronger than that from transactions. Our third result suggests that the order book and transactions may be crucial factors for explaining the non-execution and the picking-off risks; however, the impacts from the order book and transactions on the two risks may differ across firms. We will investigate this subject in detail in Section 4.

Fourth, the sums of the probabilities of both risks are very high, meaning that the probabilities that an investor faces either a non execution or a picked off risk are very high for given order lives. This result implies that traders are likely to cancel their limit orders very soon, which is consistent with recent stock investors' behavior presented by Hasbrouck and Saar (2009). Furthermore, this result would explain why such strategies as the fill-or-kill strategy become increasingly popular recently in limit order trading.

Fifth, non-execution risk is larger than picking-off risk in our sample periods for shorter cancellation times. But the picking-off risk becomes greater with longer cancellation times. This finding indicates that execution probability increases at a higher rate than the picking-off risk the longer the limit order stays in the order book, although both the rates of execution and of being picked off increase with the order life. The result indicates that if the limit order traders stay in the order book for a longer period of time, the limit orders are likely to be executed, but the investors may have to sacrifice a higher picking-off risk than the risk of non-execution.

Table 2: Summary statistics of rates of non-execution and of being picked off for limit orders placed at the best quotes.
The numbers without parentheses refer to the average rates of non-execution and of being picked off within each quartile group. The rates are presented over different hypothetical cancellation times. The numbers in parentheses are the standard deviations. The sample spans from September 1, 2006 to August 31, 2007 for 207 Nikkei 225 individual stocks listed on August 31, 2007.

		Buy limit order				Sell limit order			
	Cancellation times	1 min.	5 min.	15 min.	30 min.	1 min.	5 min.	15 min.	30 min.
1st quartile	Non-execution	0.874	0.623	0.387	0.250	0.871	0.646	0.497	0.474
(smallest group)		(0.073)	(0.134)	(0.127)	(0.095)	(0.073)	(0.131)	(0.125)	(0.097)
	Picking off	0.030	0.152	0.344	0.512	0.026	0.129	0.275	0.385
		(0.023)	(0.087)	(0.131)	(0.131)	(0.024)	(0.091)	(0.143)	(0.157)
2nd quartile	Non-execution	0.843	0.570	0.344	0.219	0.836	0.588	0.447	0.433
		(0.075)	(0.119)	(0.101)	(0.072)	(0.078)	(0.118)	(0.102)	(0.078)
	Picking off	0.036	0.172	0.372	0.540	0.032	0.152	0.312	0.430
		(0.029)	(0.092)	(0.124)	(0.115)	(0.030)	(0.096)	(0.132)	(0.135)
3rd quartile	Non-execution	0.805	0.518	0.312	0.199	0.795	0.535	0.411	0.406
		(0.092)	(0.149)	(0.130)	(0.095)	(0.096)	(0.148)	(0.129)	(0.097)
	Picking off	0.046	0.209	0.416	0.576	0.042	0.192	0.361	0.474
		(0.035)	(0.114)	(0.155)	(0.144	(0.037)	(0.121)	(0.167)	(0.169)
4th quartile	Non-execution	0.826	0.576	0.371	0.245	0.818	0.591	0.467	0.453
(largest group)		(0.102)	(0.172)	(0.168)	(0.137)	(0.107)	(0.173)	(0.169)	(0.145)
	Picking off	0.033	0.161	0.345	0.509	0.027	0.139	0.285	0.397
		(0.030)	(0.103)	(0.148)	(0.146)	(0.032)	(0.113)	(0.164)	(0.182)

3. Testing hypotheses

This section introduces six testing hypotheses by relating them to the previous studies as well as the statistical properties found in the previous section on order book, transactions, and the risks of non-execution and of being picked off. First, when the order queue on the same side as the incoming trader increases, time and price priority rules suggest that the limit order traders are likely to reduce the priority for their orders to be executed, meaning an increase in non-execution risk. In this case, investors tend to place aggressive orders, such as market orders. This is empirically found in studies conducted by Aitken, Almeida, Harris, and McInish (2007); Biais, Hillion, and Spatt (1995); Duong, Kalev, and Krishnamurti (2009); Griffiths, Smith, Turnbull, and White (2000); Hall and Hautsch (2006); Handa, Schwartz, and Tiwari (2003); and Ranaldo (2004). The previous studies imply that when non-execution risk increases as the depth on the same side as the incoming trader becomes thicker, limit order traders may post their orders inside of the spread in order to obtain a higher time priority for the execution. This practice causes the limit order, which was placed at the previous best prices, to lose price and time priorities to be traded. However, it also means a reduced possibility of the order being picked off. These interpretations yield our first hypothesis as follows:

Hypothesis 1: Non-execution risk increases but picking-off risk decreases as the order-book depth on the same side as the incoming trader becomes thicker.

Several empirical papers, such as those of Biais, Hillion, and Spatt (1995); Duong, Kalev, and Krishnamurti (2009); Griffiths, Smith, Turnbull, and White (2000); Hall and Hautsch (2006); and Ranaldo (2004) find that investors tend to place more (less) aggressive orders due to the increase in non-execution risk, as the spread falls (rises).[5] This finding indicates a negative relation between non-execution risk and the bid-ask spread. Past empirical evidence illustrates that the narrower spread is generated as investors place limit orders more often than market orders. It suggests a lower picking-off risk for limit orders that were placed at the previous best prices, as the limit orders lose the time priority to be picked off by the incoming market orders. Thus, our second hypothesis seeks to validate the relation between the risks of non-execution and

[5] In the literature, the most aggressive order is the market order, while limit orders within the spread are more aggressive than limit orders outside of the spread but are less aggressive than market orders.

of picking-off and the bid-ask spread as follows:

Hypothesis 2: Non-execution risk increases but picking-off risk decreases with the decrease in the bid-ask spread.

An increase in volatility encourages limit order trading due to a higher profit opportunity for liquidity traders, meaning a higher chance for limit orders to be executed at a favorable price. Foucault (1999) theoretically predicts this idea and Ranaldo (2004) and Beber and Caglio (2005) provide supporting evidence for it. The findings suggest a negative link between volatility and non-execution risk. On the other hand, a greater non-execution risk is indicative of a larger rate for limit orders to be picked off by market order traders. As Foucault (1999) demonstrates theoretically, a higher volatility generates a greater picking-off risk for limit order submitters. Therefore, we test the following hypothesis:

Hypothesis 3: There is a negative relation between non-execution risk and volatility, while a positive relation exists between picking-off risk and volatility.

Parlour (1998) theoretically predicts that investors are likely to place less (more) aggressive orders as the opposite side of the book becomes large (small), indicating a negative relation between non-execution risk and the depth on the opposite side to the incoming trader. This observation is empirically supported by studies conducted by Duong, Kalev, and Krishnamurti (2009); Griffiths, Smith, Turnbull, and White (2000); Hall and Hautsch (2006); and Ranaldo (2004). In addition, if the thicker depth on the same side increases the likelihood of non-execution (if Hypothesis 1 is accepted), investors tend to submit more market orders. If the market orders come from the opposite side, the investor's behavior increases the probability that limit orders posted to the same side as the incoming investor are picked off by market order traders. We empirically investigate the relation with the following hypothesis:

Hypothesis 4: Non-execution risk decreases but picking-off risk increases as the opposite side to the incoming investor becomes large.

The findings related to the order choice between market and limit orders of Duong, Kalev, and Krishnamurti (2009) imply a smaller non-execution risk and a larger picking-off risk with greater firm size on the Australian Stock Exchange, while Liu (2009) suggests that both the non-execution and the picking-off risks are greater for larger cap stocks. In addition, we saw in the previous section that order book conditions and transactions may play key roles in explaining the non-execution and the picking-off risks among our sample firms. We introduce Hypothesis 5 and investigate in detail how order book conditions and transactions are related to the non-execution and the picking-off risks, and whether different impacts are found on the two risks across our sample firms.

Hypothesis 5: Order book conditions and transactions have different influences on the non-execution and the picking-off risks among our sample firms.

Models by Admati and Pfleiderer (1998), Easley and O'Hara (1992), and Harris (1994) assume symmetry on order submissions between buyers and sellers, implying that both buy and sell orders are similarly informative. Meanwhile, Saar (2001) assumes asymmetry between buy and sell orders. Order choices by buyers and sellers differ, possibly because order book conditions and transactions affect the non-execution and picking-off risks in a different manner on buy and sell sides of the order book.

Table 1 demonstrates that buy volumes in shares are larger than sell volumes for all of the firm size groups. Sell depth in shares is greater than the buy depth for the firm size groups. We have interpreted the phenomenon as trades occurring more actively on the sell side of the order book, but quote competition among limit order traders delay the execution of the limit order placed at the previous best quotes. Consequently, non-execution risk is smaller and picking-off activities are more prevalent on the buy side of the order book than on the sell side, which is consistent with the results in Table 2 in Section 2.3 that indicate that buy limit orders tend to be executed within a shorter time but are more likely to be picked off than the sell orders. The following Hypothesis 6 is tested to investigate in detail how the differences in the probabilities of the two risks are related to differences in transaction volumes and depths between buy and sell limit orders.

Hypothesis 6: Determinants of the non-execution and the picking-off risks are asymmetric between buy and sell limit orders.

We introduce our empirical model in the following section, in which the determinants of the non-execution and the picking-off risks are estimated. We first estimate the model for buy and sell limit orders independently and test the asymmetry assumption of Hypothesis 6 by comparing the values and signs of the coefficient estimates in buy and sell limit orders.

4. Empirical analyses

4.1. Model setup

We test the hypotheses raised in the previous section by applying the technique of a binary probit analysis. Our dependent variable *y* is either non-execution risk or picking-off risk, each of which is assigned 0 or 1 representing counts of the events. For example, when the limit order is not executed, we allocate 1 to the variable for computing the non-execution risk and 0 if executed at time *t*. The variable for picking-off risk is assigned 1 if the limit order is picked off, and 0 otherwise at time *t*. We further denote the dependent variable as $y_t^{i,j}$, where *i* represents the buy or sell limit order, and *j* denotes whether the variable *y* represents the non-execution risk or the picking-off risk. We construct all of our variables for an order life of 1 minute, and estimate the two risks for buy and sell sides of the order book independently. Hasbrouck and Saar (2009) present evidence that 83% of limit orders are cancelled within 1 minute in INET, suggesting that real stock investors are interested in making a cancellation decision within 1 minute. Thus, we focus on investigating the determinants of non-execution and picking-off for a 1 minute order life that would provide real stock investors with a better idea of whether and under what conditions limit orders should be cancelled within 1 minute.

Our explanatory variables include: 1) depth on the same side as the incoming trader, 2) depth on the opposite side to the incoming trader, 3) bid-ask spread, and 4) volatility, each of which are defined in detail as follows. Following the manner of Ranaldo (2004), we compute depths on the same and opposite sides of the book by referring to the number of shares divided by 100,000 at the relevant best quotes. We investigate a spread variable at *t*, which is the difference between best ask and best bid at *t*. The depth and spread variables are computed according to the order book condition at the end of each time interval. The volatility variable is calculated from the standard deviation of the last 20 recorded transaction price returns in each interval. We denote our explanatory variable as $x_{k,t}$, where k = *depth_same* (depth on the same side as the incoming trader), *depth_opposite* (depth on the opposite side to the incoming trader), *spread* (bid-ask spread), and *volatility* (return volatility according to the last 20 recorded transaction prices). The vector of the regressors is denoted as *X*. Following the manner of Ranaldo (2004), we investigate volatility in a separate regression in order to prevent possible cross-correlation disturbances and multivariate biases.[6]

Our binary probit model takes the following form:

$$Prob\left(y_t^{i,j} = 1 \mid X\right) = \Phi\left(\alpha X_t\right) = \int_{-\infty}^{\alpha X} \phi(t)dt \tag{1}$$

$$Prob\left(y_t^{i,j} = 0 \mid X\right) = 1 - \Phi\left(\alpha X_t\right) \tag{2}$$

where i = buy or sell side of the order book, j = non-execution risk or picking-off risk, and t is the time interval. *Prob* denotes probability, Φ represents the cumulative distribution function of the standard normal distribution, and α is a vector of parameters associated with the relevant regressors in *X*. The vector αX_t denotes the following:

$$\alpha X_t = \sum_k \alpha_k^{i,j} x_{k,t} \tag{3}$$

The parameters $\alpha_k^{i,j}$ are estimated by means of a maximum likelihood method

We make additional investigations into the hypotheses presented above by computing the marginal probabilities from the probit framework. The marginal probability is computed thus:

$$\frac{\partial \Phi\left(\alpha X_t\right)}{\partial x_{k,t}} = \phi\left(\alpha X_t\right)\alpha_k^{i,j} \tag{4}$$

where $\phi(\bullet)$ is the standard normal density. The estimated marginal probabilities answer the question of how the two risks react to changes in one of the explanatory variables.

4.2. Empirical results

Table 3 summarizes the results of our binary probit regressions, and Table 4 computes the marginal probabilities in probit regressions. We report the results in four firm size groups. The medians of coefficient estimates are reported in each of the firm-sized group, and are presented

[6] However, our results usually do not change much, even when including volatility in the same regression.

as numbers without parentheses and brackets. The first numbers in brackets indicate the fraction of firms whose coefficients are positive, and the second numbers represent those with negative signs. The numbers in parentheses denote the fraction of *p*-values that is less than 0.05.

For the regression of non-execution risk in Table 3, the coefficient estimates of the depth at the same side are significantly positive for nearly all of the firms in all size groups. The results hold for both buy and sell limit orders. For example, the median of the estimates is 1.079 for buy limit orders and 1.028 for the sell order in the smallest group, and 98% of the firms in the smallest stocks show positive estimates with *p*-values less than 0.05. The result means that non-execution risk increases for the same side of the order book as the incoming trader becomes thicker. The coefficients for the picking-off risk have negative signs for the firms, illustrating the fact that the limit orders previously placed at the best quotes have a reduced likelihood of being picked off as the depth on the same side becomes thicker and new limit orders are submitted inside of the spread. For example, for the second quartile firms, the estimates are -1.108 and -1.337 for buy and sell limit orders, respectively. The signs are significant and negative for all of these group firms. These results are entirely consistent with those of the other firm groups. Therefore, these results demonstrate a clear confirmation of Hypothesis 1. The result is further supported in the marginal probability estimation presented in Table 4. The marginal probabilities of non-execution risk are positive, and those of the picking-off risk are negative for our firm size groups.

Hypothesis 2 proposes a negative relationship between non-execution risk and spread, but a positive relationship between picking-off risk and spread. Our regression results support Hypothesis 2 for nearly all of the firms. For example, the median of the estimates is -0.234 for buy limit orders and -0.211 for the sell order in the smallest group; and the signs of the estimates are negative, and their estimates are significant at the 5% level for 98% of the firms in the smallest group. As the spread falls, non-execution risk increases. When more limit orders enter the order book, the order book tends to be thicker. When limit traders seek a higher priority for the execution of their orders, they tend to place their limit orders within the spread, narrowing the spread. If such is the case, the limit orders, posted before others place limit orders inside of the spread, are less likely to be executed. This situation also explains our results related to picking-off risk. The risk of being picked off decreases as the spread becomes small, as investors are more likely to place limit orders at a in particular limit price within the spread rather than market orders during the period in which the spread is becoming narrower, so as to obtain a higher priority for the execution. The marginal probability estimations presented in Table 4 also confirm this result.

Table 3 shows the negative relation of non-execution with volatility, but the relation is positive for the picking-off risk for nearly all of the firms, which is consistent with Hypothesis 3. The result is robust on average for all size groups, as are the signs of the orders. Higher volatility means more volatile transaction prices. The phenomenon arises from the fact that investors are more likely to place market orders than limit orders. In this case, the limit orders are likely to be hit by market order traders, reducing the possibility of remaining unfilled, but increasing the chance for limit orders to be picked off by market order traders. Estimates of the marginal probabilities in Table 4 also confirm the links between the two risks and volatility.

Table 3: Binary probit regressions in 1-minute order life:
Dependent variables are rates of non-execution and of being picked off; they are assigned 1 if not executed or being picked-off, and 0 otherwise. The independent variables are *depth_same* (depth on the same side), *depth_opposite* (depth on the opposite side), *spread* (bid-ask spread), and *volatility* (volatility). The coefficient estimates are averaged for each of the firm-sized groups, and presented as numbers without parentheses and brackets. The first numbers in brackets indicate the fraction of firms whose coefficients are positive, and the second numbers are those with negative signs. The numbers in parentheses are the fraction of the *p*-values in a given size group, which is less than 0.05. The sample spans from September 1, 2006 to August 31, 2007 for all Nikkei 225 individual stocks listed on August 31, 2007.

		Buy limit order				Sell limit order			
		depth_same	*depth_opposite*	*spread*	*volatility*	*depth_same*	*depth_opposite*	*spread*	*volatility*
1st quartile (smallest group)	Non-execution	1.079 [0.98, 0.02] (0.98)	0.636 [1, 0] (0.98)	-0.234 [0.02, 0.98] (0.98)	-0.022 [0.08, 0.92] (0.98)	1.028 [0.98, 0.02] (0.98)	0.612 [0.96, 0.04] (0.96)	-0.211 [0.02, 0.98] (0.98)	-0.017 [0.12, 0.88] (0.90)
	Picking off	-1.650 [0.02, 0.98] (0.98)	-1.322 [0.04, 0.96] (0.98)	0.189 [0.94, 0.06] (0.94)	0.032 [0.96, 0.04] (1)	-1.782 [0, 1] (0.92)	-1.462 [0.04, 0.96] (1)	0.085 [0.92, 0.08] (0.78)	0.029 [0.94, 0.06] (1)
2nd quartile	Non-execution	0.869 [1, 0] (1)	0.520 [1, 0] (0.98)	-0.269 [0.13, 0.87] (1)	-0.031 [0.19, 0.81] (0.94)	0.964 [1, 0] (1)	0.500 [1, 0] (0.98)	-0.229 [0.13, 0.87] (0.98)	-0.023 [0.23, 0.77] (1)
	Picking off	-1.108 [0, 1] (1)	-1.086 [0, 1] (1)	0.189 [0.81, 0.19] (0.98)	0.043 [0.87, 0.13] (1)	-1.337 [0, 1] (1)	-1.269 [0, 1] (1)	0.107 [0.75, 0.25] (0.92)	0.037 [0.85, 0.15] (0.96)
3rd quartile	Non-execution	0.887 [1, 0] (1)	0.613 [1, 0] (1)	-0.120 [0.04, 0.96] (1)	-0.038 [0.12, 0.88] (0.98)	1.065 [1, 0] (1)	0.555 [0.98, 0.02] (1)	-0.105 [0.04, 0.96] (0.96)	-0.027 [0.12, 0.88] (0.96)
	Picking off	-1.178 [0, 1] (0.98)	-1.224 [0.02, 0.98] (1)	0.081 [0.92, 0.08] (0.92)	0.056 [0.92, 0.08] (1)	-1.260 [0, 1] (1)	-1.494 [0.02, 0.98] (1)	0.048 [0.87, 0.13] (0.88)	0.042 [0.90, 0.10] (1)
4th quartile (largest group)	Non-execution	0.588 [1, 0] (0.96)	0.611 [1, 0] (0.98)	-0.089 [0.12, 0.88] (0.98)	-0.023 [0.27, 0.73] (0.92)	0.619 [0.96, 0.04] (0.96)	0.606 [0.98, 0.02] (0.98)	-0.073 [0.12, 0.88] (0.96)	-0.009 [0.40, 0.60] (0.88)
	Picking off	-0.729 [0.02, 0.98] (0.94)	-0.866 [0.02, 0.98] (0.96)	0.045 [0.83, 0.17] (0.88)	0.055 [0.87, 0.13] (1)	-0.798 [0.02, 0.98] (0.94)	-1.246 [0.02, 0.98] (0.94)	0.028 [0.77, 0.23] (0.79)	0.042 [0.81, 0.19] (0.90)

Table 4: Marginal probabilities in binary probit regressions with 1-minute order life:
Dependent variables are rates of non-execution and being picked off; they are assigned 1 if executed or being picked-off, and 0 otherwise. The independent variables are *depth_same* (depth on the same side), *depth_opposite* (depth on the opposite side), *spread* (bid-ask spread), and *volatility* (volatility). We use the average of each explanatory variable and compute the marginal probabilities with the coefficient estimates. The averaged marginal probabilities within each firm-sized group are presented as numbers without brackets. The first numbers in brackets refer to the fraction of firms whose marginal probabilities are positive, and the second numbers indicate the fraction of firms whose marginal probabilities for the buy side are greater than those for the sell side. The sample spans from September 1, 2006 to August 31, 2007 for all Nikkei 225 individual stocks listed on August 31, 2007.

		Buy limit order				Sell limit order			
		depth_same	*depth_opposite*	*spread*	*volatility*	*depth_same*	*depth_opposite*	*spread*	*volatility*
1st quartile (smallest group)	Non-execution	0.174 [0.98, 0.02]	0.111 [1, 0]	-0.041 [0.02, 0.98]	-0.004 [0.08, 0.92]	0.193 [0.98, 0.02]	0.100 [0.96, 0.04]	-0.036 [0.02, 0.98]	-0.003 [0.12, 0.88]
	Picking off	-0.061 [0.02, 0.98]	-0.064 [0.04, 0.96]	0.006 [0.94, 0.06]	0.002 [0.96, 0.04]	-0.048 [0, 1]	-0.050 [0.04, 0.96]	0.002 [0.92, 0.08]	0.001 [0.94, 0.06]
2nd quartile	Non-execution	0.170 [1, 0]	0.126 [1, 0]	-0.059 [0.13, 0.87]	-0.007 [0.19, 0.81]	0.183 [1, 0]	0.121 [1, 0]	-0.054 [0.13, 0.87]	-0.006 [0.23, 0.77]
	Picking off	-0.047 [0, 1]	-0.043 [0, 1]	0.009 [0.81, 0.19]	0.002 [0.87, 0.13]	-0.036 [0, 1]	-0.040 [0, 1]	0.003 [0.75, 0.25]	0.001 [0.85, 0.15]
3rd quartile	Non-execution	0.208 [1, 0]	0.134 [1, 0]	-0.038 [0.04, 0.96]	-0.009 [0.12, 0.88]	0.237 [1, 0]	0.154 [0.98, 0.02]	-0.033 [0.04, 0.96]	-0.006 [0.12, 0.88]
	Picking off	-0.062 [0, 1]	-0.081 [0.02, 0.98]	0.009 [0.92, 0.08]	0.004 [0.92, 0.08]	-0.049 [0, 1]	-0.072 [0.02, 0.98]	0.004 [0.87, 0.13]	0.003 [0.90, 0.10]
4th quartile (largest group)	Non-execution	0.112 [1, 0]	0.147 [1, 0]	-0.014 [0.12, 0.88]	-0.005 [0.27, 0.73]	0.121 [0.96, 0.04]	0.139 [0.98, 0.02]	-0.012 [0.12, 0.88]	-0.002 [0.40, 0.60]
	Picking off	-0.017 [0.02, 0.98]	-0.019 [0.02, 0.98]	0.001 [0.83, 0.17]	0.002 [0.87, 0.13]	-0.007 [0.02, 0.98]	-0.009 [0.02, 0.98]	0.0001 [0.77, 0.23]	0.001 [0.81, 0.19]

Hypothesis 4 states that the coefficient estimates of the depth on the opposite side are negative for the risk of non-execution but positive for the risk of being picked off. However, we obtain the estimates presented in Tables 3 and 4 with signs opposite to those suggested in the hypothesis. A possible interpretation of this result is that as the pending volume on the opposite side becomes larger, traders expect more market orders to arrive from the opposite side. Investors can obtain more favorable prices with a reduced risk of non-execution by placing less aggressive orders. However, this course of action will stimulate quote competition among limit order traders, encouraging limit order traders to post their orders inside of the spread, rather than offering them at the best prices, in order to obtain a certain and faster execution. This paper computes the risks when limit orders are placed *at the best quotes*. Non-execution risk tends to be large, while picking-off risk will be smaller when other investors place limit orders inside of the spread. Therefore, our results imply that stock investors on the Tokyo Stock Exchange tend to be aggressive in their order choice when they expect market orders to arrive from the opposite side and post limit orders inside of the spread. This behavior increases the probability of non-execution and decreases the picking-off risk for limit order traders placing orders at the previous best quotes.

Hypothesis 5 states that the non-execution and the picking-off risks are determined in a different manner among firm size groups, which is supported by our empirical results. Although we do not see large differences in the estimated values of the coefficients, the signs of the estimates on certain coefficients differ between the smallest firms and the other size groups. For example, 8% of the firms in the smallest group show a positive influence of volatility on non-execution risk for buy limit orders, while 27% of the largest group firms have such an impact from volatility. This difference is possibly because when volatility becomes larger, limit traders in the largest group would expect a greater likelihood for the limit order to be hit by market order traders; they thus prefer to submit the limit orders immediately. However, as we have seen in Table 1, 2nd, 3rd, and 4th quartile firms are more actively traded than 1st quartile firms. This phenomenon encourages higher quote competitions, encouraging limit order traders to place their orders at the price within the spread in order to obtain a higher price priority than the other limit order traders for certain and more rapid execution. If such is the case, traders posting their limit orders at the previous best quote will have less of a chance to gain the execution.

Other than the link between volatility and picking-off risk, only 2% of the smallest firms have a positive relation between spread and non-execution risk; this amount increases to 13% for the second smallest firms for both buy and sell limit orders. In addition, 8% of the smallest stocks have a negative relation between spread and picking-off risk for sell limit orders, while 25% of the second smallest firm group have such an influence on the sell orders. The more transactions occur, the more limit orders are executed and removed from the order book, causing spread to rise. This phenomenon would make limit order traders expect more market orders to hit the limit orders in the next time period. Given the fact that 2nd, 3rd, and 4th quartile firms in Table 1 are more actively traded than 1st quartile firms, limit order traders of the 2nd, 3rd, and 4th quartile firms will place orders inside of the spread in order to compete with other limit traders and gain a higher price priority for the execution. If such is the case, our limit order trader of larger stocks, who submits at the best price, will have less of a chance to be executed as well as being picked off by market order traders.

Previous empirical studies, such as that conducted by Duong, Kalev, and Krishnamurti (2009), demonstrate that differences in liquidity and trading frequencies characterizing firm size differences determine the order choice. Our sample firms exhibit small but certain differences in liquidity and trading frequencies, as shown in Table 1; thus, we expected certain differences in the determinants of the non-execution and the picking-off risks. Our expectation is confirmed, and the results suggest that Nikkei 225 listed firms with different levels of order book and transactions have different determinants of the two risks.

In order to test Hypothesis 6, we examine whether the non-execution and the picking-off risks is determined in an asymmetric manner for buy and sell limit orders. Although the results of buy and sell limit orders are usually similar, we observe a certain asymmetry in buy and sell limit orders. For example, 27% of 4th quartile firms have a positive relation between volatility and non-execution risk for buy limit orders, versus 40% for the sell limit order. In addition, 19% of 4th quartile firms have a negative relation between volatility and picking-off risk for sell limit orders, but 13% of them have such a link for buy limit orders. In the explanation of the results for Hypothesis 5 above, the larger volatility generates higher competition for limit order traders for the larger firms than for the smallest firm group, leading them to post limit orders inside of the spread. This practice causes the non-execution risk to increase while the picking-off risk declines. The differences between the results of buy and sell orders imply a higher competition among limit order traders; thus, more limit order is accumulated on the sell side of the order book than on the buy side. This interpretation is consistent not only with the fact in Table 1 that sell side depth is thicker than buy side depth, but also with our interpretation of Table 2, according to which quote competition among limit order traders is more active on the sell side of the book. Therefore, our results support clear acceptance of Hypothesis 6.

In Tables 5 and 6, we conduct the robustness check utilizing a different one-year period, covering September 1, 2005 to August 31, 2006. LeBaron (1999) states that "high volatility periods might add extra risk to dynamic strategies implying a higher risk premium, and therefore greater predictability" (p. 139). Thus, selecting a different sample period with a higher level of return volatility may yield different results. Therefore, we selected a different one-year period, covering September 1, 2005 to August 31, 2006, in which the daily Nikkei 225 index return volatility was 28% higher than the return volatility for the period from September 1, 2006 to August 31, 2007.[7] Tables 5 and 6 summarize the results, demonstrating that our results with the sample periods from September 1, 2006 to August 31, 2007 are not sensitive, even in periods with different risk features.

[7] We use this index from DataStream.

Table 5: Binary probit regressions with 1-minute order life:
Dependent variables are rates of non-execution or being picked off; they are assigned a 1 if not executed or being picked-off, and a 0 otherwise. The independent variables are *depth_same* (depth on the same side), *depth_opposite* (depth on the opposite side), *spread* (bid-ask spread), and *volatility* (volatility). The coefficient estimates are averaged in each of the firm-sized groups and presented as numbers without parentheses and brackets. The first numbers in brackets indicate the fraction of firms whose coefficients are positive, and the second numbers are those with negative signs. The numbers in parentheses are the fraction of *p*-values in a given size-group that is less than 0.05. The sample spans from September 1, 2005 to August 31, 2006 for all Nikkei 225 individual stocks listed on August 31, 2007.

		Buy limit order				Sell limit order			
		depth_same	*depth_opposite*	*spread*	*volatility*	*depth_same*	*depth_opposite*	*spread*	*volatility*
1st quartile (smallest group)	Non-execution	0.588 [1,0] (0.98)	0.459 [0.94, 0.06] (0.98)	-0.184 [0.02, 0.98] (0.94)	-0.014 [0.06, 0.94] (0.96)	0.624 [1, 0] (1)	0.622 [0.94, 0.06] (0.92)	-0.169 [0, 1] (0.98)	-0.012 [0.16, 0.84] (0.88)
	Picking off	-0.881 [0, 1] (1)	-1.071 [0, 1] (1)	0.118 [0.96, 0.04] (0.90)	0.025 [0.98, 0.02] (0.98)	-1.386 [0, 1] (0.94)	-1.778 [0.02, 0.98] (1)	0.083 [0.98, 0.02] (0.90)	0.023 [0.98, 0.02] (0.98)
2nd quartile	Non-execution	0.688 [1, 0] (0.98)	0.579 [1, 0] (1)	-0.187 [0.15, 0.85] (0.98)	-0.025 [0.15, 0.85] (0.96)	0.709 [1, 0] (1)	0.641 [1, 0] (1)	-0.168 [0.15, 0.85] (0.96)	-0.017 [0.19, 0.81] (0.92)
	Picking off	-1.024 [0, 1] (1)	-1.156 [0, 1] (1)	0.131 [0.83, 0.17] (0.92)	0.039 [0.81, 0.19] (0.96)	-1.075 [0, 1] (1)	-1.498 [0.04, 0.96] (1)	0.099 [0.81, 0.19] (0.98)	0.031 [0.83, 0.17] (0.98)
3rd quartile	Non-execution	0.794 [0.98, 0.02] (0.98)	0.514 [1, 0] (1)	-0.090 [0.06, 0.94] (0.94)	-0.025 [0.12, 0.88] (0.98)	0.722 [1, 0] (0.98)	0.646 [1, 0] (0.98)	-0.081 [0.06, 0.94] (0.94)	-0.017 [0.19, 0.81] (0.98)
	Picking off	-1.073 [0, 1] (1)	-1.199 [0.02, 0.98] (1)	0.081 [0.90, 0.10] (0.94)	0.046 [0.90, 0.10] (1)	-1.106 [0.02, 0.98] (0.96)	-1.573 [0, 1] (1)	0.053 [0.90, 0.10] (0.88)	0.031 [0.88, 0.12] (1)
4th quartile (largest group)	Non-execution	0.772 [0.98, 0.02] (0.96)	0.708 [1, 0] (0.98)	-0.074 [0.23, 0.77] (0.94)	-0.021 [0.35, 0.65] (0.92)	0.759 [1, 0] (1)	0.854 [1, 0] (1)	-0.057 [0.21, 0.79] (0.92)	-0.005 [0.46, 0.54] (0.94)
	Picking off	-0.795 [0, 1] (0.96)	-0.879 [0.06, 0.94] (0.94)	0.036 [0.73, 0.27] (0.98)	0.044 [0.77, 0.23] (0.96)	-1.066 [0.02, 0.98] (0.94)	-1.748 [0, 1] (0.98)	0.033 [0.71, 0.29] (0.87)	0.032 [0.69, 0.31] (0.90)

Table 6: Marginal probabilities in binary probit regressions with 1-minute order life:
Dependent variables are rates of non-execution or being picked off; they are assigned a 1 if executed or being picked-off, and a 0 otherwise. The independent variables are *depth_same* (depth on the same side), *depth_opposite* (depth on the opposite side), *spread* (bid-ask spread), and *volatility* (volatility). We use the average of each explanatory variable and compute the marginal probabilities with the coefficient estimates. The averaged marginal probabilities within each firm-sized group are presented as numbers without brackets. The first numbers in brackets refer to the fraction of firms whose marginal probabilities are positive, and the second numbers indicate the fraction of firms whose marginal probabilities for the buy side are greater than those for the sell side. The sample spans from September 1, 2005 to August 31, 2006 for all Nikkei 225 individual stocks listed on August 31, 2007.

		Buy limit order				Sell limit order			
		depth_same	*depth_opposite*	*spread*	*volatility*	*depth_same*	*depth_opposite*	*spread*	*volatility*
1st quartile (smallest group)	Non-execution	0.107	0.092	-0.033	-0.003	0.116	0.115	-0.031	-0.002
		[1, 0]	[0.94, 0.06]	[0.02, 0.98]	[0.06, 0.94]	[1, 0]	[0.94, 0.06]	[0, 1]	[0.16, 0.84]
	Picking off	-0.048	-0.050	0.005	0.002	-0.052	-0.070	0.003	0.001
		[0, 1]	[0, 1]	[0.96, 0.04]	[0.98, 0.02]	[0, 1]	[0.02, 0.98]	[0.98, 0.02]	[0.98, 0.02]
2nd quartile	Non-execution	0.176	0.147	-0.041	-0.006	0.178	0.161	-0.036	-0.004
		[1, 0]	[1, 0]	[0.15, 0.85]	[0.15, 0.85]	[1, 0]	[1, 0]	[0.15, 0.85]	[0.19, 0.81]
	Picking off	-0.069	-0.076	0.008	0.003	-0.068	-0.098	0.005	0.002
		[0, 1]	[0, 1]	[0.83, 0.17]	[0.81, 0.19]	[0, 1]	[0.06, 0.94]	[0.81, 0.19]	[0.83, 0.17]
3rd quartile	Non-execution	0.242	0.164	-0.029	-0.008	0.223	0.207	-0.028	-0.006
		[0.98, 0.02]	[1, 0]	[0.06, 0.94]	[0.12, 0.88]	[1, 0]	[1, 0]	[0.06, 0.94]	[0.19, 0.81]
	Picking off	-0.096	-0.117	0.008	0.004	-0.082	-0.134	0.005	0.002
		[0, 1]	[0.02, 0.98]	[0.90, 0.10]	[0.90, 0.10]	[0.02, 0.98]	[0, 1]	[0.90, 0.10]	[0.88, 0.12]
4th quartile (largest group)	Non-execution	0.177	0.161	-0.013	-0.004	0.144	0.188	-0.013	-0.001
		[0.98, 0.02]	[1, 0]	[0.23, 0.77]	[0.35, 0.65]	[1, 0]	[1, 0]	[0.21, 0.79]	[0.46, 0.54]
	Picking off	-0.031	-0.037	0.001	0.002	-0.014	-0.026	0.000	0.001
		[0, 1]	[0.06, 0.94]	[0.73, 0.27]	[0.77, 0.23]	[0.02, 0.98]	[0, 1]	[0.71, 0.29]	[0.69, 0.31]

5. Conclusion

This paper quantitatively determines the sources of the non-execution and the picking-off risks utilizing the dataset on the order book and transactions for individual stocks on the Tokyo Stock Exchange from September 1, 2006 to August 31, 2007. We find that the limit orders posted at the best prices are more likely to be unfilled and to be picked off when: 1) the depths on the same and opposite sides for the incoming trader are thicker, 2) the bid-ask spread falls, and 3) the volatility is higher. The quantitative results are not perfectly symmetrical between buy and sell limit orders and between the smallest size and the groups of other sizes. The asymmetric results are attributed to the differences in the order book conditions and transactions between the buy and sell sides of the order book and between the smallest size and the groups of other sizes. All of the results are very robust within a sample period, which has a higher return volatility and thus a greater risk premium. Our findings suggest that real-time pre- and post-trade information on order book and transactions is highly valuable to stock investors, who trade individual securities and/or manage a portfolio of individual stocks, such as ETFs.

Our empirical study quantitatively measures the non-execution and the picking-off risks; it thus assists real stock investors with reducing the monitoring cost, making a more profitable order choice between market and limit orders and exposing/hiding/canceling/revising limit orders, and understanding the price formation process in an order-driven market. Our findings are crucial for investors for better risk management in actual stock markets.

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國科會補助計畫衍生研發成果推廣資料表

日期:2013/09/19

國科會補助計畫	計畫名稱: 日本股票市場投資專家對於預期決策過程的實證分析
	計畫主持人: 山本[illegible]市
	計畫編號: 100-2410-H-004-079-MY2　　　　學門領域: 財務經濟學

無研發成果推廣資料

100 年度專題研究計畫研究成果彙整表

計畫主持人：山本栰市			**計畫編號：**100-2410-H-004-079-MY2				
計畫名稱：日本股票市場投資專家對於預期決策過程的實證分析							
成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	Due to the big support from NSC, the first one was published to Journal of Economic Dynamics and Control, (SSCI: Impact factor 1.117) titled: ’’’’ Strategy switching in the Japanese stock market.’’’’ ’ Strategy switching in the Japanese stock market,’ Journal of Economic Dynamics and Control 37, 2010-2022. The second one has been completed and published

							contents of these papers are pretty much the same as I proposed in my NSC project.
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果(無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	Due to the big support from NSC, the paper, titled '''' Strategy switching in the Japanese stock market,'' was selected as Best paper prize for junior researchers, Association of Behavioral Economics and Finance Annual Conference, 2011, http://www.iser.osaka-u.ac.jp/abef/event/20111210/syourei_award_5th.pdf.

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ■達成目標 □未達成目標（請說明，以 100 字為限） □實驗失敗 □因故實驗中斷 □其他原因 說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：■已發表 □未發表之文稿 □撰寫中 □無 專利：□已獲得 □申請中 ■無 技轉：□已技轉 □洽談中 ■無 其他：（以 100 字為限）
3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限） I would like to emphasize that I am grateful to NSC for having provided me funds to attend an international conference, hire research assistants, buy research-related stuffs. I believe that all opportunities that NSC provided to me have helped me greatly improve my papers. In my NSC research project, I proposed two research ideas. The first project provides evidence on the determinants of the professionals' expectations in Japanese stock market by using a monthly forecast micro survey dataset on the TOPIX distributed by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group. In the second research project, I document the determinants of the expectation heterogeneity of stock price forecasters on the Japanese Nikkei Stock Average by using the QUICK survey data. Due to the big support from NSC, the first one was published to Journal of Economic Dynamics and Control, (SSCI: Impact factor 1.117) titled: ''''Strategy switching in the Japanese stock market.'''' 'Strategy switching in the Japanese stock market,' Journal of Economic Dynamics and Control 37, 2010-2022. In addition, this research paper was selected as Best paper prize for junior

researchers, Association of Behavioral Economics and Finance Annual Conference, 2011,
http://www.iser.osaka-u.ac.jp/abef/event/20111210/syourei_award_5th.pdf.
The second one has been completed and published to: Pacific-Basin Finance Journal 20, 723-744 (SSCI), titled: ’’’’ Belief changes and expectation heterogeneity in buy- and sell-side professionals in the Japanese stock market’’’’ The contents of these papers are pretty much the same as I proposed in my NSC project.