博士論文

Essays on Heterogeneous Investors and Asset Prices

（異質的投資家と資産価格に関する研究）

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Financial markets all over the world have experienced the episodes of instability such as asset price bubbles and crashes, or excessive volatility of asset returns. In particular, the recent global financial crisis from 2007 has highlighted the importance and the difficulty of sustaining the stability of the financial system as a whole. In August 2007, the risk of subprime loan was recognized by investors and it induced withdrawals of money from money managers, hedge funds, mutual funds and other institutional investors.

In particular, the concept of "systemic risk" has been accepted broadly. Systemic risk is the possibility that events at the individual level trigger the significant instability or the collapse of financial system. In order to prevent the collapse of financial systems, economists and policy makers have discussed about the *macro-prudential policy*. The aim of macro-prudential policy is to achieve the stability of financial systems as a whole while micro-prudential policy aims to achieve the stability of individual financial institutions. Micro-prudential policy is enforced by a regulation at the individual investor level. However, it is ambiguous to enforce macro-prudential policy unlike micro-prudential policy in the sense that it is not clear to achieve the system-wide stability.

What is real nature of the instability of financial markets or financial systems? Systemic risk was a major contributor to the financial crisis of 2008. It is also induced by investors behavior which is unrelated with fundamentals of assets. If investors expect that others run the market, she also try to sell assets and withdraw her money from the market. Collective selling of assets lowers asset prices. Thus, herding behavior can amplify price drops. Systemic risk stems from the herding behavior of investors such as market run and distress selling. Even if regulation and monitoring maintain the financial robustness of individual investors, the *very* behavior to maintain the financial robustness can induce the disastrous risk. Thus, we need the policy to achieve the stability of financial systems as a whole.

Many researchers have proposed the mechanisms behind the instability of financial markets. Minsky (1976, 2008, 1992) advocated the view that excessive expansion of bank credit due to optimism can fuel a speculative euphoria. Kindleberger and Aliber (2011) emphasized that irrationally optimistic expectations frequently induce the asset price bubbles. Shiller (2015) highlighted that psychological biased investors form a feedback mechanism, through which initial price increases caused by certain initial precipitating factors such as new technology innovations feed back into higher asset prices through enhanced investor confidence. The rise of asset prices based on non-fundamental reasons lead to the collapse of prices. Asset price drops are often accompanied by the damage of portfolio values of investors. This results in distress selling of (possibly unrelated) assets because investors, especially short-term investors, call for liquidity. Accordingly, financial markets face the risk that stems from investors' behavior, beliefs and so forth.

In this chapter, we discuss the instability of asset markets by taking account for the interaction of heterogeneous agents in financial markets. The importance of heterogeneity of investors in the functioning of asset markets have been recognized by financial economists. Trading occurs when traders have different valuations about assets. If there was no heterogeneity, there would be no trade. The other outcomes of heterogeneity of investors have been investigated for a long time. There are several types of heterogeneity of investors: beliefs, information, investment horizon, funding structure, strategy and so forth. We discuss the heterogeneity in financial markets in section 1.1.

We have argued that financial markets or financial systems are unstable. The risk has been measured mainly by the volatility (standard deviation) of asset returns. However, volatility is inadequate to describe the real risk because the probability of extreme loss depends on the higher-moments other than mean and volatility. In addition to volatility, recently, down-side risk measures like Value-at-Risk (VaR) are used by institutional investors. Money managers and financial economists have improved the risk measures in order to capture the real nature of risk and manage money safely. In section 1.2, we discuss some empirical facts in financial markets.

1.1 Elements of Heterogeneity in Financial Markets

We discuss the heterogeneity of investors in this section. However, there are many kinds of heterogeneity. Researchers focus on the heterogeneity in beliefs, funding structures, investment horizons and strategies. The heterogeneity can generate risk or instability which do not appear in the markets with homogeneous investors.[1]

1.1.1 Heterogeneous Beliefs

Standard asset pricing models, like the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966), the intertemporal CAPM (I-CAPM) of Merton (1973), and the consumption-based asset pricing model of Lucas (1978) and Breeden (1979), share the complete agreement assumption: all investors know the true joint distribution of asset payoffs. However, this assumption is unrealistic and researchers have proposed models to relax it. In this subsection, we focus on the heterogeneity of beliefs, disagreement or differences of opinions.

Beliefs about future returns of securities are the most important in financial economics. Mean variance analysis proposed by Markowitz (1952) assumes that the risk averse investor has the expected utility which is the function of the expected returns and the variances of returns: The expected utility is increasing with the expected returns and decreasing with the variances of returns. In his analysis, investors select their portfolios given the relevant beliefs about future performance of financial securities. As a result, investors select the minimum variance portfolio of all portfolios which have the same expected returns.

While mean variance analysis describes the problem of selecting optimal portfolios of risky assets, the Capital Asset Pricing Model developed by Sharpe (1964), Lintner (1965) and Mossin (1966) investigates the properties of a market for a risky assets by means of the general equilibrium model. The CAPM inquires into "the characteristics of the whole market for such assets when the individual demands are interacting to determine the prices and the allocation of the existing supply of assets among individuals. (Mossin, 1966, p.768)" The key message of the model is that the expected excess return on a risky financial asset is given by the product of the market-beta of the asset and the expected excess return on the market portfolio.

[1] Hommes (2006) provides the comprehensive survey of the heterogeneous agent models in financial markets. Fama and French (2007) discuss how disagreement and tastes for assets can affect asset prices by using a simple framework. Kirman (2006) explains the heterogeneity from the perspectives of both economics and finance.

However, the CAPM is based on several simplifying assumptions, "including the absence of taxes, transaction costs and single (uniform) holding period for assessment of uncertain outcomes. (Lintner, 1969, p.347)" One of the other critical assumptions is an assumptions that all investors have identical joint probability distributions over end-of-period outcomes.[2] In the context of mean-variance framework, investors agree about the mean vector and variance matrix of the probability distribution of returns for the risky assets.

Lintner (1969) and Sharpe (1970) considered the implications of heterogeneity of expectations in the CAPM, they reached similar conclusions; "in a somewhat superficial sense the equilibrium relationships derived for a world of complete agreement can be said to apply to a world in which there is disagreement, if certain values are considered to be averages. (Sharpe, 1970, p.291)" In other words, asset prices depend on weighted averages of investor assessments of expected payoffs and the covariance matrix. Mayshar (1983) presents a simple model of exchange in capital market where divergence of opinion not only exists, but is essential. It is essential because of its association with endogenous limitations on the number of active market participations. In the case of limited participation of investors, asset prices depend not on the average investors but on marginal investors.

In other market environments, heterogeneous beliefs have important implications for asset markets. When participants disagree with each other, an investor takes a position based on his unique expectations have different risk from other participants. Such trading risk differs fundamentally from the traditional risk that are priced in asset values. This implies that investors trading when dispersion in beliefs exists could require additional compensation for bearing the risk. In fact, there is significant controversy about how disagreement risk affect expected returns and asset prices in the literature.

On one hand, numerous theoretical literature says that divergence in beliefs or opinions should lead to a positive risk premium. For example, Varian (1985, 1989) and many other researchers argue that the equity premium puzzle could be explained in terms of a risk premium for heterogeneous beliefs or differences of opinion. As a result, investors should be compensated for bearing trading risk. On the other hand, Miller (1977) demonstrates that the association of differences of opinion with short-sale constraints generates overvaluations of assets. This occurs because market prices reflect only the optimistic view because short selling

[2]The other critical assumptions are the existence of a riskless asset available for holding and borrowing at a fixed, exogenously determined interest rate and the acceptance of a mean-variance criterion for portfolio decisions.

by pessimistic investors is prohibited. Based on the same framework, Scheinkman and Xiong (2003) derive the overpricing of asset and excess volatility. Other models of the differences of opinion can introduce the excess volatility and positive trading volume.

The origin of the heterogeneity in beliefs also has been controversial. Black (1986) insists that heterogeneity of beliefs can be generated by heterogeneous information. Due to differences of information, investors result in forming different beliefs. In addition, (Black, 1986, p.531) introduced *noise traders* who trade "on noise as if it were information." Black (1986) has argued that, "[i]f there is no noise trading, there will be very little trading in individual assets." We can interpret noise as heterogeneous information. In effect, noise is necessary when trades occur.

Although Black (1986) considers heterogeneous information as the source of heterogeneous beliefs, other researchers have proposed some different cases. De Long, Shleifer, Summers, and Waldmann (1990a) introduce the *noise trader approach* which has two types of agents: *rational arbitrageurs* and *noise traders*. In their model, noise traders have biased beliefs (because of some reasons) and they demand assets based on their biased beliefs. Noise traders themselves create a risk in the price that discourage rational traders from betting against them.

Some researchers introduce the model of differences of opinions. In this model, investors have heterogeneous priors and 'agree to disagree' about their interpretations of public signals, in contrast to rational expectation models in which investors share common priors and disagree due to asymmetric information. Differential interpretation of the same information can generate posterior heterogeneity in beliefs. By assumption, investors can observe the beliefs of other investors but they are confident of their beliefs. The literature of differences of opinions show the possibility of abnormal trading volume around the statement of public information and the relationship between volume and volatility.

1.1.2 Investment Horizon and Funding Structure

Next, we discuss the heterogeneity that stems from the difference of investor types. One can observe that there are several types of investors such as individual investors, hedge funds, mutual funds and pension funds. These investors participate in financial markets for different objects from each other.

Modern institutional investors manage funds of other investors. The purpose of fund managers is maximizing profits from delegated portfolio and earning fee from managing the investors' funds. The standard theories of asset pricing predict that prices in financial markets are determined by households that optimize their consumption and investment over their life cycle. In these theories, there is no implication of portfolio management or trading behavior by institutional investors.

Extensive empirical work shows that institutions have important effects on asset prices. However, there has been little theoretical work on equilibrium in the presence of professional money management. Brennan (1993) is the first attempt to introduce institutional investors into an asset pricing model.

There is a difference in investment strategies across institutional investors. In particular, investment horizons are different across investors. Some institutional investors maximize their profits from portfolios in shorter horizon but other investors maximize their profits in longer horizon. The difference of horizons stems from numerous factors: investment objectives, regal regulations, investor clienteles, competitive pressure and organizational structures.

Investment horizon depends on funding structures. If investors finance their investment on asset by short-term funds, they may trade assets more frequently than those with long-term funds. The global financial crisis showed that investors with short-term funds (such as Repo) can amplify the instability of financial markets.

The reason why heterogeneous funding structures across investors have influences on asset prices is that their *flow-driven trading* has impacts on asset prices. The fund-driven trading is trades which are generated by non-fundamental fund flows. Greenwood and Thesmar (2011) investigate the relationship between the stock ownership structure and non-fundamental risks. They define an asset to be fragile if it is susceptible to non-fundamental shifts in demand. An asset can be fragile because of concentrated ownership, or because its owner face correlated or volatile liquidity shocks. Cella, Ellul, and Giannetti (2013) study the price impact of investment horizons during financial turmoils. In particular, they identify investment horizons of institutional investors by the frequency of adjusting their portfolio.

In addition, Bushee and Noe (2000) investigate whether corporate disclosure practices affect the composition of its institutional investor ownership and its stock return volatility. They found that yearly improvements in disclosure rankings are associated with increases in ownership primarily by "transient" institutions, which are characterized by aggressive trading based on short-term trading strategies.

The other origin of heterogeneous investment horizon is expectation formation. The difference between long-term and short-term investors exists in formation of expectations. Long-term investors form their expectations based on fundamentals while short-term investors form their expectations based on past price observations. The former is called *fundamentalist* and the latter is called *chartist*. Frankel and Froot (1991) conclude that

> ... short-term and long-term expectation behave very differently from one another. In terms of the distinction between fundamentalists and chartists views, we associate the longer-term expectations, which are consistently stabilizing, with the fundamentalists, and the shorter term forecasts, which seem to have a destabilizing nature, with the chartists expectations. (Frankel and Froot, 1991, pp.98-101)

"Without a dividend or cash flow anchor, short-horizon investors focus on forming an expectation about the end-of-horizon selling price." The shorter the holding period, the more the beliefs of others rather than long-term fundamentals become central to investment decisions.

Keynes (1936) argued that investor's sentiment and psychology play in important role in financial markets:

> Investment based on genuine long-term expectation is so difficult as to be scarcely practicable. He who attempts it must surely lead much more laborious days and run greater risks than he who tries to guess better than the crowd how the crowd eill have; and, given equal intelligence, he may make more disastrous mistakes.(Keynes, 1936, p.157)

According to Keynes, it is hard to compute an objective measure of 'market fundamentals' and, if possible at all, it is costly gather all relevant information. Keynes (1936) introduce the metaphor *Beauty Contest* for explaining the nature of asset markets:

> ... professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so tat each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgment, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average

> opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees. (Keynes, 1936, p.156)

Keynes explains the importance of higher-order expectations: Investors attempt to expect how the crowd will behave. Since it is possible to resell the stock, it may not be enough for investors to pick the stock they find most attractive, as they must also consider which stocks others will find attractive. As a result, investors need to form beliefs about the average valuation, the average opinion about the average valuation, and so on; in doing so they engage in higher-order reasoning. Some theoretical models study the implications of higher-order expectations Allen, Morris, and Shin (2006) and Banerjee, Kaniel, and Kremer (2009).

1.1.3 Interaction within Investment Strategies

One of the school in heterogeneous agent models emphasize the interaction between agents. Kirman (1991, 1993) introduces the local interaction and switching behaviors. In his model, agents choose their action stochastically and the switching probability depends on the number of agents who chose actions. In Kirman (1991), he applies this model to foreign exchange market there are fundamentalists and chartists as Frankel and Froot (1990), and show the property of the price process. The simulation results show the empirical facts of volatility clustering. The interaction-based approach or the interacting agent models become popular in analysis in asset price dynamics.

Lux (1995) explains the formation and cyclical behavior of bubbles as self-fulfilling prophecies of market participants, whose readiness to mimic other participants depends on actual returns, rather than irrelevant information, leading to market prices which are different from fundamental value. In this model, a change in investor sentiment from confidence to one lacking would eventually lead to a complete collapse of the bubble.

Lux and Marchesi (1999, 2000) explain the volatility clustering, which will be explained in the next section, of asset return time-series by using an interacting agent model which is comprised of fundamentalist, chartists and noise traders. These models suggest that different investing strategies can affect on price behavior.

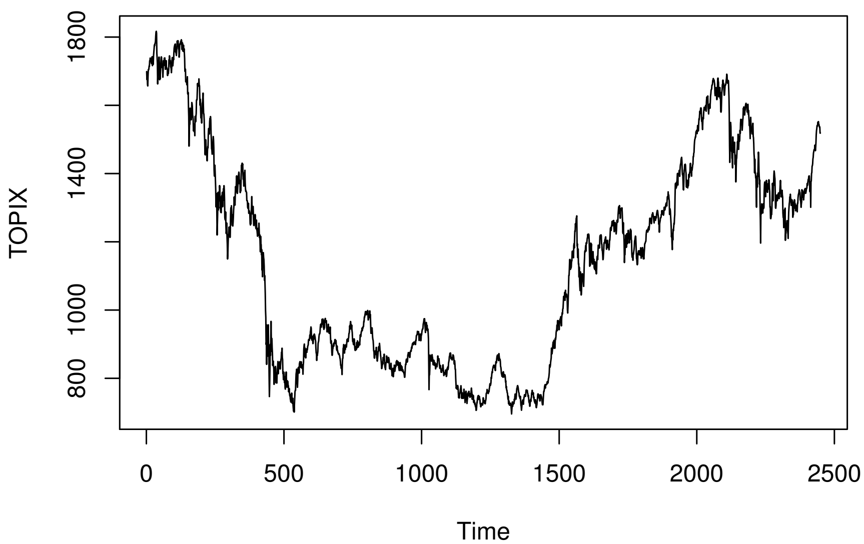


Figure 1.1: Evolution of TOPIX

1.2 Stylized Empirical Facts in Financial Markets

The empirical studies have found that asset price dynamics have numerous remarkable nature. Figure 1.1 shows the evolution of TOPIX. Is shows that the index behaves stochastically. The other asset prices also show similar patterns: The asset prices change stochastically and it is difficult to predict the price changes. Accordingly, the randomness of asset price changes or returns is described as stochastic processes. Recently, the availability of high frequency data have improved the accuracy of analysis of asset price behaviors. In this section, we discuss the empirical facts of the time series of financial asset return processes.

Stochastic modeling for the movement of security prices is pioneered by Louis Bachelier in his Ph.D thesis, *Theórie de la Spéculation*, in 1900 (Bachelier, 2011). Bachelier introduced the Brownian motion as behaviors of bond price. In his explanation, *randomness* is caused by buy and sell orders of investors.

For a long time, Bachelier's pathbreaking work has not been realized by economists. Samuelson and his colleagues found Bachelier's work and improved financial models to fit the real financial market data. Samuelson suggested to use the ge-

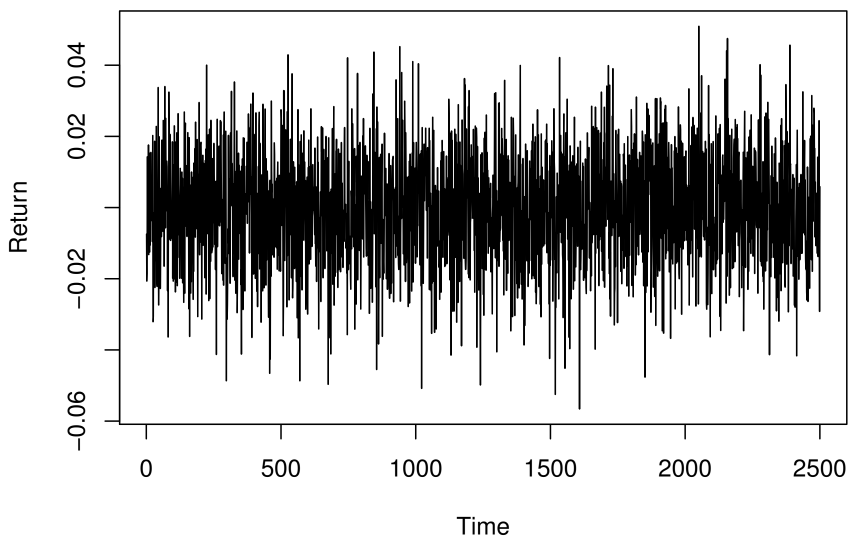


Figure 1.2: Random numbers drawn from normal distribution

ometric Brownian motion instead of the (arithmetic) Brownian motion because there is a possibility that the price becomes negative if we use the Brownian motion as a price process. This specification means that it is assumed that financial asset returns are independently and normally distributed.

Normality assumption is not suitable in order to explain the financial market data at short time scales. If the price process is perfectly described by geometric Brownian motion, the time series of returns is depicted like the pattern in Fig. 1.2. On the other hand, the real time series of TOPIX returns is shown in Fig. 1.3. There is a large difference between two time series: The time series of TOPIX returns have some extremely large returns.

Probability distributions of security returns have the leptokurtic nature, i.e., have heavier tails and a higher peak than a normal distribution. Mandelbrot (1963) and Fama (1963) insists that the probability distributions of asset price changes are a stable distribution. A stable distribution is a family of probability distributions with infinite variance except normal distribution.

After their contributions, numerous researchers have investigated the shape of asset returns. The common feature of probability distributions of asset returns are

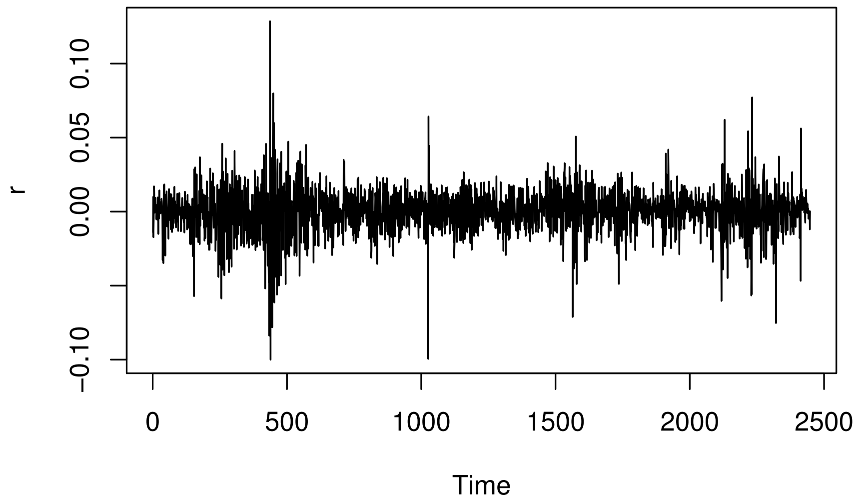


Figure 1.3: Daily Return of TOPIX

the following:

Fact 1. *Return distributions over short horizons show fat tails: Return probability density functions are leptokurtic and have power laws.*

Recently, the availability of high frequency data have improved the accuracy of analysis of asset price behaviors. Each transaction time is recorded so we can calculate the intraday returns. Intraday returns have power law distribution with index about 3. The empirical distribution approach the normal distribution as time scale becomes longer. However, its convergence is very slow: returns over the longer time-scale than month show the normal distribution.

The most important feature in their findings is that the probability distributions of price changes have fat-tails: The probability of extremely large changes is larger than normal distribution which has the same variance. Figure 1.4 plots the histogram of daily returns of TOPIX and normal distribution with the same mean and variance as empirical mean and variance.. It shows excess kurtosis in comparison with the normal distribution.

The second characteristics of financial time-series data is about autocorrelations:

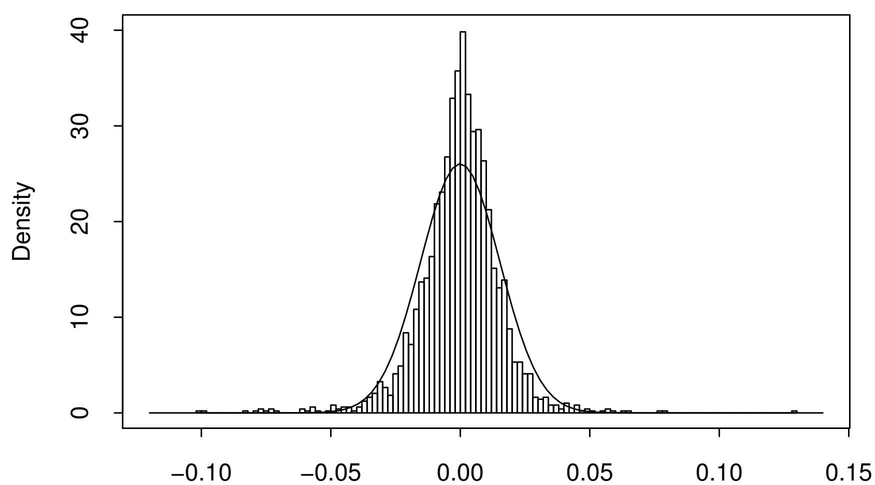


Figure 1.4: Histogram of Daily Return of TOPIX
Note: Histogram of daily return of TOPIX and density function (solid line) of normal distribution with the empirical mean and variance.

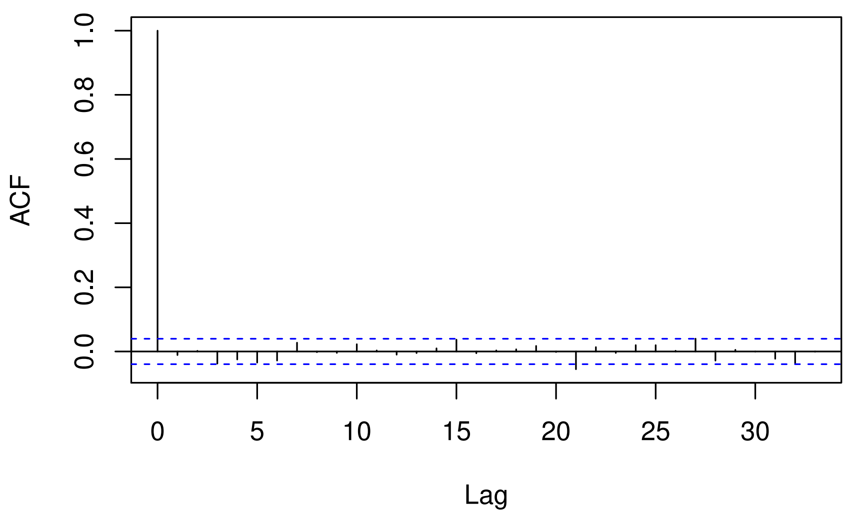


Figure 1.5: Autocorrelation of Daily Return of TOPIX

Fact 2. *No autocorrelation in return process: There are no autocorrelations of the asset returns.*

The autocorrelation of daily return of TOPIX is plotted in Figure 1.5. It shows that there is no autocorrelation even at the first lag, i.e., at one day. This fact suggests that investors cannot earn profits by predicting the pattern of price changes. Suppose that there is negative correlations between current and future price changes. After price rises, investors can earn profits by short selling. The profit taking behavior based on some autocorrelation results in disappearing any autocorrelation patterns in asset prices.

The next empirical fact is about dynamics of volatility:

Fact 3. *Volatility clustering: The autocorrelations of the square and absolute returns show very strong persistence that last for long time periods (months).*

The fact suggests that volatility varies over time and has a long memory. Figure 1.6 plots the autocorrelation of squared returns as a measure of volatility. It encourage the research on econometric models of volatility dynamics such as *generalized autoregressive conditional heteroskedasticity* (GARCH) models and

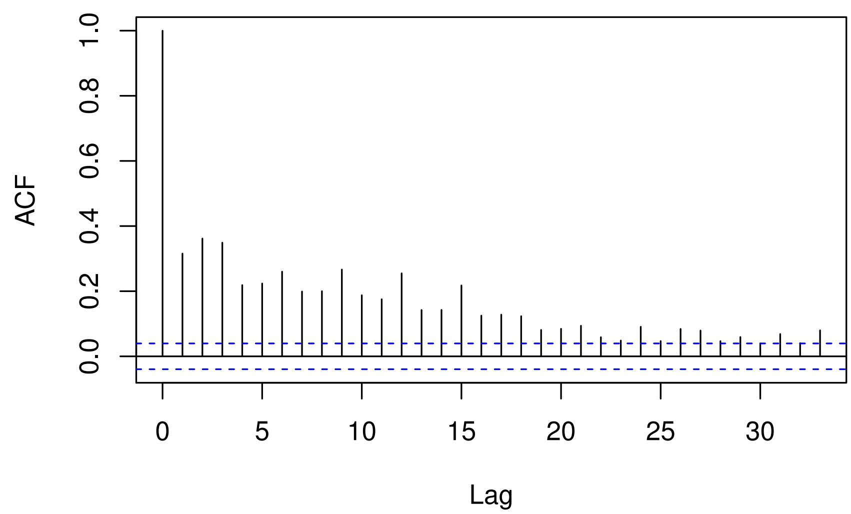


Figure 1.6: Autocorrelation of Squared Daily Return of TOPIX

stochastic volatility models.[3] Both GARCH and SV models assume that volatility is autocorrelated. The time-varying property can generate the leptokurtosis of the stock returns.

Numerous models have been developed in order to explain these empirical facts. Models which are different from traditional finance models suggest that the interaction of agents plays an important role in reproducing statistical regularities.

1.3 Outline

We discussed the elements of heterogeneity and the statistical facts of the financial markets in this chapter. We also focus on the heterogeneity of investors and the resulting instability. The aim of my research is to understand the instability of financial markets, especially, stock markets.

The rise of asset prices based on non-fundamental reasons lead to the collapse of prices. Asset price drops are often accompanied by the damage of portfolio

[3]See Engle (2004) and Taylor (2011)

values of investors. This results in distress selling of (possibly unrelated) assets because investors, especially short-term investors, call for liquidity. If investors expect that others run the market, she also try to sell assets and withdraw her money from the market. Collective selling of assets lowers asset prices. The interaction of heterogeneity and collective behavior of investors can generate the instability of financial markets.

The remainder of my thesis is organized as follows. Chapter 2 presents return-volatility relation in bull-bear market. We empirically investigate the relationship between bull-bear market cycles of stock price and trading volume by using the data of Japanese stock market. The result shows that bull markets are associated with high volumes while bear markets with low volumes.

Chapter 3 presents price impact of short-term investors who face liquidity shocks. We investigate the model where short and long horizon investors trade stocks. Short-term investor faces the risk of exogenously forced liquidation, and the occurrences of liquidity shocks are correlated across short-term investors. This results in the massive decline is experienced in the stocks which are held by mostly short-term investors.

Chapter 4 presents the relationship between stock return dynamics and trading behaviors of different investor types in the first section of Tokyo Stock Exchange. Investor types include brokered trading by corporations, financial firms, individuals and foreigners. We start investigating whether different trading groups have different trading patterns. We define the investor behaviors as net trading flows and trading fractions in the total trading value at each period. We empirically examine the relationship between market return and different trading activities. For both measures, trading activity of foreign investors is differently correlated with returns from domestic investors. We investigate the relation between volatility and trading activity. First, we show that the contemporaneous correlations between volatility and foreign investors are significant. Second, the results of dynamic relations show that trading flows of foreign investors are negatively correlated with the subsequent volatility, although fluctuations of the trading share are not associated with the subsequent volatility.

Chapter 2

Trading Volume, Stock Return and Bull-Bear Markets

Abstract We empirically investigate the relationship between bull-bear market cycles of stock price and trading volume by using the data of Japanese stock market. Trading activities are measured by trading volume, trading value and market turnover. By using two-state Markov switching model, we identify two regimes of trading activities. One has a strong feedback from past returns while another has a weak feedback and we define the former as the "feedback regime." We also identify the regimes of bull market and bear market. By using full sample smoothed probability, we derive the periods of being in each regime and we examine the link of both feedback regimes and bull markets. The result shows the periods of feedback regime sometimes coincide with bull market. Finally, we employ the bivariate Markov switching model to analyze returns and trading activity simultaneously. We find that both feedback and no-feedback regimes coexist with both bull and bear market.

2.1 Introduction

Trading volume is one of the important measures of trading activities in financial markets. Trading volume has increased as the size of financial market (measured by market capitalization) and real economy have increased. Financial innovation such as information technology also have contributed to the increases of trading activity. From the long-term perspective, the innovation has supported the upward trend of trading activities. From the short-term standpoint, trading volume is strongly related to the heterogeneity of investors. Because investors assign different value to an asset and investors revise their beliefs and asset holdings heterogeneously, trades occur. If there were no differences in investors, there would be no transactions. Accordingly, the heterogeneity generates fluctuations of trading volume around the trend.

Empirical studies of financial economics have focused on the relationship between trading volume and asset returns in financial markets. Karpoff (1987) surveys return-volume and absolute return-volume relationships. Gallant, Rossi, and Tauchen (1992) undertake a comprehensive investigation of price and volume comovement by using semi-nonparametric estimate of the joint density of current price change and volume conditional on past price changes and volume.

Recently, several empirical studies, motivated by the theoretical predictions in the field of behavioral finance, have found the relationship between trading volume and past returns. Gervais and Odean (2001) show that "greater overconfidence leads to higher trading volume" and that "this suggests that trading volume will be greater after market gains and lower after market." Statman, Thorley, and Vorkink (2006) find that stock turnover is positively related to lagged returns for many months and the relationship holds for both market-wide and individual security turnover. Glaser and Weber (2009) find that both past market returns as well as past portfolio returns affect trading activity of individual investors.

Are investors always overconfident? Of course, it is natural to consider that investors' confidence varies over time. During the periods of high performance of stock returns, investors tend to become overconfident. However, investors may lose confidence after the price declines. Therefore, we can speculate that the relationship between trading activity and past stock returns varies over time. Our main purpose is to investigate whether there are regimes of trading activities in stock markets. In addition, we investigate the relationship between volumes and return during market cycles such as bull and bear markets.

Our study is related to two strands other than the literature on investor overconfidence. The first strand is the literature about the relation between investor heterogeneous beliefs and trading volume. Beaver (1968, p.69) offers the following intuitions: “An important distinction between price and volume tests is that the former reflects changes in the expectations of the market as a whole while the latter reflects changes in the expectations of individual investors.” Revisions of individual investors’ expectations generate disagreement about valuations of financial assets. Furthermore, Karpoff (1986) suggests that “[u]nusually high volume can result from heterogeneous reactions to the information, but it does not necessarily reflect disagreement among traders; it can also reflect consensus among traders with diverse priors (Karpoff, 1986, p.1084).”

Thus, existing studies of trading volumes have focused on disagreement and expectation revisions. Several accounting studies have investigated the link between trading volume and diversity in investors’ prior beliefs by using the level of dispersion in analysts’ earnings forecasts (Bamber, Barron, and Stober, 1997). In addition, the empirical association between trading volume and belief revisions is also studied (Barron, 1995). Kandel and Pearson (1995) explain a theoretical model of differential interpretations about public signals and investigate empirically the relation between volume and forecast dispersions around earnings announcement. Carlin, Longstaff, and Matoba (2014) studies the relationships between disagreement, trading volume and asset prices by using the level of disagreement among Wall Street mortgage dealers about prepayment speeds. This literature found that the degrees of *ex ante* disagreement and forecast revisions are positively related to volumes.

Trading volume is also important in the models of “mixture of distributions hypothesis”(MDH) such as Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and Andersen (1996). These models provide explanations of the kurtosis in the empirical distributions of speculative price changes. They assume that the number of information arrival is stochastic and the resulting trading volume is also stochastic. Mixture of distribution models predict the positive associations of volume with the variability of the corresponding price change over fixed time intervals.

Clark (1973, p.145) explains the intuitions of the relationship between trading volumes and price changes: “If the information is uncertain (i.e., some traders shift expectations up and others down on the basis of the information), or if only “inside” traders get the information first, then large price changes will be coincident with high volumes. On the other hand, very large price changes will probably be due to information that is perceived by all traders to move the price in one direction.” Although the MDH models are based on the stochastic information arrivals, the resulting relations between volume and return can be interpreted as to be generated by the degree of heterogeneity.

The second strand is the literature about the bull and bear markets. Bull-bear market cycles is the important topic of financial market (Hamilton and Lin, 1996; Maheu and McCurdy, 2000; Perez-Quiros and Timmermann, 2000). There are distinct periods of time when equity prices tend to rise and fall. Typically, the periods when stock prices rise have low volatility, and vice versa. These periods of time are referred to as bull and bear markets, respectively. In other words, bull markets are the regime of high return/low volatility and bear markets is the regime of low return/high volatility.

We employ the Markov switching models in order to examine the existence of different regimes in time series of trading volume and market returns in section 2.3. The Markov switching model assumes that the observed data are drawn from multiple distributions which depend on the state of the world. The state variable is unobservable and its dynamics is described as a Markov chain. Hamilton (1989) demonstrates the filtering method to calculate the log likelihood function. Thus, we derive the maximum likelihood estimator (MLE) by maximizing the log likelihood function numerically.

In section 2.3, we construct the bivariate Markov switching model to deal with return and trading volume simultaneously. Although we restrict the specification and reduce the number of parameters, the log likelihood function is too complex to derive the MLE by simple maximization methods. Thus, we adopt the Expectation-Maximization algorithm introduced by Dempster, Laird, and Rubin (1977) because it provides the tractable way to derive the MLE.

The rest of this chapter is organized as follows. In section 4.2, we explain the data we use in this chapter. We also explain a simple Markov switching model of stock returns. In section 2.3, we extend the models to a bivariate model in order to analyze the time series data of returns and trading volume simultaneously. Section 4.5 provides some concluding remarks.

2.2 Data and Summary Statistics

Data source of trading activity for this study is *Trading Volume & Trading Value* obtained from the Japan Exchange Group[1]. Monthly trading volume and trading value information is available in each market from 1985 to the present. Trading volume is the shares traded in the market and trading value is the yen-value of

[1]We obtained the data from the web site of the Japan Exchange Group - http://www.jpx.co.jp/

equities traded in the market at given periods. We also used the data from *Market Capitalization* obtained from the Japan Exchange Group. Market capitalization information at the end of month by market section since May, 1949 is available. In this study, we use market capitalization data from January 1985 in order to calculate the market turnover:

$$\tau_t \equiv \frac{\text{the yen value of all shares traded}}{\text{the total yen value of the market}} \times 100 = \frac{\text{Trading Value}_t}{\text{Market Capitalization}_t} \times 100.$$

Turnover, τ_t, represents the degree of trading activity in the market (see Lo and Wang (2000)).

The price data that we use in this study is Nikkei Stock Average (Nikkei 225). Monthly stock return R_t is defined as the difference of logarithm of price:

$$R_t = (\log P_t - \log P_{t-1}) \times 100$$

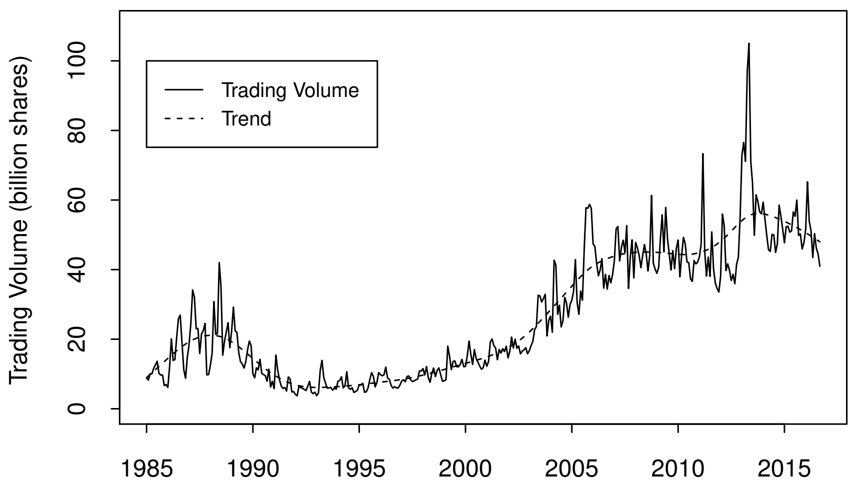
where P_t is the price at the end of month. The sample periods of this study is from January 1985 to September 2016. Figure 2.3 plots the evolution of Nikkei and monthly returns.

Figure 2.1 shows trading volume and trading value and figure 2.2 plots market turnover during sample periods. Both figures plot the trend of each time-series. Each time-series of trading activity has similar patterns while the magnitudes of growth are different.

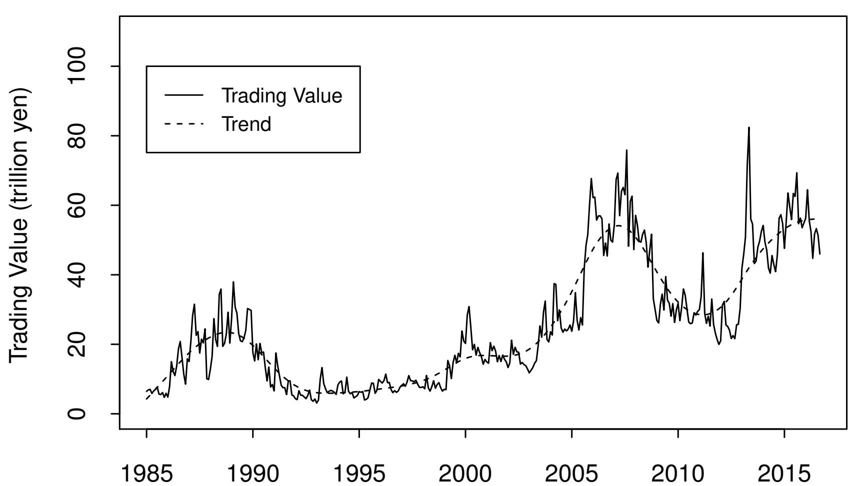
In the late of 1980's, trading activity has grown because of the bubble in the Japanese stock market and decreased eventually after the collapse of the bubble (see also figure 2.3 which plots the evolution of Nikkei225). Trading activity has recovered gradually and become more active than the bubble period after about 2003. The growth of trading activity continued until 2007-2008 when the Subprime mortgage crisis and the collapse of Lehman Brothers occurred. Although trading activity became less active, it became active again from the late of 2012 to 2013, because of "Abenomics" and "Kuroda easing." All data of trading activity has the peak in May 2013.This peak corresponds to the period around the crash on March 23.[2] The time variations of trading activity show cycles and trends: During some periods, trading is active. During other periods, trading less active.

Since the trends in figure 2.1 and 2.2 indicate that the time-series data of trading activities is nonstationary, we adjust the data by employing Hodrick and Prescott (1997) algorithm following Statman et al. (2006) (see also Lo and Wang

[2]Stock prices continued to soar after Abenomics and finally crashed by 7.6% on May 23.



(a) Trading Volume



(b) Trading Value

Figure 2.1: Trading volume and trading value: From Jan. 1985 to Sep. 2016.
Note: These figures plot (a) monthly trading volume and (b) trading value in the first section of Tokyo Stock Exchange. Solid lines represent raw data and dotted line represent its trend calculated by Hodrick-Prescott algorithm.

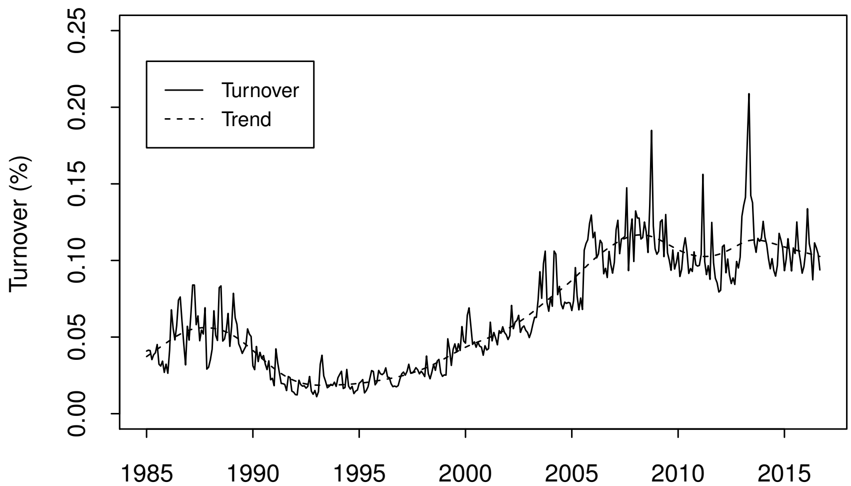
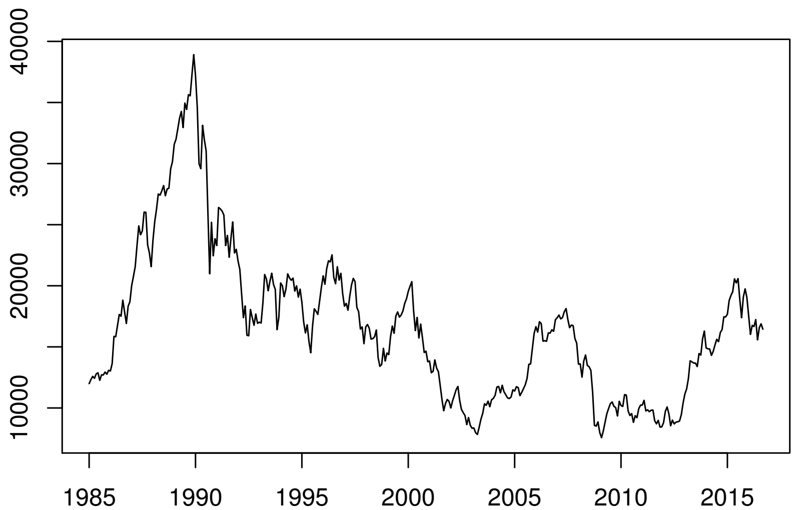


Figure 2.2: Monthly value-weighted turnover.
Note: This figure plots the monthly market turnover in the 1st section of the Tokyo Stock Exchange. Market turnover is defined as trading value divided by market capitalization. Solid lines represent calculated time-series and dotted line represent its trend calculated by Hodrick-Prescott algorithm.

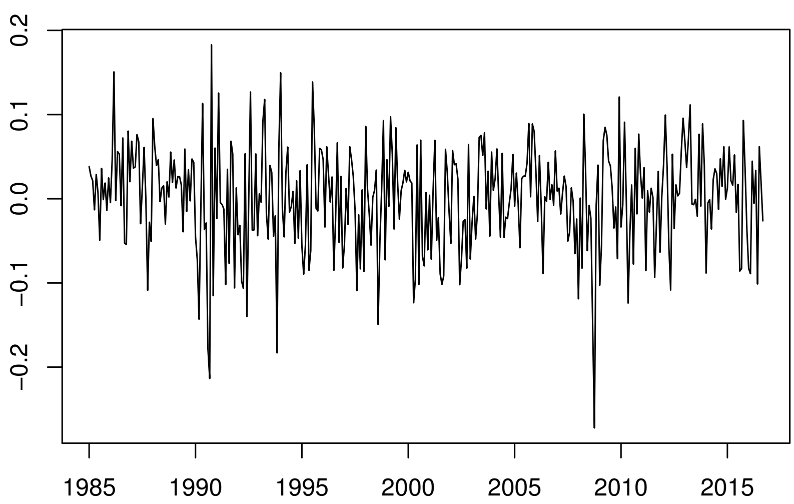
(2000) for detrending time series data of turnover).[3] The detrended time-series of turnover (trading volume, trading value) used in this study is the monthly difference between market turnover (trading volume, trading value) and its trend.

Table 2.1 shows some descriptive statistics of time series data of market return and trading activities. The mean monthly return of the sample period is 0.09% and standard deviation is 6.1%. Sample period contains the period in which asset prices fell after the collapse of bubbles, so it leads to such a low mean return. Minimum return is -27.22% which is the drop after the collapse of Lehman Brothers in

[3] The Hodrick and Prescott (1997) algorithm provides trend series by minimizing the variance of the raw series around the trend, subject to a penalty on the second difference of the trend. We follow the common practice of setting the penalty parameter $\eta = 14400$ for monthly observations as Statman et al. (2006).



(a) Nikkei 225



(b) Monthly Returns

Figure 2.3: Evolution of Nikkei 225 and Monthly Return: From Jan. 1985 to Sep. 2016.

Table 2.1: Descriptive statistics

	Mean	Std. Dev.	Min	Max
Market Return (%)	0.09	6.10	-27.22	18.29
Trading Volume[1]	26.29	17.33	3.73	105.04
Trading Value[2]	24.96	18.03	3.09	82.42
Turnover (%)	6.55	3.81	1.10	20.89
Augmented Dickey-Fuller Test	Dickey-Fuller		p-value	
a. Raw Data				
Trading Volume	-2.6118		0.3188	
Trading Value	-2.33		0.4378	
Turnover	-2.2948		0.4526	
b. Adjusted Data				
Trading Volume	-6.8613		< 0.01	
Trading Value	-5.8901		< 0.01	
Turnover	-6.6855		< 0.01	

[1] Figures are multiplied by 10^{-9}.
[2] Figures are multiplied by 10^{-12}.

September 2008. Maximum return is 18.29% in October 1990, which corresponds to the reversal after the large drops in the stock price.

Mean and standard deviation of each trading activity are also reported. As mentioned above, all measures of trading activities peak in May 2013. Table 2.1 shows the results of the augmented Dickey-Fuller test. The purpose of augmented Dickey-Fuller test is to check whether the time series has unit root or not. Accordingly, the null hypothesis is nonstationarity and the alternative hypothesis is stationarity. Test statistics for raw data cannot reject the null hypothesis. On the other hand, test statistics of adjusted data by Hodrick-Prescott filter show significantly small values. In the subsequent sections, we use the data of monthly return and the data of trading activity such as trading volume, trading value and market turnover adjusted by HP algorithm.

2.2.1 Bull-Bear Market Regimes in the TSE

A series of studies have shown that the time series of stock price changes are characterized by two regimes (for example, Hamilton and Lin (1996); Maheu and

McCurdy (2000); Perez-Quiros and Timmermann (2000); Pagan and Sossounov (2003); Gonzalez, Powell, Shi, and Wilson (2005)). Most empirical studies using the Markov switching model identify two regimes in the mean and volatility of the stock returns. Markov switching model has been applied to analysis of business cycles (i.e., time series of GDP) or time series data of asset prices. The time series of these variables are often described by the "boom" and "recession" for business cycles, or "bull market" and "bear market" for financial markets. In the financial markets, one is the bull market which is characterized by high return and low volatility and another is the bear market which is characterized by low return and high volatility. The cycle of bull-bear markets has been confirmed empirically in numerous stock markets.

In order to explain the existence of two different regimes in stock return processes, we also apply the first-order Markov switching model to the univariate process of log return of Nikkei 225. Markov switching model assumes that stock returns are drawn from two different probability distributions which depend on the unobservable state variable. The estimation methods of Markov switching models can provide the estimates of the probability of being in each state by using observable variables such as GDP or asset prices.

We define s_t^* as a binary, unobservable state variable which follows a first-order Markov chain;

$$s_t^* = 0, 1$$

and transition probability

$$\mathbf{P} = \begin{pmatrix} \Pr\{s_t^* = 0 | s_{t-1}^* = 0\} & \Pr\{s_t^* = 1 | s_{t-1}^* = 0\} \\ \Pr\{s_t^* = 0 | s_{t-1}^* = 1\} & \Pr\{s_t^* = 1 | s_{t-1}^* = 1\} \end{pmatrix} = \begin{pmatrix} q_0 & 1 - q_0 \\ 1 - q_1 & q_1 \end{pmatrix}$$

where

$$q_0 \equiv \frac{1}{1 + \exp \phi_0}, \qquad \text{and} \qquad q_1 \equiv \frac{1}{1 + \exp \phi_1}.$$

We assume that transition probability is time invariant. Equivalently, the transition dynamics of regimes are assumed not to depend on the other variables such as trading volumes and returns.

Assume market return evolves as follows:

$$R_t = \mu_{s_t^*} + \sigma_{s_t^*} \varepsilon_t \tag{2.1}$$

where ε_t is a standard Gaussian variable. Equation (2.1) means that, at the state 0, the average return is μ_0 and the standard deviation is σ_0, while, at the state 1, the average return is μ_1 and the standard deviation is σ_1.

We estimate the four specifications: The first specification assumes that stock returns are drawn from one distribution with fixed mean and variance.

$$R_t = \mu + \sigma\varepsilon_t. \tag{2.2}$$

The second has switching means and a constant variance:

$$R_t = \begin{cases} \mu_0 + \sigma\varepsilon_t & \text{if} \quad s_t^* = 0 \\ \mu_1 + \sigma\varepsilon_t & \text{if} \quad s_t^* = 1. \end{cases} \tag{2.3}$$

In contrast, the third specification has a constant mean and switching variances:

$$R_t = \begin{cases} \mu + \sigma_0\varepsilon_t & \text{if} \quad s_t^* = 0 \\ \mu + \sigma_1\varepsilon_t & \text{if} \quad s_t^* = 1. \end{cases} \tag{2.4}$$

The last specification assumes that both parameters depend on the state variable:

$$R_t = \begin{cases} \mu_0 + \sigma_0\varepsilon_t & \text{if} \quad s_t^* = 0 \\ \mu_1 + \sigma_1\varepsilon_t & \text{if} \quad s_t^* = 1. \end{cases} \tag{2.5}$$

We estimate at most six parameters $\{\mu_0, \mu_1, \sigma_0, \sigma_1, \phi_0, \phi_1\}$ by the maximum likelihood method. We estimate the parameters in Eq.(2.8) by the maximum likelihood method. In order to obtain the maximum likelihood estimators (MLE), we construct the filter as Hamilton (1989, 1994) and maximize the log likelihood function numerically. We use turnovers, trading volumes and trading values as V_t in the regression equations.

For the purpose of calculation of the log likelihood function, we introduce the indicator variables:

$$I(s_t = i) = \begin{cases} 1 & \text{if} \quad s_t^* = i \\ 0 & \text{otherwise,} \end{cases}$$

where $i = 0, 1$. By using the indicator variables, the realization of the Markov chain is denoted in the vector ξ_t as

$$\xi_t = \begin{pmatrix} I(s_t^* = 0) \\ I(s_t^* = 1) \end{pmatrix}$$

We can write the conditional density function of V_t as

$$f(R_t|\mathscr{Y}_{t-1}, s_t^*) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left\{-\frac{(R_t - \mu_{s_t^*})^2}{2\sigma_{s_t^*}^2}\right\}.$$

where $\mathscr{Y}_{t-1} = \{R_{t-1}, ..., R_0\}$. Let η_t be the vector of the conditional density

$$\eta_t = \begin{pmatrix} f(R_t|\mathscr{Y}_{t-1}, s_t^* = 0) \\ f(R_t|\mathscr{Y}_{t-1}, s_t^* = 1) \end{pmatrix}.$$

By the definition of ξ_t, we can express the conditional expectation of ξ_t under the information up to time τ as

$$\hat{\xi}_{t|\tau} = E[\xi_t|\mathscr{Y}_\tau] = \begin{pmatrix} \Pr\{s_t^* = 0|\mathscr{Y}_\tau\} \\ \Pr\{s_t^* = 1|\mathscr{Y}_\tau\} \end{pmatrix}$$

The filtering algorithm computes $\hat{\xi}_{t|t}$ by deriving the joint probability density of ξ_t and R_t conditioned on observation $\mathscr{Y}_t$.

$$\hat{\xi}_{t|t} = \frac{\eta_t \odot \hat{\xi}_{t|t-1}}{\mathbf{1}'(\eta_t \odot \hat{\xi}_{t|t-1})},$$
$$\hat{\xi}_{t+1|t} = P\hat{\xi}_{t|t}$$

where $\odot$ denotes the element-wise matrix multiplication.

By denoting parameters as $\lambda = (\mu_0, \mu_1, \sigma_0, \sigma_1, \phi_0, \phi_1)$[4], the log likelihood function is expressed as $L(\lambda) = \sum_{t=1}^{T} \ln f(R_t|\mathscr{Y}_{t-1}, \lambda)$, and its right-hand term is

$$f(R_t|\mathscr{Y}_{t-1}, \lambda) = \mathbf{1}'(\eta_t \odot \hat{\xi}_{t|t-1}).$$

We derive MLEs for θ by maximizing the log likelihood function numerically.[5]

Table 2.2 shows the estimation results of one-state regression model and two-state Markov switching model. Log-likelihood is the highest for the return process with switching in mean and standard deviation. Because $\mu_0 > \mu_1$ and $\sigma_0^2 < \sigma_1^2$, we can interpret state 0 as bull-market (high-return/low-volatility state).

[4]Of course, the number of parameters depend on specifications.

[5]We maximize the log likelihood function by using maxLik package in R introduced by Henningsen and Toomet (2011).

Table 2.2: Estimation result of return dynamics.

Parameter	Coefficient (Std. Error)			
	Eq.(2.2)	Eq.(2.3)	Eq.(2.4)	Eq.(2.5)
μ	0.0930		0.5940**	
	(0.3127)		(0.2959)	
μ_0		0.3513***		1.9873***
		(0.3054)		(0.4017)
μ_1		-18.8088***		-1.4087**
		(2.2692)		(0.6388)
σ	6.0880***	5.6624***		
	(0.2211)	(0.2154)		
σ_0			3.0117***	3.9862***
			(0.3925)	(0.3596)
σ_1			6.7557***	6.9782***
			(0.3282)	(0.3748)
ϕ_0		-4.7104***	-2.1652***	-2.6089***
		(0.7582)	(0.4812)	(0.6998)
ϕ_1		0.5257	-3.5608***	-2.9244***
		(1.1223)	(0.5608)	(0.8265)
Log-likelihood	-1228.83	-1215.90	-1217.41	-1209.46

Note: This table reports parameter estimates of four specifications of the monthly return in the stock market:

$$R_t = \mu_{s_t^*} + \sigma_{s_t^*}\varepsilon_t, \qquad \varepsilon_t \sim N(0,1).$$

The estimated parameters of the single state specification are reported in column 1. The parameters with switching in mean in column 2, with switching in variance in column 3 and with switching in mean and variance in column 4. The numbers in parentheses are standard errors of estimated parameters. *,** and *** denote the levels of significance at 10%, 5%, and 1%, respectively.

We can estimate the probability of being in each state ($\hat{\Pr}\{s_t = i|\mathscr{Y}_T\}$ for $i = 0, 1$) by using the filtering methods by Kim (1994) (see also Hamilton (1994) and Krolzig (2013)). In Markov switching model, the full-sample smoothed inference $\hat{\xi}_{t|T}$ provide the estimation of the probability of being in each state.[6] At first, we derive

$$\hat{\xi}_{T-1|T} = \hat{\xi}_{T-1|T-1} \odot \{P'(\hat{\xi}_{T|T} \oslash \hat{\xi}_{T|T-1})\}$$

where $\oslash$ denotes the element-wise matrix devision. For $t = T-2, ..., 1$, given $\hat{\xi}_{t|t}$ and $\hat{\xi}_{t+1|t}$ from maximum likelihood estimation, and $\hat{\xi}_{t+1|T}$ from a previous iteration, smoothing probability are derived as

$$\hat{\xi}_{t|T} = \hat{\xi}_{t+1|T-1} \odot \{P'(\hat{\xi}_{t+1|T} \oslash \hat{\xi}_{t+1|t})\}.$$

This filtering procedure provide

$$\hat{\xi}_{t|T} = \begin{pmatrix} \hat{\Pr}\{s_t = 0|\mathscr{Y}_T\} \\ \hat{\Pr}\{s_t = 1|\mathscr{Y}_T\} \end{pmatrix}$$

and, hereafter, we focus on full-sample smoothed probability at state 0: $\hat{\Pr}\{s_t = 0|\mathscr{Y}_T\}$ for $t = 1, \ldots, T$

In order to identify the bull-bear regimes, define D_t as a dummy variable which equals one when the full sample smoothed probability of being in state 0, that is, in bull regime, is larger than 0.5:

$$D_t = 1 \qquad \text{if} \qquad \hat{\Pr}\{s_t^* = 0|\mathscr{Y}_T\} > 0.5. \tag{2.6}$$

By using this series of dummy variable, define the periods of being in state 0 (bull market) as

$$T_{Bull} \equiv \{t \in T|D_t = 1\}. \tag{2.7}$$

Figure 2.4 (b) shows estimated periods of bull markets (shaded area) with market returns. From January 1985 to September 2016, the time series of stock return has 6 bull-bear cycles. Table 2.3 reports the estimated periods of being in bull regimes.

The first and second periods correspond to the episode of “bubbles” in the real estate and stock markets in Japan. The discontinuity between the first and second

[6] $\hat{\xi}_{t|T}$ is the conditional expectation of ξ_t with respect to all available information at time T. The expectation of ξ_t is comprised of the probability of being each state as explained in the construction of the log likelihood function.

Table 2.3: The estimated periods of bull regimes from Jan. 1985 to Sep. 2016

	Bull Regimes		Duration (months)
1	January 1985	August 1987	32
2	January 1988	December 1989	24
3	October 1995	May 1996	8
4	February 1999	February 2000	13
5	April 2003	June 2007	51
6	August 2012	June 2015	25

Note: The periods of bull regimes ($s_t^* = 0$) are estimated by using the dummy variable defined in Eq. (2.6). Sample period is from January 1985 to September 2016 (381 Observations).

periods suggests that it stems from “Black Monday” on October 19, 1987.

The fifth period of bull market, which is the longest period of all our estimations, was based on good performance of the Japanese economy as well as the world economy. This bull market was over when subprime loans problems were revealed.

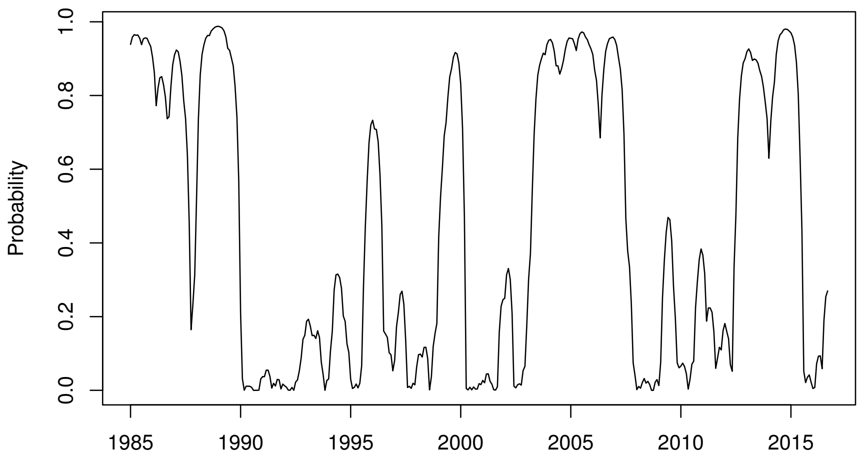
Finally, it is natural to think of the sixth period as the bull market originated from Abenomics and Kuroda easing as mentioned before.

2.3 Are There Regimes in Trading Activity?

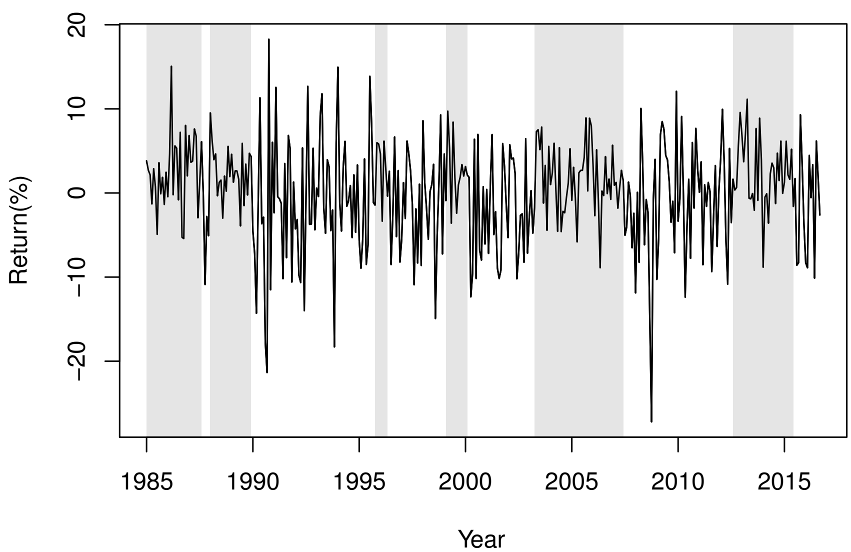
2.3.1 Bivariate Markov Switching Model

As explained in section 2.1, the recent theoretical models argue that past stock returns affect subsequent stock trading volume. Some empirical studies also found the fact that trading volume is associated positively with past returns. Behavioral finance literature assumes that investors become overconfident of their trading skills during periods of high portfolio performances. Investor overconfidence induces excessive trading. Thus, the past performance of the stock markets have an positive influence on trading behavior of investors.

However, it is natural to consider that the enhancement of confidence by the past performance differs depends on the market environment or investors’ experiences. In other words, 1% rises in the midst of a rally and of a downturn of stock prices may have different effects on trading behavior.



(a) Smoothed Probability



(b) Stock Return and Bull Regime

Figure 2.4: Smoothing Probability and Bull Regime.
Note: (a) The smoothed probability of being in bull state and (b) Monthly returns and bull regimes (shaded area).

Market environment, such as bull or bear markets, may affect on the sensitivity of trading volume to stock return. In other words, stock returns may have different effects on the subsequent trading activity between bull and bear markets. Bull market, that is, the periods when stock prices are rising with low volatility, tends to make high performances of portfolio returns. During the period, a large fraction of investors have the expectations that stock prices continue to rise. The continuation of bull market reinforces such expectations and makes investors more confident. As a result, the overconfidence may generate much more intensive trading activities.

On the other hand, during bear market, that is, the periods when stock prices are falling with high volatility, tends to make lower performances of portfolio returns. During the period unlike bull regimes, a large fraction of investors have the expectations that stock prices continue to fall and they hardly revise their expectations even if stock prices rise. If price changes have little impacts on the changes in beliefs of investors and the degree of heterogeneity among them, the induced trading volume is expected to be small.

To sum up, we examine the following hypothesis in this section:

Hypothesis 1. *The past returns have positive effects on the subsequent trading activity during bull market regimes, while they have small effects on the subsequent trading activity during bear market regimes.*

In order to examine the existence of different regimes, we employ the first-order Markov switching model but we extend the model to a bivariate model. At first, we define s_t as a binary, unobservable state variable which follows a first-order Markov chain;

$$s_t = 0, 1$$

and transition probability

$$\mathbf{P} = \begin{pmatrix} \Pr\{s_t = 0|s_{t-1} = 0\} & \Pr\{s_t = 1|s_{t-1} = 0\} \\ \Pr\{s_t = 0|s_{t-1} = 1\} & \Pr\{s_t = 1|s_{t-1} = 1\} \end{pmatrix} = \begin{pmatrix} p_0 & 1-p_0 \\ 1-p_1 & p_1 \end{pmatrix}$$

where

$$p_0 \equiv \frac{1}{1+\exp\theta_0}, \qquad \text{and} \qquad p_1 \equiv \frac{1}{1+\exp\theta_1}.$$

We assume that transition probability is time invariant. Equivalently, the transition dynamics of regimes are assumed not to depend on the other variables such as trading volumes and returns.

This Markov chain expresses the underlying dynamics of regimes such as business cycles or bull-bear market cycles in the existing literature. Although we assume that the transition probabilities are fixed parameters in this study, we can also generalize them by introducing time varying transition probabilities (TVTP). Diebold, Lee, and Weinbach (1994b) and Filardo (1994) study the business cycles by applying Markov switching models with TVTP. In their models, the transition probability depends on the exogenous variables. Schaller and Norden (1997) and Chen (2007) analyze the stock return dynamics Markov switching models with TVTP. Schaller and Norden (1997) analyze stock market returns to specify the transition probability to depend on the past price/dividend ratio and find that there is asymmetric response to the past price/dividend ratio. Chen (2007) studies the effect of monetary policy on stock returns by entering monetary policy measures into transition probability and finds out the fact that a contractionary monetary policy makes a switching probability to the bear market regime higher. Maheu and McCurdy (2000) also consider the duration dependence of the transition probability. In this chapter, we assume that the Markov chain of underlying state dynamics has the simplest form of transition probabilities.

In addition to the Markov chain of the underlying regimes, we assume that trading volume evolves as following equation:

$$V_t = m_{s_t} + \alpha_{s_t} V_{t-1} + \beta_{s_t} R_{t-1} + v_{s_t} \varepsilon_{2,t}, \qquad \varepsilon_{2,t} \sim N(0,1). \tag{2.8}$$

All parameters in Eq.(2.8) are possibly regime-dependent. m_{s_t} represents the mean trading volume, α_{s_t} the inertia of trading volume, β_{s_t} the impact of the past return on trading volumes, and v_{s_t} the standard deviation of trading volume of the state s_t.

We enter the past return in the Eq.(2.8) in order to capture the effect of investor overconfidence. Overconfidence hypothesis predicts that the coefficient β_{s_t} is positive. It is natural to ask how long durations past returns have an effect on trading volume. Statman et al. (2006) investigate the lead-lag relationship between returns and trading volume by using VAR model. They set the number of monthly lags as 10 based on the Schwartz Information Criteria. On the other hand, we enter only first lag into Eq.(2.8) because our main purpose is to examine the existence of different regimes.

We also enter the lagged trading volume (V_{t-1}) into Eq.(2.8) because time series of trading volume is autocorrelated positively. Trading volume is large after the periods in which trading volume is large. Therefore, we express the coefficient of V_{t-1} as “inertia” in this chapter. Finally, trading volume is driven by an error term $\varepsilon_{2,t}$. We can interpret $\varepsilon_{2,t}$ as trades caused by heterogeneity such us disagreement and belief revisions.

We restrict the specifications of return and trading volume dynamics: Specifically, in the equation of trading volume, we assume that a constant term and an autoregressive coefficient of volume are state independent.

$$\begin{aligned} R_t &= \mu_{S_t} + \sigma_{S_t}\varepsilon_{1,t} \\ V_t &= m + \alpha V_{t-1} + \beta_{S_t} R_{t-1} + v_{S_t}\varepsilon_{2,t}. \end{aligned} \tag{2.9}$$

The purpose of this specification is to simplify the estimation by reducing the number of parameters.

Next, we explain the construction of log likelihood function. Denote the set of parameters in the state i ($i = 1,2$) as $\psi_i = (\mu_i, \sigma_i, m, \alpha, \beta_i, v_i)$. The marginal distribution of state i is defined as

$$\begin{aligned} & f(y_t|s_t = i; \psi_i) \\ &= \frac{1}{\sqrt{2\pi\sigma^2 v_i^2}} \exp\left\{ -\frac{1}{2}\left(\frac{(R_t-\mu_i)^2}{\sigma_i^2} + \frac{(V_t - m - \alpha V_{t-1} - \beta_i R_{t-1})^2}{v_i^2} \right) \right\} \end{aligned}$$

Thus, by denoting $\theta = (\mu_0, \mu_1, \sigma_0, \sigma_1, m, \alpha, \beta_0, \beta_1, v_0, v_1, p_0, p_1, \rho)$ the complete-data likelihood is[7]

$$\begin{aligned} f(\underline{y}_T, \underline{s}_T|\theta) &= f(y_1, s_1|\theta)\prod_{t=2}^{T} f(y_t, s_t|\underline{y}_{t-1}, \underline{s}_{t-1}; \theta) \\ &= f(y_1|s_1,\theta)p(s_1)\prod_{t=2}^{T} f(y_t|s_t, \underline{y}_{t-1}, \underline{s}_{t-1}; \theta)p(s_t|\underline{y}_{t-1}, \underline{s}_{t-1}; \theta) \\ &= f(y_1|s_1,\theta)p(s_1)\prod_{t=2}^{T} f(y_t|s_t;\theta)p(s_t|s_{t-1};\theta), \end{aligned}$$

here f denotes any density function and underline denotes past history of the variable from $t = 1$ to the variable subscript, that is, $\underline{y}_t = \{y_1, ..., y_t\}$.

[7] "Complete data" refers to the hypothetical assumption that both $\{y_t\}$ and $\{y_t\}$ are observed.

We can write the complete-data likelihood in terms of indicator functions,

$$
\begin{aligned}
f(\underline{y}_T, \underline{s}_T|\theta) = \mathbf{1}(s_1 = 1) f(y_1|s_1 = 1; \psi_1)\rho + \mathbf{1}(s_1 = 0) f(y_1|s_1 = 0; \psi_0)(1-\rho) \\
\times \prod_{t=2}^{T} \{ \mathbf{1}(s_t = 1, s_{t-1} = 1) f(y_t|s_t = 1; \psi_1) p_1 \\
+ \mathbf{1}(s_t = 0, s_{t-1} = 1) f(y_t|s_t = 0; \psi_0)(1-p_1) \\
+ \mathbf{1}(s_t = 1, s_{t-1} = 0) f(y_t|s_t = 1; \psi_1)(1-p_0) \\
+ \mathbf{1}(s_t = 0, s_{t-1} = 0) f(y_t|s_t = 0; \psi_0) p_0 \}.
\end{aligned}
$$

Conversion to log form yields

$$
\begin{aligned}
\log f(\underline{y}_T, \underline{s}_T|\theta) = \mathbf{1}(s_1 = 1)[\log f(y_1|s_1 = 1; \psi_1) + \log \rho] \\
+ \mathbf{1}(s_1 = 0)[\log f(y_1|s_1 = 0; \psi_0) + \log(1-\rho)] \\
+ \sum_{t=2}^{T} \{ \mathbf{1}(s_t = 1) \log f(y_t|s_t = 1; \psi_1) + \mathbf{1}(s_t = 0) \log f(y_t|s_t = 0; \psi_0) \\
+ \mathbf{1}(s_t = 1, s_{t-1} = 1) \log(p_1) + \mathbf{1}(s_t = 0, s_{t-1} = 1) \log(1-p_1) \\
+ \mathbf{1}(s_t = 1, s_{t-1} = 0) \log(1-p_0) + \mathbf{1}(s_t = 0, s_{t-1} = 0) \log(p_0) \}
\end{aligned}
$$

The complete-data log likelihood function cannot be constructed in practice, because the complete data are not observed. Conceptually, the incomplete-data log likelihood may be obtained by summing over all possible state sequences,

$$
\log f(y_T|\theta) = \log \left(\sum_{s_1=0}^{1} \sum_{s_2=0}^{1} \cdots \sum_{s_T=0}^{1} \log f(y_T, s_T|\theta) \right),
$$

and then maximized with respect to θ.

From the practical point of view, it is difficult or intractable to estimate the MLE by using usual maximization incomplete-data log likelihood. Thus, we use the Expectation-Maximization (EM) algorithm introduced by Dempster et al. (1977) for deriving the maximum likelihood estimators. "The EM algorithm is an iterative ML estimation technique designed for general class of models where the observed time series depends on some unobservable stochastic variables. (Krolzig, 2013)" Hamilton (1990) shows that the EM algorithm.

Each iteration of the EM algorithm consists of two steps: expectation step and maximization step. In expectation step, the expected complete-data log likelihood conditional upon the observed data is calculated by using full sample smoothed probabilities based on the previous estimators of parameters. In maximization step, updating the parameter estimates conditional upon the smoothed state probabilities by maximizing the expected log likelihood. Iterating to the convergence provides the MLE. The procedure of EM algorithm is as follows:

1. Pick $\theta^{(0)}$.
2. Get:
$$\begin{aligned}
&\Pr(s_t = 0|y_t; \theta^{(0)}) \quad \forall t, \\
&\Pr(s_t = 1|y_t; \theta^{(0)}) \quad \forall t, \\
&\Pr(s_t = 0, s_{t-1} = 0|y_t; \theta^{(0)}) \quad \forall t, \\
&\Pr(s_t = 0, s_{t-1} = 1|y_t; \theta^{(0)}) \quad \forall t, \\
&\Pr(s_t = 1, s_{t-1} = 0|y_t; \theta^{(0)}) \quad \forall t, \\
&\Pr(s_t = 1, s_{t-1} = 1|y_t; \theta^{(0)}) \quad \forall t;
\end{aligned}$$
construct $E \log f(y_T, s_T|\theta^{(0)})$ by replacing 1's with P's.
3. Set $\theta^{(1)} = \arg\max_\theta E[\log f(y_T, s_T|\theta^{(0)})]$.
4. Iterate to converge.

The estimator $\bar{\theta}$ that converges is the MLE obtained by EM algorithm.

Diebold, Lee, Weinbach, and Hargreaves (1994a) explains the procedure of the EM algorithm for two-state Markov switching model with time-varying transition probabilities. Although our model has bivariate dependent variables, the procedure for deriving MLE is basically the same as shown in Diebold et al. (1994a).

2.3.2 Estimation Results

Table 2.4 reports the estimated parameters of the specification (2.9) for turnovers, trading volumes and trading values. The process of stock return has two different regimes in terms of mean return and volatility: One regime ($s_t = 0$) is characterized by high mean stock return and low variance, while another regime ($s_t = 1$) is characterized by low mean stock return and high variance. This result is the same as the existing literature of bull-bear market cycles.

Next, we interpret the estimated parameters in equations of trading activity. The result shows that $\beta_0 > \beta_1$ for all variables of trading activity. In state 0, the effect of past returns on trading activities is larger than one of state 1. In particular, the coefficient of past returns in state 1 is zero for the case of turnover and trading volume. In summary, we find out the different regimes in which the effect of past returns on trading activities depends on the current regimes. Hereafter, we call the state 0 "feedback regime."

In one regime ($s_t = 0$), trading activities have a positive relation with past stock returns, while, in another regime ($s_t = 1$), they have no significant relations. We can interpret the findings as follows: In the former regime, investors react the past return because the stock performance affects their beliefs and the resulting changes in beliefs induce trades. On the other hand, the past return has no influences on investors' beliefs because investors assign little weight on the past return when they revise their beliefs under more uncertain circumstances. This differences of market environment can affect belief revision processes through the accuracy of information or confidence of investors.

The results show that the variance of trading activity at state 0 is higher than state 1. It means that trading volume fluctuates wildly at the same time when it is affected by past returns strongly (i.e., feedback regime). We can interpret this coincidence as the following: Trading volume is generated by heterogeneity of investors such as disagreement and belief revisions as suggested by existing literature. When investors are confident of the accuracy of their private information, they revise their beliefs based on the information. Thus, the information arrivals can change the degree of disagreement across investors over time. A revision of a belief induces a change in asset holdings, and it causes trading with other market participants who also try to change their positions. If the information arrival induce large disagreement, it generates large trading volume, and vise versa. To the contrary, they revise their beliefs less actively when they are uncertain about their private information. In this case, the resulting changes of disagreement are small and the variation of trading volume is also small. Therefore, the variance of error term is large in the regime in which the coefficient of past returns is large.

Panel (a) of Figure 2.5 plots the estimated probability of being in state 0 for bivariate Markov switching model of return and adjusted turnover. Panel (a) of Figure 2.7 and 2.9 also plot the estimated probability of being in state 0 for trading volume and trading value, respectively. The probability that the market is at state 0 is high when the line is close to 1. All figures show that there is at least three prolong periods in state 0 during the entire period. The first period is from 1985 to 1990. This period corresponds to the bubble episode in Japanese stock and

Table 2.4: Estimation result of bivariate MS models for turnover.

Parameter	Coefficient (Std. Error)		
	Turnover	Trading Volume	Trading Value
μ_0	1.4559***	0.987125**	1.17287***
	(0.3452)	(0.384242)	(0.34131)
μ_1	-0.9370**	-1.089970**	-1.07543*
	(0.4582)	(0.474124)	(0.56096)
σ_0	4.4738***	5.579890***	4.83945***
	(0.2507)	(0.271205)	(0.24094)
σ_1	6.8850***	6.519543***	7.00649***
	(0.3239)	(0.360746)	(0.35061)
m	-0.0518	0.246518	0.22232
	(0.0514)	(0.131080)	(0.15116)
α	0.3838***	0.514541***	0.56346***
	(0.0460)	(0.042163)	(0.03968)
β_0	0.1263***	0.351642***	0.42028***
	(0.0234)	(0.082920)	(0.07989)
β_1	0.0031	0.002883	0.02612
	(0.0083)	(0.020944)	(0.02372)
v_0	1.3885***	6.727509***	5.89613***
	(0.0780)	(0.324620)	(0.29751)
v_1	0.8397***	1.736068***	2.16390***
	(0.0405)	(0.095226)	(0.11241)
θ_0	-3.6498***	-3.746422***	-3.40853***
	(0.4943)	(0.428079)	(0.42808)
θ_1	-4.1490***	-3.319474***	3.22676***
	(0.5415)	(0.411285)	(0.37073)
Log-likelihood	-1791.65	-2303.229	-2290.212

Note: This table reports parameter estimates of 2 state bivariate Markov switching model of the adjusted turnover, trading volume and trading value in the stock market.The numbers in parentheses are standard errors of estimated parameters. *,** and *** denote the levels of significance at 10%, 5%, and 1%, respectively.

real estate market. It is natural to imagine that the rise of asset price enhance speculative trading of some investor groups. The stock price was the highest in December 1989.

In order to identify the two regimes, define D_t as a dummy variable which equals one when the full sample smoothed probability of being in state 0, that is, in feedback regime, is larger than 0.5:

$$D_t = 1 \qquad \text{if} \qquad \hat{\Pr}\{s_t = 0|\mathscr{Y}_T\} > 0.5.$$

By using this series of dummy variable, define the periods of being in state 0 (feedback regime) as

$$T_F \equiv \{t \in T|D_t = 1\}.$$

Figure 2.6, 2.8 and 2.10 (b) show estimated periods of feedback regimes (shaded area) with each trading activity. The estimated periods of state 0 and their durations are also shown in Table 2.5.

In contrast to the smoothed probabilities of turnover time series, we can find different characteristics of trading volume in figure 2.7 and trading value in figure 2.9. The difference is the period after 2003.

This means that, when we measure the trading activity by (adjusted) trading volume, the bull market coincides with the feedback period and the bear market coincides with the no-feedback period.

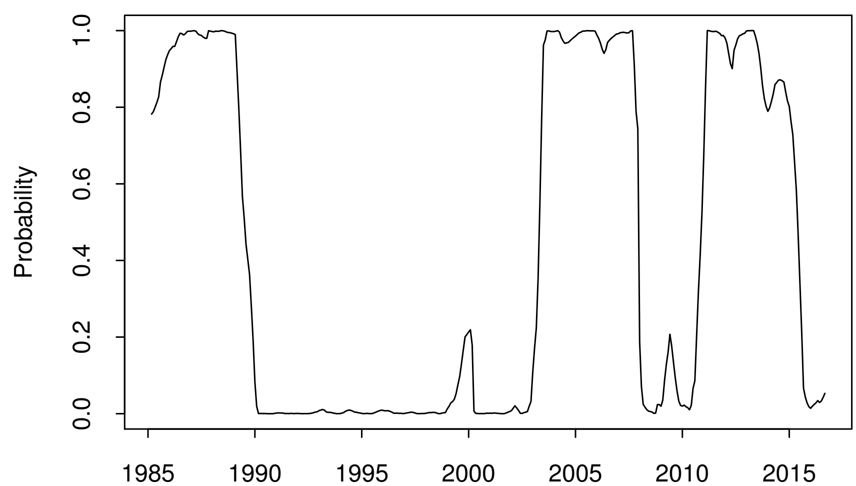
Table 2.5: The estimated periods of feedback regimes

	Feedback Regimes		Duration (months)
Adjusted Turnover			
1	March 1985	July 1989	53
2	May 2003	December 2007	56
3	December 2010	May 2015	53
Trading Volume			
1	November 1985	January 1990	51
2	March 1993	April 1993	2
3	June 2003	September 2016	160
Trading Value			
1	June 1986	January 1990	44
2	September 1999	March 2000	7
3	June 2003	June 2008	56
4	November 2008	April 2010	18
5	January 2011	September 2016	69

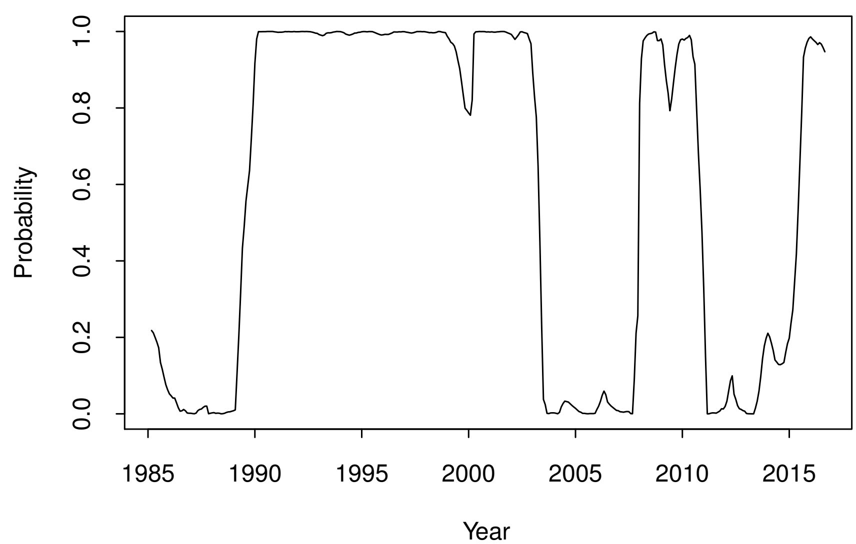
Note: The periods of feedback regimes are defined as

$$T_F \equiv \{t \in T | D_t = 1\} \text{ and } D_t = 1 \text{ if } \hat{\Pr}\{s_t = 0 | \mathscr{Y}_T\} > 0.5.$$

Sample period is from February 1985 to September 2016.

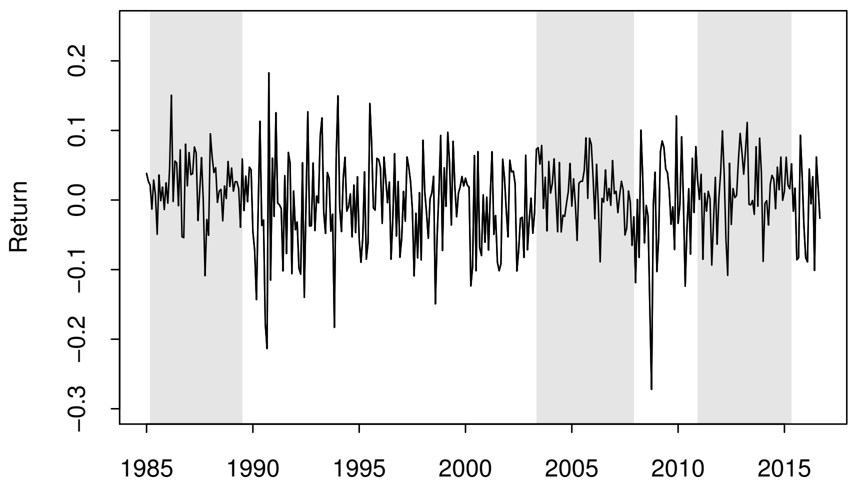


(a) Smoothed Probability of being in state 1

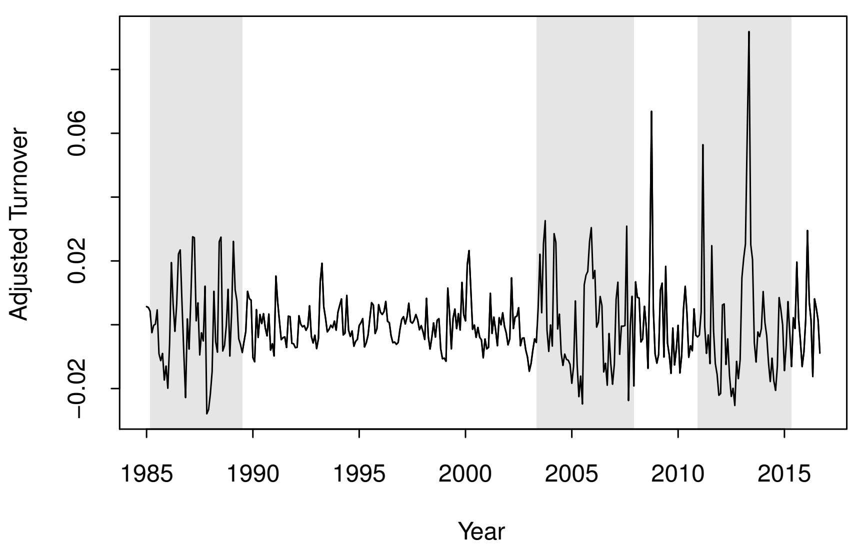


(b) Smoothed Probability of being in state 2

Figure 2.5: Smoothed Probability of Bivariate Markov Switching Model: Turnover

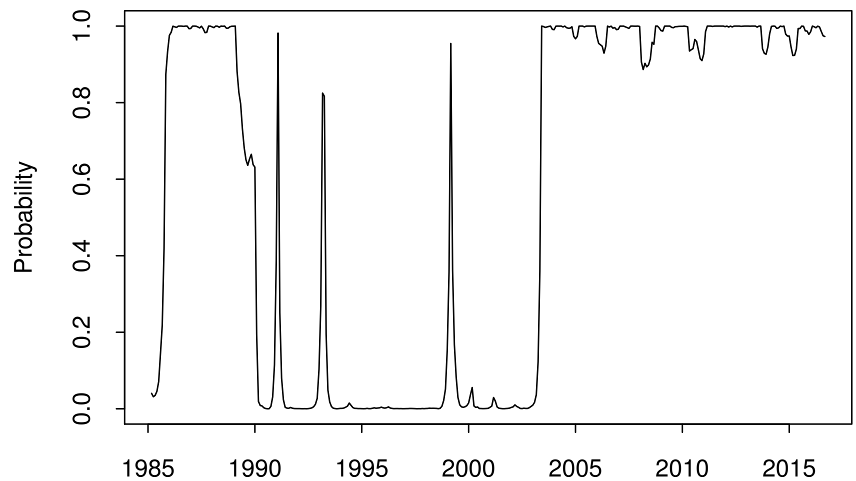


(c) Bull period and return

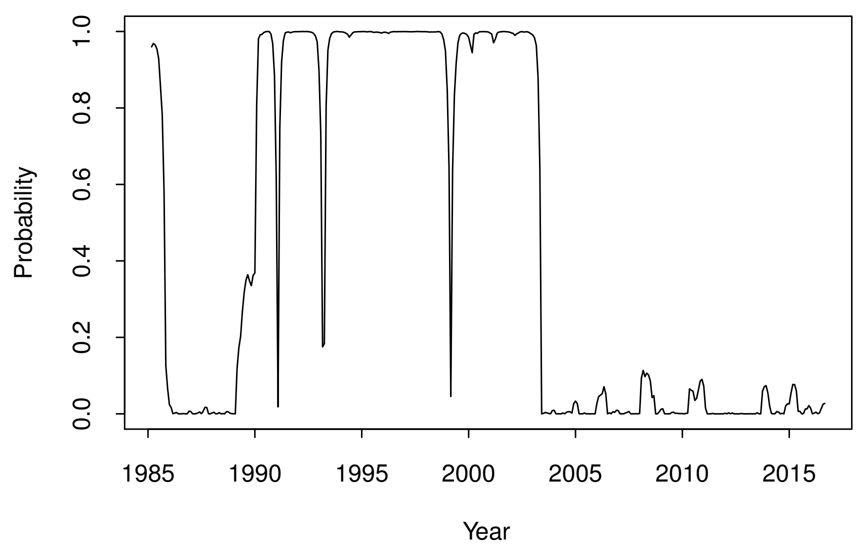


(d) Bull period and adjusted turnover

Figure 2.6: Estimated period and time series of return and adjusted turnover

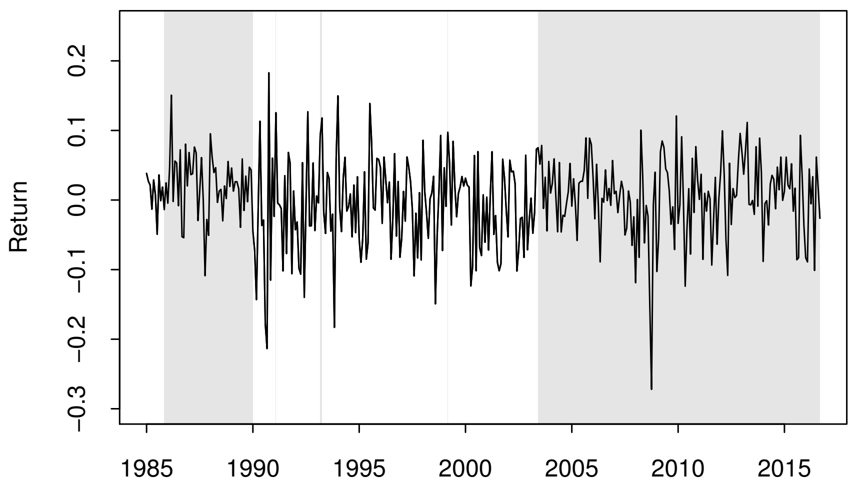


(a) Smoothed Probability of being in state 1

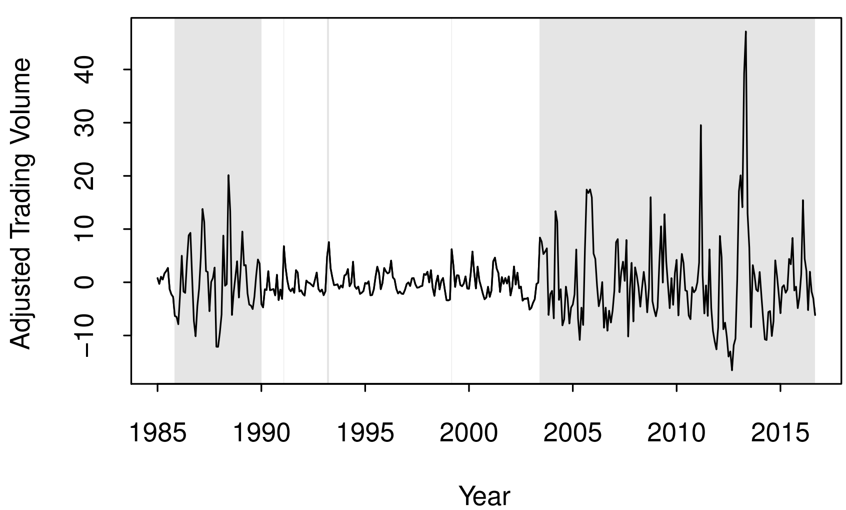


(b) Smoothed Probability of being in state 2

Figure 2.7: Smoothed Probability of Bivariate Markov Switching Model: Trading Volume

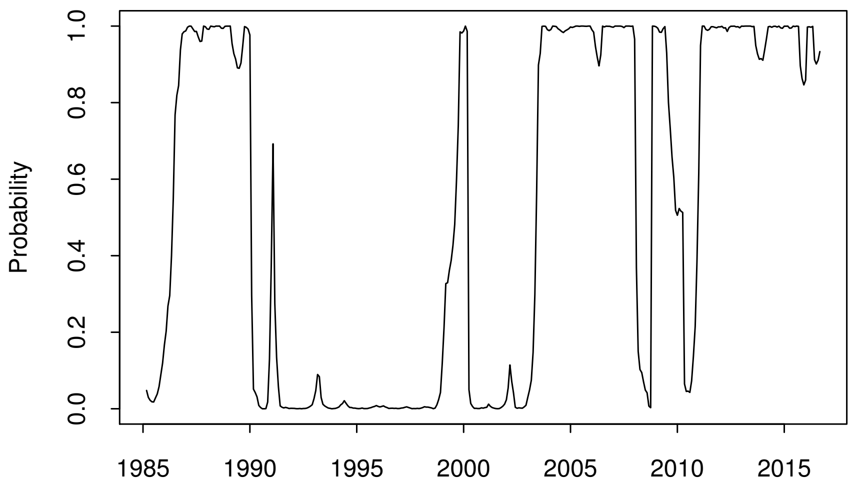


(c) Feedback period and return

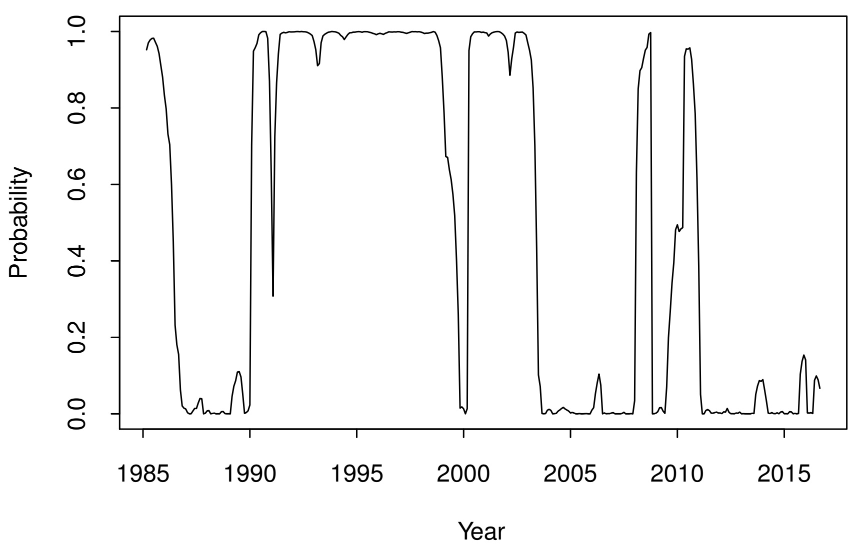


(d) Feedback period and adjusted trading volume

Figure 2.8: Estimated period and time series of return and adjusted trading volume

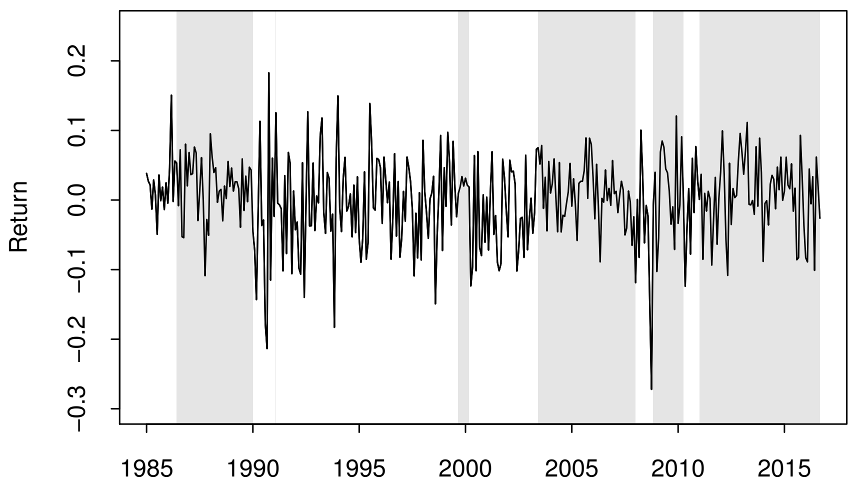


(a) Smoothed Probability of being in state 1

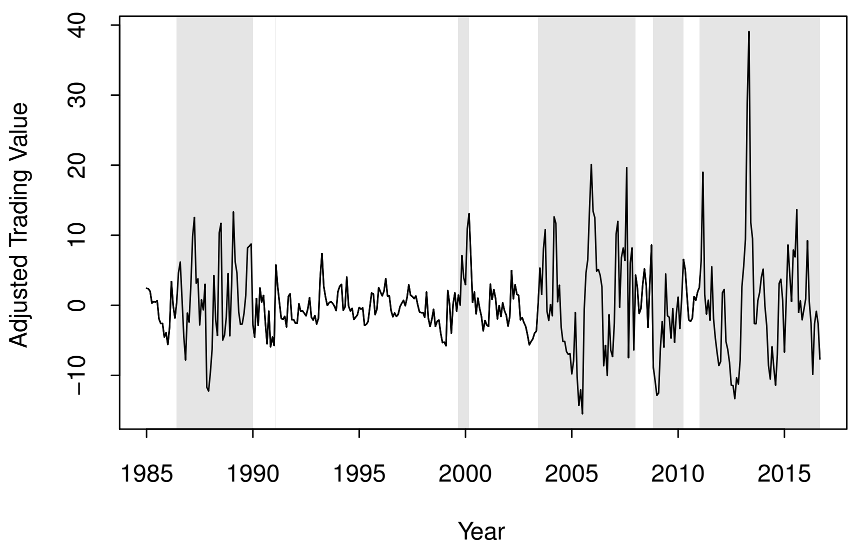


(b) Smoothed Probability of being in state 2

Figure 2.9: Smoothed Probability of Bivariate Markov Switching Model: Trading Value



(c) Feedback period and return



(d) Feedback period and adjusted trading value

Figure 2.10: Estimated period and time series of return and adjusted trading value

2.4 Conclusion

In this chapter, we empirically investigate the relationship between measures of trading activity, return, and bull-bear market cycles in Japanese stock market. Trading activities are measured by trading volume, trading value and market turnover. Theoretical models of overconfidence hypothesis in behavioral finance predict and several empirical studies have found the positive relations between asset returns and subsequent trading volume. In the overconfidence models, investors are overly confident about the precision of their private information and biased self-attribution causes the degree of overconfidence to vary with realized market outcomes.

At first, we employ the two state Markov switching model for the time series of market returns. The results show that there are two distinct regimes, that is, bull market and bear market: We define the state of high mean and low volatility as bull market, and the state of low mean and high volatility as bear market. We also calculated the estimated periods of bull the regime and found that there are six periods of the bull market in our sample periods. These periods are well explained by the episodes in Japanese financial markets and macroeconomy such as bubbles in the latter of 1980's.

Next, we employ two state bivariate Markov switching model in order to analyze time series of return and trading activity. We found that trading activity has positive relation with past return during bull markets while small relation with past return during bear markets. We can interpret the findings as follows: In the former regime, investors react the past return because the stock performance affects their beliefs and the resulting changes in beliefs induce trades. On the other hand, the past return has no influences on investors' beliefs because investors assign little weight on the past return when they revise their beliefs under more uncertain circumstances. This differences of market environment can affect belief revision processes through the accuracy of information or confidence of investors.

The results show that the variance of trading activity at bull state is higher than bear state. It means that trading volume fluctuates wildly at the same time when it is affected by past returns strongly. We interpreted the coincidence as the following: Trading volume is generated by heterogeneity of investors such as disagreement and belief revisions. When investors are confident of the accuracy of their private information, they revise their beliefs based on the information. Thus, the information arrivals can change the degree of disagreement across investors over time. A revision of a belief induces a change in asset holdings, and it causes trading with other market participants who also try to change their positions. If the information arrival induces large disagreement, it generates large trading volume, and vise versa. To the contrary, they revise their beliefs less actively when they are uncertain about their private information. In this case, the resulting changes of disagreement are small and the variation of trading volume is also small. Therefore, the variance of error term is large in the regime in which the coefficient of past returns is large.

Interestingly, turnover, trading volume and trading value show different patterns of dynamics of smoothed probability. The main difference is the period after 2003. The estimated feedback period of turnover does not include the financial crisis from 2007, while the periods of trading volume and trading value show no or short periods of no-feedback. Turnover is calculated by dividing the trading volume by market capitalization so we can think of it as the value-weight turnover. In contrast, trading volume is the simple sum of shares traded in individual security market. It is necessary to investigate the appropriate measure of trading activity.

An important explanation for the existence of distinct regimes of trading activity is the interaction between uncertainty and overconfidence of investors. During the periods of good performance of asset like bull market, investors become confident of their investment skills. This behavioral assumption generate the positive correlation between trading volume and past return. On the other hand, traders may become uncertain about their information. In this situation, traders may become less sensitive to returns than market without uncertainty. This may generate no relation between volume and return during both bull and bear market. Theoretical justification is promising subjects for future research.

Chapter 3

Price Impact, Funding Shock and Stock Ownership Structure

Abstract This paper considers the relationship between stock return processes and stock ownership structures. We employ two types investors: Long-horizon investors and short-horizon investors. We characterize the short-horizon investors as the investors who face the volatile exogenous fund flows. Therefore, they trade stocks by non-fundamental reason. This flow-driven trading influence the stock return process. Our result shows that the rises in the proportion of short-term investors and in the correlation between fund flows across short-term investors increase stock return volatility.

3.1 Introduction

Investment horizon is heterogeneous among investors: From seconds to several years. Also, the ownership structure of financial assets is different from each other. For example, some assets are held by mostly short-term investors, other assets are held by long-term investors. Topics on investment horizons have attracted attention because the heterogeneity has large impact on asset price dynamics. This paper considers the relationship between stock return processes and stock ownership structures.

Some empirical studies examine the relationship between investors' horizon and asset price dynamics. Cella et al. (2013) shows that during the recent episodes of market turmoils, institutional investors with short trading horizons sell their stock-holdings to a larger amount than institutional investors with longer trading horizons. This create price pressure for stocks held mostly by short-term investors, which induce larger price decline, and subsequent reversals, than stocks held mostly by long-term investors. Greenwood and Thesmar (2011) investigate the relationship between the share-holders structure and non-fundamental risk. They "define an asset to be fragile if it is susceptible to non-fundamental shifts in demand. An asset can be fragile because of concentrated ownership, or because its owners face correlated or volatile liquidity shocks.(Greenwood and Thesmar, 2011, p.471)" Bushee and Noe (2000) investigate the relationship between firm's disclosure practices, the ownership composition of its institutional investor and its stock return volatility.

Some empirical studies on asset return volatility also suggest that heterogeneous investment horizons have influence of the volatility dynamics. Heterogeneous Market Hypothesis states that market participants have different investment horizons (see, Müller, Dacorogna, Davé, Olsen, Pictet, and von Weizsäcker, 1997; Lynch, Zumbach, et al., 2003; Corsi, 2009). Corsi (2009) introduces the autoregressive model of realized volatility with three different time horizons: day, week and month. The model can reproduce empirically observed regularity, for example, fat-tails of return distributions and volatility clustering, and have a superior forecasting power of future volatility. The model presumes that investors have expectations about volatility which is calculated by using past return data in different time intervals. The interaction of heterogeneous expectations about volatility create long-memory processes of realized volatility.

What determines the composition of investment horizons? Amihud and Mendelson (1986) explain the allocation of assets which have different transaction costs (i.e., liquidity) to investors' portfolios. Investors who have long holding periods tend to hold illiquid assets.

Moreover, short-term investors trade assets based on the non-fundamental component such as the expectations about actions of other traders. Bernardo and Welch (2004) explain a run on a financial market. In their model, investors may suffer from a liquidity shock and thus conjectures that other investor intend to sell assets cause a market run. Morris and Shin (2004) introduce the model with short and long-term traders and selling asset by short-term traders with loss limit increases the other traders' incentives to sell. In addition, some researchers investigate theoretical models that short-horizon investors have several impacts on asset prices(for example, Froot, Scharfstein, and Stein, 1992; Allen et al., 2006; Banerjee et al., 2009). If the holding period is shorter, the beliefs of others rather than long-term fundamentals become more central to investment decisions.

The difference between long-term and short-term investors exists in formation of expectations. Keynes (1936) introduce the metaphor *Beauty Contest* for explaining the nature of asset markets. Keynes explains the importance of higher-order expectations: Investors attempt to expect how the crowd will behave. Some theoretical models study the implications of higher-order expectations Allen et al. (2006) and Banerjee et al. (2009).

The other source of heterogeneous investment horizons is investors' funding structures. If investors rely on the relatively volatile funds, they have more possibility to trade by non-fundamental fund-flow. It is important to analyze the price impact of flow-driven trading because it generates the other risk of stocks (see Greenwood and Thesmar (2011) for empirical findings).

Our analysis is related to the literature of *limits to arbitrage* to originate with Shleifer and Vishny (1997), which demonstrates the importance of demand shocks on asset prices and returns. In the traditional finance paradigm, demand shocks are absorbed by arbitrageurs, who can use sophisticated trading strategies to ensure that assets remain at their "correct" price. Shleifer (2000) states that "[w]hen, in contrast, the arbitrageur manages other people's money, and his investors do not know or understand exactly what he is doing, they only observe him losing money when prices move further out of line. They may infer from this loss that the arbitrageur is not as competent as they previously thought, refuse to provide him with more capital, and even withdraw some of the capital although the expected return from the trade has increased."

In the next section, we model the economy with two assets and two types of investors. One of the investors is short-term investors. They form the optimal portfolios by investing wealth but they face the risk of exogenous fund flows. Another type is long term-investors. Unlike the short-term investors, we assume that they have stable funding structures. In summary, short-term investors rely on relatively volatile and short-term funding although long-term investors have stable and long-term funding. Under this condition, we find that the return variance become larger than the absence of the fund flows.

3.2 The Model

We construct a discrete time model in which investors trade two assets at time $t = 0,1,2$. We assume that there exist two assets: a risky asset in finite supply with a random terminal price P_2 and a risk-free asset in infinitely elastic supply with a payoff of r_f. Stock trades occur at time period $t = 0$ and $t = 1$. There are N investors in this economy and they are grouped into two types of investors: Short-term investors and long-term investors.

Short-term investors face the risk of redemption of their capital. They can suffer a wealth shock at time 1. In contrast to short-term traders, long-term investors face no funding risks. This means that their funds are stable. We denote N^S as the number of short-term investors and N^L as one of long-term investors.

In this economy, the stock return is defined as

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad \text{for} \quad t = 1,2. \tag{3.1}$$

Each investor has the mean-variance utility function for portfolio return.[1]

$$E_t[U_i] = E_t[R^p_{t+1}] - \frac{\gamma}{2} Var_t[R^p_{t+1}] \tag{3.2}$$

where

$$R^p_{t+1} = \alpha_{i,t} R_{t+1} + (1-\alpha_{i,t}) r_f. \tag{3.3}$$

In Eq.(3.3), $\alpha_{i,t}$ is the proportion of the stock holding.

At each time period t, each investor optimize their expected utility $E[U_i(R^p_{t+1})]$.

$$\max_{\alpha_{i,t}} E_t[U_i(R^p_{t+1})] = E_t[R^p_{t+1}] - \frac{\gamma}{2} Var_t[R^p_{t+1}] \tag{3.4}$$

[1] This specification approximates the maximization problem of the power-type utility with terminal wealth.

where

$$E_t[R^p_{t+1}] = \alpha E_t[R_{t+1}] + (1-\alpha)r_f, \qquad Var_t[R^p_{t+1}] = \alpha^2 Var(R_t). \tag{3.5}$$

From Eq.(3.4) and (3.5), we obtain the proportion of the optimal stock holding:

$$\alpha^*_{i,t} = \frac{E_t[R_{t+1}] - r_f}{\gamma Var_t(R_{t+1})}. \tag{3.6}$$

Eq. (3.6) says that an investor allocates the proportion α^* of his wealth to stocks. Defining $h_{i,t}$ as an investor i's demand for a risky asset, by using Eq. (3.6),

$$h_{i,t} = \frac{\alpha^*_t W_{i,t}}{P_t}. \tag{3.7}$$

We assume that the supply of risky asset is fixed and normalized to 1. By using Eq.(3.6), the market clearing condition implies

$$\sum_{i=1}^{N} h_{i,t} = \sum_{i=1}^{N} \frac{\alpha^*_t W_{i,t}}{P_t} = 1 \tag{3.8}$$

Therefore, we can obtain the market clearing price function:

$$P_t = \sum_{i=1}^{N} \alpha^*_t W_{i,t} \quad \text{for} \quad t = 0, 1. \tag{3.9}$$

Eq. (3.9) suggests that the market clearing price P_t and the wealth of investors $\{W_{1,t}, \ldots, W_{N,t}\}$ are determined simultaneously. The homogeneous expectations assumption implies the identical optimal proportion of stock holding α^*_t.

We also assume that beliefs of investors are stationary or time-invariant.

Assumption 1. *Investors form the expectation and variance of stock return as follows:*

$$E_t[R_{t+1}] = \mu \qquad \textit{and} \qquad Var_t(R_{t+1}) = \sigma^2. \tag{3.10}$$

This assumption implies that the optimal proportion of risky asset is fixed, that is,

$$\alpha^*_t = \alpha^* = \frac{\mu - r}{\gamma\sigma^2} \tag{3.11}$$

At time t, short-term traders may face the exogenous fund flows and they may be forced to liquidate (or expand) their portfolios. The wealth of investor i evolves from time 0 to 1 as the following:

$$W_{i,1} = W_{i,0}(1 + R_1^p + X_i), \tag{3.12}$$

where X_i is the exogenous fund flows into short term investor i.

We assume that exogenous fund flows are correlated across investors.

Assumption 2 (Correlated Fund Flows)**.** *We assume that short-term investors face the exogenous fund flows X_i at time t and fund flows are correlated across all short-term investors. Furthermore, we assume that fund flows X_i are specified as the following stochastic process:*

$$X_i = \sqrt{\rho}Y + \sqrt{1-\rho}Z_i \tag{3.13}$$

where Y and Z_i for all i are mutually independent normal random variables with mean zero and variance σ_X^2.

Eq.(3.13) implies that $E[X_i] = 0$ and $Var(X_i) = \sigma_X^2$ for all i. The correlation coefficient of fund flows is obtained as follows:

$$\begin{aligned} Cov(X_i, X_j) &= Cov(\sqrt{\rho}Y + \sqrt{1-\rho}Z_i, \sqrt{\rho}Y + \sqrt{1-\rho}Z_j) \\ &= E[(\sqrt{\rho}Y + \sqrt{1-\rho}Z_i)(\sqrt{\rho}Y_t + \sqrt{1-\rho}Z_j)] \\ &= \rho\sigma_X^2 \end{aligned} \tag{3.14}$$

and then

$$Corr(X_i, X_j) = \frac{Cov(X_i, X_j)}{\sqrt{Var(X_i)Var(X_j)}} = \rho. \tag{3.15}$$

Y is a systematic factor that affect all short-horizon investors and Z_i is an idiosyncratic factor.

Let define total wealth in the economy as $W_t \equiv \sum_{i=1}^N W_{i,t}$ and the investor i's proportion of wealth as

$$w_{i,t} \equiv \frac{W_{i,t}}{W_t}. \tag{3.16}$$

Hence, the total wealth evolves as

$$\begin{aligned}
\frac{W_1}{W_0} = \frac{\sum_{i=1}^{N^S+N^L} W_{i,1}}{W_0} &= \sum_{i=1}^{N^S+N^L} w_{i,0}[1+R_1^p+X_i] \\
&= \sum_{i=1}^{N^S+N^L} w_{i,0}[1+R_1^p] + \sum_{i=1}^{N^S} w_{i,0}X_i \\
&= 1+R_1^p + \sum_{i=1}^{N^S} w_{i,0}X_i
\end{aligned} \tag{3.17}$$

Let define the weighted sum of fund flow shocks as follows:

$$X^S \equiv \sum_{i=1}^{N^S} w_{i,0}X_i.$$

Given the proportions of wealth of short-term investors $\{w_{i,0}\}_{i=1}^{N^S}$, X^S is a random variable that has normal distribution with zero mean and variance

$$Var_0(X^S) = \sigma_X^2[\rho\phi_0^2 + (1-\rho)\lambda_0]$$

where $\phi_0 = \sum_{i=1}^{N^S} w_{i,0}$ and $\lambda_0 = \sum_{i=1}^{N^S} w_{i,0}^2$

By Eq. (3.9) and the definition W_t, for time $t=0$ and $t=1$, we obtain

$$\alpha^* W_0 = P_0 \tag{3.18}$$

and

$$\alpha^* W_1 = P_1. \tag{3.19}$$

According to these expressions, we obtain

$$\frac{W_1}{W_0} = \frac{P_1}{P_0}. \tag{3.20}$$

One can obtain from Eq. (3.17) and (3.20),

$$\frac{P_1}{P_0} = 1+R_1 = 1+R_1^p + \sum_{i=1}^{N} w_{i,0}X_i \tag{3.21}$$

Replacing the portfolio return R_t^p by (3.3), we obtain

$$1 + R_1 = 1 + \alpha^* R_1 + (1 - \alpha^*) r_f + \sum_{i=1}^{N} w_{i,0} X_i. \tag{3.22}$$

Solving for R_t from (3.22) and the assumption of $X_{i,t}$ gives

$$\begin{aligned} R_1 &= r_f + \frac{1}{1-\alpha^*} \sum_{i=1}^{N^S} w_{i,0} X_i \\ &= r_f + \frac{1}{1-\alpha^*} \sum_{i=1}^{N^S} w_{i,0} [\sqrt{\rho} Y + \sqrt{1-\rho} Z_i] \\ &= r_f + \frac{1}{1-\alpha^*} [\sqrt{\rho} \sum_{i=1}^{N^S} w_{i,0} Y + \sqrt{1-\rho} \sum_{i=1}^{N^S} w_{i,0} Z_i] \end{aligned}$$

By assumption of correlated fund flows, we can get the following specification of stock returns.

Proposition 1. *The stock return from time 0 to 1 is characterized by the following equation:*

$$R_1 = r_f + \frac{1}{1-\alpha^*} [\sqrt{\rho} \tilde{Y} + \sqrt{1-\rho} \tilde{Z}] \tag{3.23}$$

where

$$\tilde{Y} = \sum_{i=1}^{N^S} w_{i,0} Y_t \qquad \text{and} \qquad \tilde{Z}_t = \sum_{i=1}^{N^S} w_{i,0} Z_i. \tag{3.24}$$

$\tilde{Y}$ is a normal random variable with mean zero and variance ϕ_0^2 and $\tilde{Z}$ is a normal random variables with zero mean and variance λ_0, that is,

$$\tilde{Y} \sim N(0, \phi_0^2), \quad \tilde{Z} \sim N(0, \lambda_0), \quad \phi_0 = \sum_{i=1}^{N^S} w_{i,0}, \quad \lambda_0 = \sum_{i=1}^{N^S} w_{i,0}^2.$$

Proposition 1 suggests that the fund-flow shocks influence the stock return through the wealth of investors. induced by the systematic factor Y_t

Moreover, we obtain the following result about the expected return and volatility.

Proposition 2. *The expected return and variance of the stock return are given as* *follows:*

$$E_0[R_1] = r_f,$$

and

$$Var_0(R_1) = \left(\frac{1}{1-\alpha^*}\right)^2 \sigma_X^2[\rho\phi_0^2 + (1-\rho)\lambda_0].$$

Proposition 3. *The stock return variance is an increasing function of the correlation of fund flows and the proportion of wealth of short-term investors:*

$$\frac{\partial Var_0(R_1)}{\partial \rho} = \left(\frac{1}{1-\alpha^*}\right)^2 \sigma_X^2[\phi_0^2 - \lambda_0] > 0,$$
$$\frac{\partial Var(R_1)}{\partial \phi_0} = 2\left(\frac{1}{1-\alpha^*}\right)^2 \sigma_X^2\phi_0 > 0.$$

This result shows that the rises in the proportion of short-term investors and in the correlation between fund flows across short-term investors increase stock return volatility. This results are consistent with the empirical findings such as Greenwood and Thesmar (2011) and Chichernea, Petkevich, and Zykaj (2015). Flow-driven trading generates the additional risk for the stock returns.

3.3 Conclusion

In this analysis, we study the relationship between the stock return process and ownership structure. We employ two types investors: Long-horizon investors and short-horizon investors. We characterize the short-horizon investors as the investors who face the exogenous fund flows. Investors who have fragile funding structures tend to purchase or liquidate their stock holding in order to form the optimal portfolio. The exogenous fund flows induce the portfolio adjustments and non-fundamental trading. This flow-driven trading influence the stock return process. In reality, non-fundamental behavior of investors who face the fund flows such as hedge funds and its impact on asset prices has been observed. This paper aims to explain the impact of fund flows on stock volatility.

Our result shows that the rises in the proportion of short-term investors and in the correlation between fund flows across short-term investors increase stock return volatility. This results are consistent with the empirical findings such as Greenwood and Thesmar (2011) and Chichernea et al. (2015).

Traditional asset pricing models have not focus on the ownership structures and non-fundamental trading like flow-driven trading by hedge funds. Price impact by flow-driven trading can cause the different type of risks. It is difficult to estimate this type of risk because we cannot capture perfectly the fund-flows of investors and their correlation. Therefore, we need farther research on this topic.

Chapter 4

Heterogeneous Investor Behaviors and Market Volatility in Tokyo Stock Exchange

Abstract This paper examines the relationship between weekly stock market volatility and trading activities of different investor groups, such as individuals, institutions and foreigners, in the first section of the Tokyo Stock Exchange. We define the investor behavior as net trading flows and trading fractions in the total trading value at each period. We empirically examine the relationship between market return and different trading activities. For both measures, trading activity of foreign investors is differently correlated with returns from domestic investors. We investigate the relation between volatility and trading activity. First, we show that the contemporaneous correlations between volatility and foreign investors are significant. Second, the results of dynamic relations show that trading flows of foreign investors are negatively correlated with the subsequent volatility, although fluctuations of the trading share are not associated with the subsequent volatility.

4.1 Introduction

Stock return volatility is varying over time. This empirical fact has stimulated the research on the econometric models of volatility dynamics and causes of changes in volatility. The autoregressive conditional heteroskedasticity (ARCH) and extended models have been developed in order to explain the persistence of volatility (i.e., volatility clustering) and have provided a good fit for many financial return time series (see, Engle (2004)). On the other hand, how economic and financial variables have influences on volatility has been investigated. Schwert (1989), for example, has analyzed the relation between stock return volatility and macroeconomic volatility, economic activity, financial leverage, and stock trading activity.

Trading volume is one of the measures that provide the degree of trading activity in financial markets. There is extensive evidence on the relation between return volatility and trading volume. Karpoff (1987) cites many studies that document a positive relation between price volatility and trading volume in financial markets. Lamoureux and Lastrapes (1990) enter trading volume directly into the GARCH volatility equation in their analysis of individual stock returns data. Schwert (1989) uses monthly aggregates of daily data and finds a positive relationship between estimated volatility and current and lagged volume growth rates in linear distributed lag regressions and VAR models. [1] Despite so many empirical studies on the volatility-volume relation, there is no general consensus about what actually drives the relation.

In this paper, we empirically investigate whether the difference of investor type have an additional relationship with the stock return volatility. In order to examine the relation between heterogeneous investor behavior and market volatility, we use weekly trading volume data from the Tokyo Stock Exchange (TSE). The data of *Trading by Type of Investors* is comprised of shares traded and their yen value for both buy and sell trades for each investor type. The TSE categorizes the brokerage trading of member of securities companies by classifying in those by individuals, foreigners, corporations and securities customers. This categorization of investors can make detailed examination of volatility-volume relation. It is natural to raise a question: Do different types of investors have different effects on stock price dynamics, or are there any different relation between volatility and

[1] Various theoretical models are proposed to explain this relation. These include mixture of distributions models (Clark, 1973), asymmetric information models, and differences of opinion models. "An appealing explanation for the presence of ARCH is based upon the hypothesis that daily returns are generated by a mixture of distributions, in which the rate of daily information arrival is stochastic mixing variable. (Lamoureux and Lastrapes, 1990, p.221)"

trading activities of different categories?

Recent empirical studies, mainly in behavioral finance, have found that different investor types follow different trading patterns. The traders who have different trading patterns are categorized by trend-chasing (or momentum) traders and contrarians. Trend-chasing traders follow the trend of price changes, that is, they buy stocks when the price increases and sell when the price decreases. On the other hand, contrarians sell stocks when the price falls and buy when the price rises. A lot of empirical studies have found that individual investors trade in a contrarian pattern while foreign investors follow the price trend. For example, Kamesaka, Nofsinger, and Kawakita (2003) and Bae, Yamada, and Ito (2008) investigate the trading behavior of different investor types in TSE. The evidence that foreign investors trade like trend-chasers can be found in a series of papers such as Brennan and Cao (1997), Choe, Kho, and Stulz (1999), Froot, O'connell, and Seasholes (2001) and Boyer and Zheng (2009).

Theoretical literature suggests that heterogeneous behavior can amplify market volatility. A noisy rational expectations model of Wang (1993) suggests that volatility increases with non-informational or liquidity-driven trading. In this model, trades of uninformed traders are positively correlated with returns so they behave *like* trend-chasers. De Long, Shleifer, Summers, and Waldmann (1990b) predict that the interaction between positive feedback traders and rational (forward-looking) speculators can increase volatility. In addition, interacting agent models like Kirman (1991) analyze price stability based on fundamentalist/chartist models. In his model, fundamentalists trade assets based on their accurate knowledge about fundamentals, while chartists trade assets based on their technical analysis on recent price movements. The model shows when chartists dominates the market, the volatility of the exchange rate is high. Based on theoretical predictions, we can predict that the increase in fraction of trend-chasing traders associates with the increase in market volatility. Therefore, the main aim of this paper is to examine the relation between market volatility and the fraction or intensity of trades of trend-following traders.

Empirical study of contemporaneous relation between volatility and trading activity of foreigners finds that high market volatility associates with high trading share of foreign investors and negative net trading flows. In other words, when the presence of foreign investors is large or foreign investors are net sellers, the market volatility is high. Our paper is related to the two existing papers by Hamao and Mei (2001) and Bae et al. (2008) that also analyze stock return volatility and different investor types. Hamao and Mei (2001) investigate the impact of foreign trading on market volatility by using monthly data from 1974 to 1992. They define trading of different types as absolute values of net purchases, purchases, or sales (all divided by market capitalization), and their empirical result shows that there is no evidence supporting the following claim: "Trading by foreign investors tends to increase market volatility more than trading domestic investors. (Hamao and Mei, 2001, p.715)" Bae et al. (2008) identify who supplies and demands market liquidity and examine the relation between market volatility and trades of different investor types. They state that different investor groups have different effects on the market liquidity, then market volatility fluctuates significantly depending on which investor types participate in trades. Different from these two papers, we consider the *asymmetric volatility effect* in the analysis of volatility dynamics. Over the past several decades researchers have documented strong evidence that volatility is asymmetric in equity market: negative returns are generally associated with upward revisions of the conditional volatility while positive returns are associated with smaller upward or even downward revisions of the conditional volatility. This paper finds that, taking account of foreign trading flows and shares, the asymmetric volatility effect disappears.

The remainder of the paper is organized as follows. In section 4.2, we explain the data that we use in empirical studies. In section 4.3, we examine correlation between returns and trading activities by different investor groups in order to capture different patterns of investors. In section 4.4 explains the empirical results of relationship between volatility and investor behavior. Section 4.5 is a conclusion in our study.

4.2 Data and Measures of Trading behavior

4.2.1 Trading behavior and Stock Return Volatility

Data source of trading activity in this study is *Trading by Type of Investors* obtained from the Japan Exchange Group. Trading volume and their yen value, i.e., trading value, for both buy and sell trades for each investor type are available from February 2008 to the present. The data cover all trades of brokered by member securities companies of TSE with a capitalization of at least 3 billion yen. The TSE categorizes the brokerage trading of member of securities companies by classifying in those by individuals, foreigners, corporations and securities customers. Corporations are decomposed into finer categories; investment trusts, business customers, financial institutions and others. This study focuses on trading behavior of individuals, foreigners, corporations and securities customers.

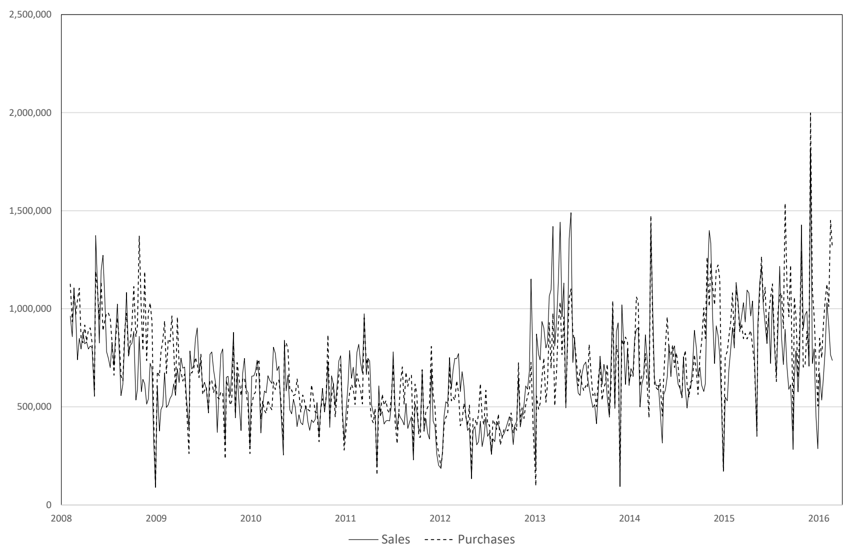


Figure 4.1: Trading value of corporations

This paper mainly use the data of trading value of each investor. Both purchasing and selling values are described in Figure 4.1 to 4.4. These figures show differences and similarities of trading activities among different investor types. A remarkable feature of time-series of all trading values is a surge after the late of 2012, that is, after "Abenomics" and "Kuroda easing", as explained later. The peak of trading values is in the late of May 2013 when stock price crashed[2]. After that, trading values of individuals and financial customers have decreased, while those of corporations and foreigners have increased. These figures suggest that different investors have different trading activities.

The price data we use is the closing level of the TOPIX (Tokyo Stock Price Index) at daily frequency. Sample period is from February 4, 2008 to February 26, 2016. The purpose of the paper is to examine the relation between stock return volatility and trading behavior of different investor types, and the data of trading activities is available at weekly frequency, so we calculate and estimate the volatility of stock returns at the same frequency. In order to calculate the weekly

[2]Stock price aggressively decreased on May 23, 2013.

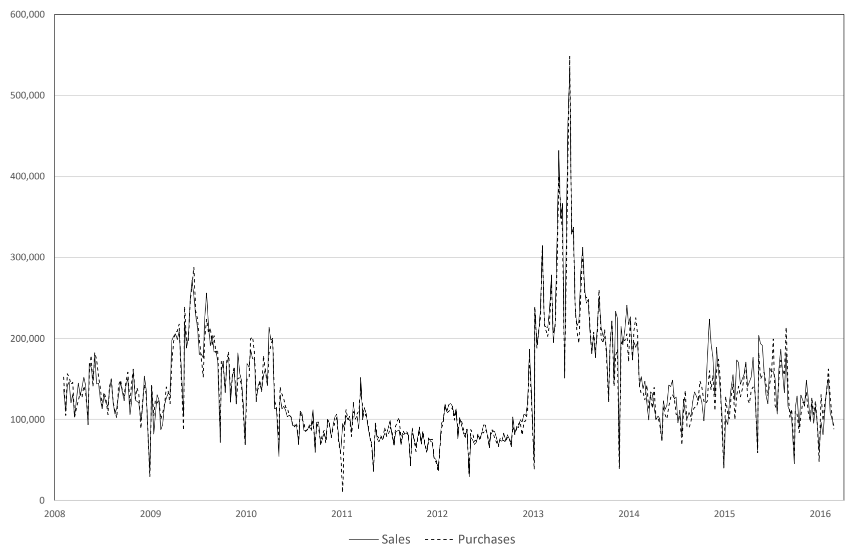


Figure 4.2: Trading value of financial customers

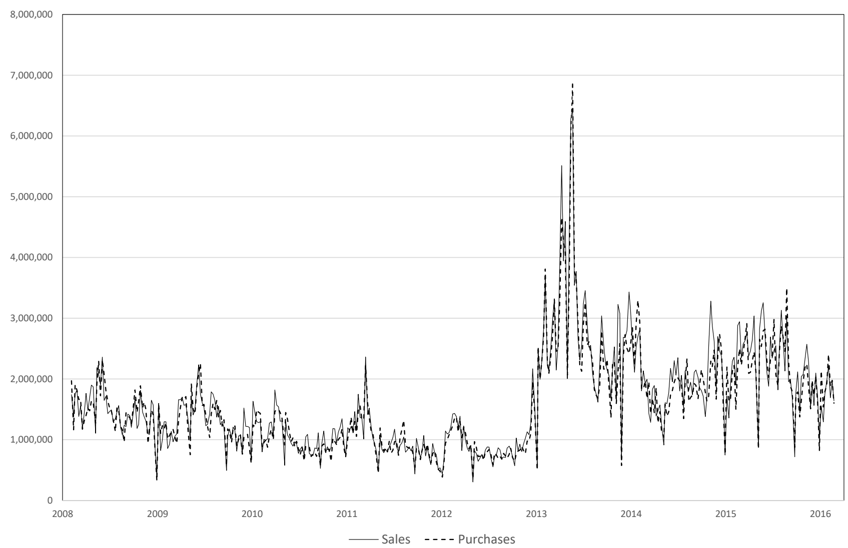


Figure 4.3: Trading value of individuals

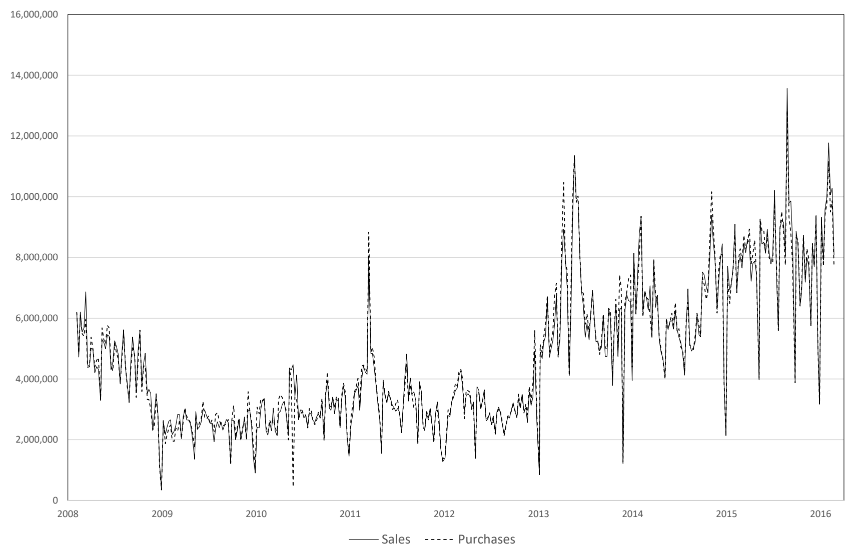


Figure 4.4: Trading value of foreigners

volatility, the raw price index series, P_τ, is differenced in the logs to create the raw price change series, $r_\tau \equiv \log P_\tau - \log P_{\tau-1}$. The weekly realized volatility, defined as RV_t, at time period t is calculated by

$$RV_t = \sqrt{\frac{1}{N_t} \sum_{\tau=\tau_t}^{\tau_t+N_t-1} r_\tau^2} \tag{4.1}$$

where N_t is the number of trading day in the week t, and τ_t is the first day of the week. It means standard deviations of daily returns within a week. Figure 4.5 shows the dynamics of TOPIX and the volatility of its return. The volatility has significantly high levels after the collapse of Lehman Brothers in 2008 and the Earthquake in 2011. During other periods, the volatility fluctuates over time.

We also use weekly returns of the TOPIX in the volatility analysis in order to investigate the asymmetric volatility. Here, we calculate weekly stock returns, R_t, of the week t by using the closing level of the last day of the current week and the previous week.

4.2.2 Measures of Trading behavior

In this subsection, we investigate the different measures of trading behavior of different investor groups. As shown in Figure 4.1 to 4.4, both purchasing and selling values move in a similar pattern for each trading group. In order to capture the differences between investor groups, we define several measures of trading behavior. At first, we define the trading values of each investor type as follows:

$$V_t^i \equiv \frac{1}{2}(\text{Purchasing Value}_{i,t} + \text{Selling Value}_{i,t}), \tag{4.2}$$

where $i(\in I)$ indicates investor groups and let I denote as the set of investor groups: corporations, security firms, individuals and foreigners, that is, average values of purchasing and selling values. Trading values as definition 4.2 simply show the values traded by each investor group within a week.

The data of Trading by Type of Investors also has the data of total trading values in the first section of TSE, i.e., the total values of shares traded in the first section of TSE. Total trading values V_t are comprised of values of all brokered trading (by above four groups) and proprietary trading (by security firms). The literature of the volume-volatility relation usually uses trading volume, trading value and turnover as measures of trading activities in stock markets. Our purpose

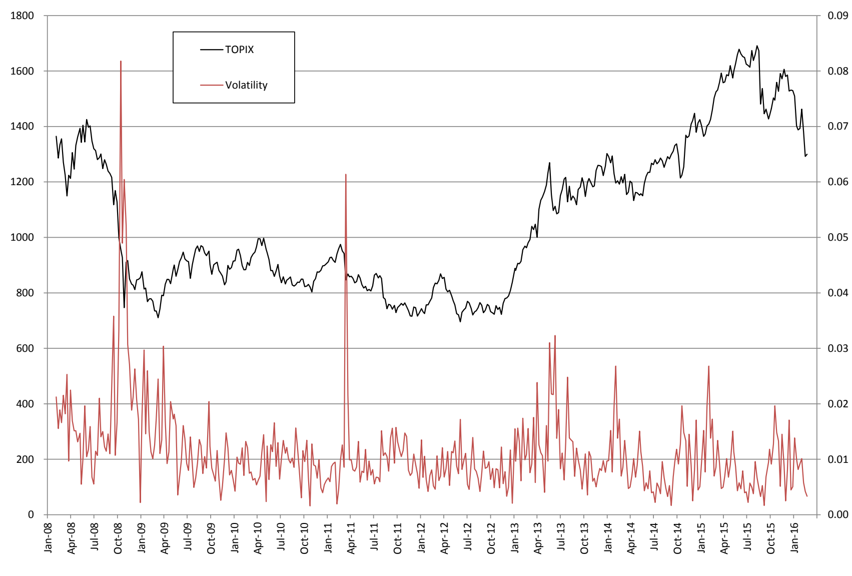


Figure 4.5: TOPIX and weekly realized volatility: From February 2008 to February 2016. Weekly realized volatility is calculated by equation (4.1).

Table 4.1: Correlations: Total trading values and trading values by different investor types.

	Corporations	Security Firms	Individuals	Foreigners
$Corr(V_t, V_t^i)$	0.87	0.64	0.88	0.94

is to examine whether there is an additional effect of differences in trading behavior. Trading values of different investor types are significantly correlated with the total trading value (see Table 4.1). For this reason, trading values are insufficient to capture the heterogeneity of investors.

In order to capture the different trading patterns of investor groups, we introduce net trading flows (or net purchasing values) which are calculated by

$$NTF_t^i \equiv \text{Purchasing Value}_{i,t} - \text{Selling Value}_{i,t}$$

for investor type $i \in I$. Net trading flows represent imbalances between amounts to buy and to sell stocks. When $NTF_t^i < 0$, investor type i is net seller at time period t. When $NTF_t^i > 0$, investor type i is net buyer at time period t. Figure 4.6 shows weekly net trading flows of different investor types and apparent heterogeneity between domestic and foreign investors. Figure 4.7 also shows monthly net purchasing values of each individual investor groups. These figures clearly show that the periods of being net buyer (or net seller) tend to continue for several months.

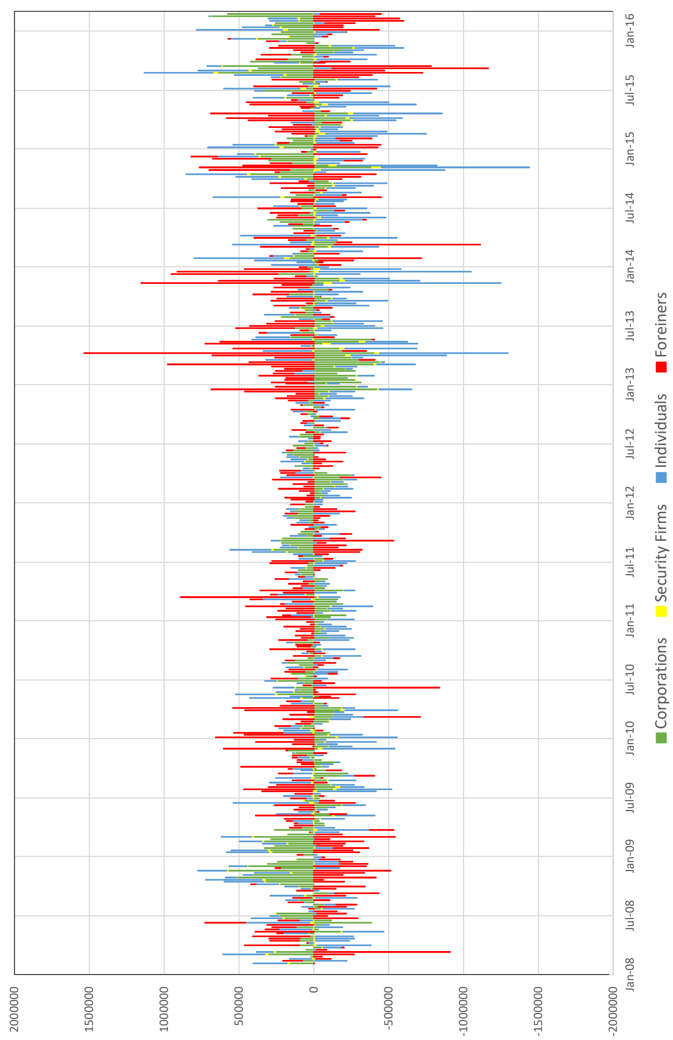


Figure 4.6: Weekly net purchasing values (million yen) of different investor types in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. Investor types include foreign investors, individuals, security firms and institutions. *Source*: Japan Exchange Group.

Figure 4.8 to 4.11 show the evolution of TOPIX and the net trading flows of each different investor group. These figures show some striking patterns of trading behavior. For example, in figure 4.8, the net trading flow of institutions has a strong cyclicality: When price index rises, institutions tend to sell stocks, and vice versa. Likewise, security firms and individuals has the same patterns as institutions but relationships between net flows and price are weak (Figure 4.9 and 4.10). On the other hand, the net trading flow of foreigners has an adverse relation to domestic investors (Figure 4.11). When price index rises, foreigners tend to buy stocks, and vice versa.

Figure 4.11 also shows the recent experience of "Abenomics" since the late of 2012. Since the late 2012, Japanese stock prices started to rise and the yen started to weaken outstandingly. In this period, Shinzo Abe, the President of Japan's Liberal Democratic Party at that time, started to place unprecedentedly strong pressure on the Bank of Japan to ease monetary policy aggressively. The BOJ responded in early April 2013 by announcing "Quantitative and Qualitative Easing" (QQE). Such a series of events regarding monetary policy has created sharp responses of asset prices. Behind the rise of asset prices, foreign investors have bought aggressively stocks in response to Abenomics and monetary easing, while domestic investors (individuals and corporations) have stayed on the sideline (Ueda, 2013; Fukuda, 2015). Foreign investors have been large net buyers during the period. One may speculate that investors differently interpret the effectiveness of monetary policy and have different expectations after Abenomics and Kuroda easing. Accordingly, the Japanese stock market has been characterized by heterogeneous trading behavior of foreign and domestic investors.

The interrelation between stock returns and investment flows of domestic and foreign investors has been investigated for several decades. Empirical studies suggest that foreign investors behave like trend-followers and domestic investors behave like contrarians: Flows from foreign investors are positively correlated with contemporaneous returns while flows from foreign investors are negatively correlated with contemporaneous returns. Brennan and Cao (1997) provide an information based explanation of trend-chasing behavior of foreign investors. They argue that, if foreign investors are less informed relative to domestic investors, foreign investors need to gather more information from market prices. Therefore, when prices of domestic stock rises, foreign investors tend to buy more, which generate trend-following patterns.[3]

[3] See also Brennan, Cao, Strong, and Xu (2005) for theoretical study. Froot et al. (2001) investigate daily international portfolio flows and their relationship with equity returns.

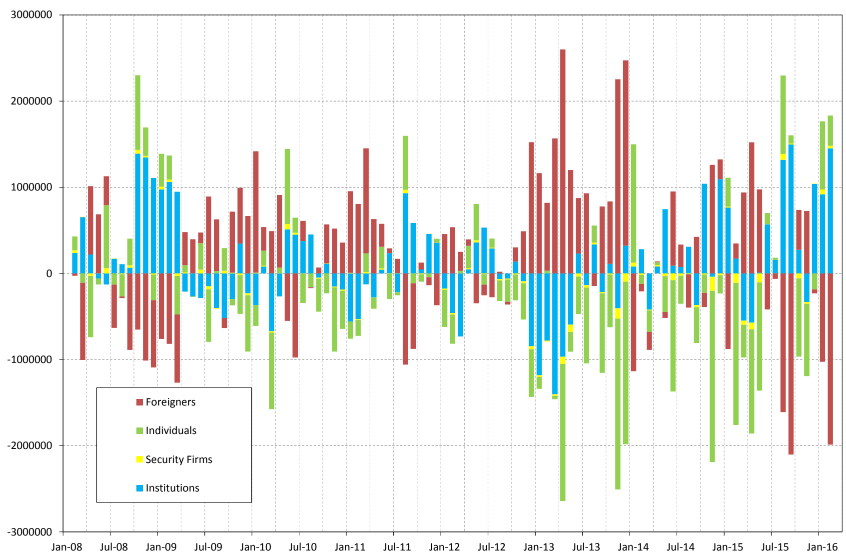


Figure 4.7: Monthly net purchasing values (million yen) of different investor types in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. Investor types include foreign investors, individuals, security firms and institutions. *Source*: Japan Exchange Group.

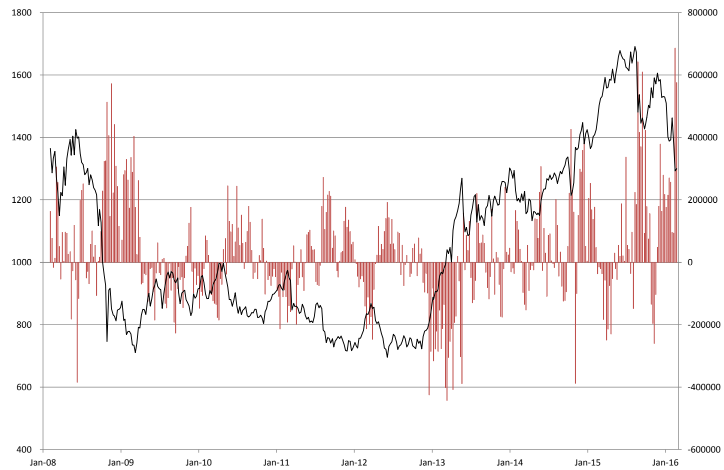


Figure 4.8: TOPIX (black line; left axis) and net purchasing value (million yen) of institutions (red bar; right axis) in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. *Source*: Japan Exchange Group.

The second measure of trading behavior of different investors group is a *share of trading volume*. The share of each type is calculated by

$$S_t^i = \frac{(\text{Purchasing Value}_{i,t} + \text{Selling Value}_{i,t})/2}{\text{Total Trading Value}_t}.$$

Figure 8 shows the evolution of shares of investor types in trading volumes.

Trading share is the proportion of trading volume of each investor type to total trading volume. Because this study uses value-weighted trading volume (i.e., the unit is yen), the definition of trading shares are transformed as follows:

$$\begin{aligned} S_t^i &= \frac{(\text{Purchasing Value}_{i,t} + \text{Selling Value}_{i,t})/2}{\text{Market Capitalization}_t} \Bigg/ \frac{\text{Total Trading Value}_t}{\text{Market Capitalization}_t} \\ &= \frac{\text{Trading Value}_{i,t}}{\text{Market Capitalization}_t} \Bigg/ \frac{\text{Total Trading Value}_t}{\text{Market Capitalization}_t} \\ &= \frac{\text{Turnover}_{i,t}}{\text{Turnover}_{M,t}} \end{aligned}$$

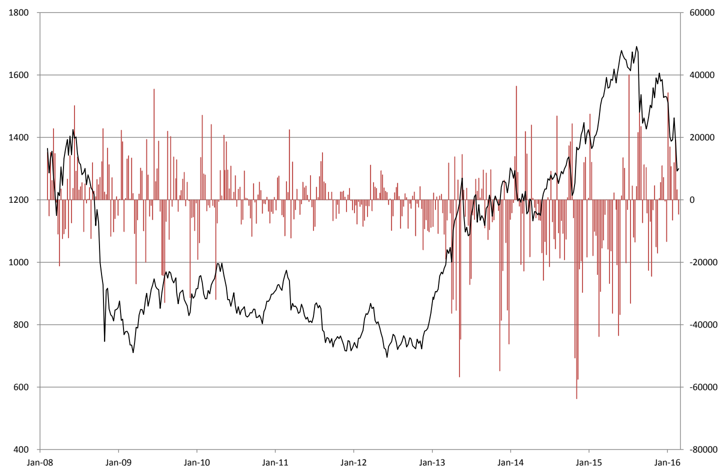


Figure 4.9: TOPIX (black line; left axis) and net purchasing value (million yen) of security firms (red bar; right axis) in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. *Source*: Japan Exchange Group.

where $\text{Turnover}_{i,t}$ is turnover ratio of each investors group and $\text{Turnover}_{M,t}$ is market-level turnover ratio. The last expression means that the trading share indicates the ratio of turnover of each investors group to the market level turnover. Turnover is calculated by dividing the total number of shares traded over a period by the average number of shares outstanding for the period. It represents the degree of trading activity relative to market size. Thus, the measure of trading share indicates the degree of contribution by each investor type to the trading activity in the entire market. Equivalently, trading share represents the participation rate of each type in the transactions. Therefore, when the trading share of one investor group is high, the participation rate or the intensity of trade in the market is high.

The time series of trading values shows nonstationarity (see, Andersen (1996) and Lo and Wang (2000)). We use the method of four-lag moving-average normalization (Lo and Wang (2000)) as follows:

$$\hat{V}_t = \frac{V_t}{(V_{t-1}+V_{t-2}+V_{t-3}+V_{t-4})/4} \tag{4.3}$$

Table 4.2: Summary statistics and unit root test.

	Summary statistics				Unit root test
	Mean	Std. dev.	Skew.	Kurt.	ADF-stat.
Market return ($\times 10^2$)	-0.0024	3.1131	-1.25	9.44	-20.30*
Total Trading Value ($\times 10^{-6}$)	9.2900	3.6516	0.61	3.11	-3.15
a. Net trading flow ($\times 10^{-6}$)					
Corporations	0.0267	0.1670	0.52	4.50	-3.70*
Security Firms	-0.0020	0.0145	-0.79	5.32	-7.18*
Individuals	-0.0477	0.2300	-0.70	5.59	-7.48*
Foreigners	0.0450	0.2793	0.28	6.84	-5.25*
b. Trading shares					
Corporations	0.08	0.01	0.53	3.72	-4.58*
Security Firms	0.02	0.01	0.86	2.98	-2.34
Individuals	0.17	0.03	0.62	3.86	-2.98
Foreigners	0.49	0.09	-0.38	2.22	-3.39

* : p-value < 0.05

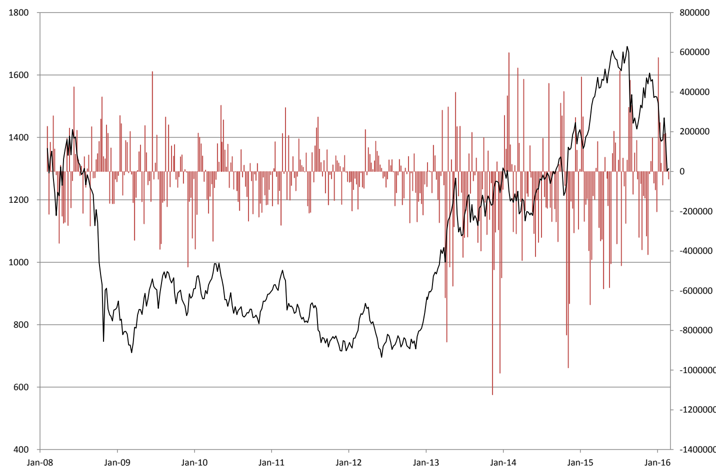


Figure 4.10: TOPIX (black line; left axis) and net purchasing value (million yen) of individuals (red bar; right axis) in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. *Source*: Japan Exchange Group.

where V_t is trading volume at time period t and $\hat{V}_t$ is detrended trading volume.[4] Trading shares also show nonstationarity as shown in Table 4.2. The result of the augmented Dickey-Fuller (ADF) test are reported in Table 4.2. The hypothesis of unit root process are not rejected for all series except for individuals. Thus, we also adjust time-series of trading shares by using the same method:

$$\hat{S}_t^i = \frac{S_t^i}{(S_{t-1}^i + S_{t-2}^i + S_{t-3}^i + S_{t-4}^i)/4} \tag{4.4}$$

Table 4.2 also shows some statistics of market returns, trading values, net trading flows and trading shares.

[4]Lo and Wang (2000) introduce several detrending procedures and their characteristics in the weekly frequency.

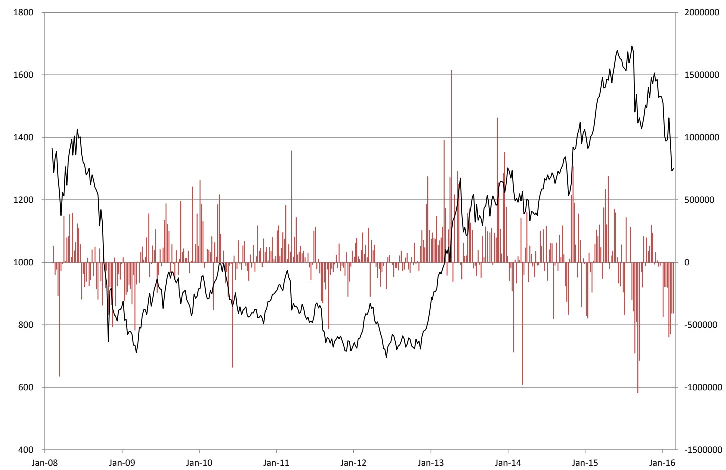


Figure 4.11: TOPIX (black line; left axis) and net purchasing value (million yen) of foreigners (red bar; right axis) in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. *Source*: Japan Exchange Group.

4.3 Relationship between Return and Heterogeneous Trading Activity

4.3.1 Contemporaneous Correlations

In the previous section, we introduced two measures of trading behavior for different investors groups: Net trading flows and trading shares. Before moving on empirical analysis about the relation between volatility and these measures, we discuss the relation between these measures and stock returns and highlight the heterogeneity in trading behavior.

Table 4.3 shows correlations between returns and trading activities of different investor groups. Panel a in Table 4.3 shows the contemporaneous correlations between returns and trading flows of different investor groups. Returns are positively correlated with domestic investors (corporations, security firms and individual investors) and negatively correlated with foreign investors. Accordingly, flows of foreign investors are negatively correlated with those of other groups. This result suggests that (i) foreign investors buy stocks on balance when stock prices rise

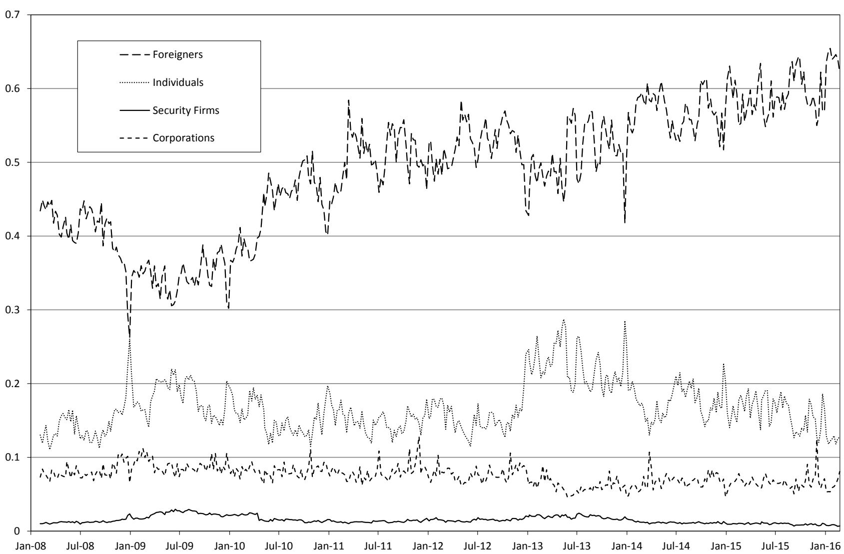


Figure 4.12: Shares in trading volumes of different investor types in the 1st section of Tokyo Stock Exchange: February 2008 through February 2016. Investor types include foreign investors, individuals, security firms and institutions. *Source*: Japan Exchange Group.

and vice versa, and (ii) domestic investors tend to be the counterparty of foreign investors for trading in TSE.

Panel b shows correlations between returns and trading shares of different investor groups. Returns are positively and significantly correlated with trading shares of security firms and individuals, and negatively and significantly correlated with that of foreign investors. In other words, foreign investors tend to trade stocks more intensively when stock prices decrease rather than when prices rise.[5] This positive correlation is referred as "trend-chasing" behavior. On the other hand, domestic investors have negative correlations with current returns, thus they are "contrarians" in the sense that they tend to purchase stocks on balance when

[5]It should be noted that adjusted trading shares used in statistical analysis are defined as the difference between a share in trading value and its trend (four-lags moving average). Therefore, we can interpret the positive correlation as an association of positive returns and increases in shares from the trend.

prices fall. These result shows that there is a different relations between returns and trading behavior of domestic investors and foreign investors.

By definition, when a share in trading volume of one group increases, shares of other groups decrease. Thus, one can predict that all shares of trading values have negative correlations. The result shows that the degrees of correlations is different across groups. Corporations have no correlations with other domestic investor groups but negative correlation with foreigners. Security firms have a positive correlation with individuals but a negative correlation with foreigners, and individuals have a positive correlation with foreigners. The share of foreigners is positively correlated with those of security firms and individuals, therefore, when a foreigners' proportion rises, both proportions of individuals and security firms decrease. Accordingly, the correlation between shares of security firms and individuals is positive.

Panel c shows the correlations between the net trading flow and the trading share for each investor groups. These two variables of all groups except corporations are negatively correlated with each other. Thus, for three groups, we can speculate that, when they are net buyers, their shares in trading values decrease. They tend to trade more intensively when they sell stocks on balance rather than when they buy stocks on balance.

It should be noted that the nature of high correlations involves a multicollinearity problem if we use all variables as regressors. Therefore, we use only trading behavior of foreigners to avoid multicollinearity problem in the following regression analysis.

Table 4.3: Correlations

a. Correlations: Net trading flow.

	Return	Corporations	Security Firms	Individuals	Foreigners
Corporations	-0.3500*	1.0000			
Security Firms	-0.2820*	0.2687*	1.0000		
Individuals	-0.2576*	0.2652*	0.9187*	1.0000	
Foreigners	0.2728*	-0.5889*	-0.6923*	-0.7153*	1.0000

* indicates that p-value < 0.01.

b. Correlations: Shares in (detrended) trading volume.

	Return	Corporations	Security Firms	Individuals	Foreigners
Corporations	0.0483	1.0000			
Security Firms	0.3034*	-0.0346	1.0000		
Individuals	0.3914*	-0.0369	0.7401*	1.0000	
Foreigners	-0.3589*	-0.3359*	-0.5387*	-0.6587*	1.0000

* indicates that p-value < 0.01.

c. Correlations: Net trading flows and shares in (detrended) trading volume.

	Corporations	Security Firms	Individuals	Foreigners
$Corr(NTF^i, \hat{S}^i)$	0.10	-0.21	-0.39	-0.17

4.3.2 VAR model

Next, we employ the VAR model for return and each measure for trading activity by following Boyer and Zheng (2009) and Kamesaka et al. (2003). Boyer and Zheng (2009) investigate the interaction between return and net trading flows of different investor groups by using first-order VAR model. Kamesaka et al. (2003) estimate coefficients of bivariate VAR model of TOPIX returns and net investment flows for each investor groups in order to avoid multicollinearity problem because of large correlations between flows.

We use VAR model in order to study the interaction of market return and trading activity of different investor groups. The general form of the VAR model is

$$\mathbf{Y}_t = \alpha + \beta \mathbf{Y}_{t-1} + \mathbf{e}_t \tag{4.5}$$

where $\mathbf{Y}_t$ is a 2×1 vector, α is a 2×1parameter vector, β is a 2×2 parameter matrix, and $\mathbf{e}_t$ is a 2×1 vector of residuals. Random variables in $\mathbf{Y}_t$ include market return and measures of trading activity of one investor group: corporations, financial firms, individuals and foreigners.

Estimation results for the VAR model which includes net trading flows of four investor types are give in Table 4.4. First, net trading flows of all investor types exhibit a positive autocorrelation. Trading flows of all investor types are significantly related to their own previous trading flows. Second, only a coefficient of lagged returns on flows of corporations is statistically significant and negative. This result that behavior of corporations are contrarian in the sense that they tend to purchase stocks on balance after stock prices decline. Other investors flows have no significant relations with first lagged returns, thus they do not follow feedback trading intertemporally at a weekly frequency.

Estimation results for the VAR model which includes adjusted trading shares of four investor types are given in Table 4.5. The result is similar to the case of net trading flows. First, all adjusted trading shares of different investor groups are positively autocorrelated. The intensity of trading by all investor types persists to the subsequent periods. Second, the trading share of corporations is correlated with past returns negatively and significantly. Correlations of other shares with past returns are not statistically significant, thus we cannot reject the hypothesis that past returns have no effects on the current trading shares.

In summary, both measures of trading activities by different investor types are positively autocorrelated but have no correlation with past returns (except corporations). Trading activities persist to the subsequent periods. Contemporaneous correlations obtained in the previous subsection suggests that returns are significantly correlated with trading activities. In the case of trading flows, the correlations of returns with domestic investors are negative while that with foreign investors is positive. In the sense of intra-period, domestic investors are contrarians and foreign investors are trend-chasers. On the other hand, in the case of adjusted trading flows, the correlations of returns with domestic investors are positive while that with foreign investors is negative. This result suggest that, foreign investors trade more actively during the periods of rises in prices than those of falls in prices. For both measures, a trading behavior of foreign investors has unique relations with current returns, therefore we use measures of foreigners in the subsequent analysis in order to avoid multicollinearity problems.

Table 4.4: VAR estimates: Dependent variables include net trading flows and returns

Dep. Var.	Parameters (Std. Err.)						Adjusted R^2
	Const.		R_{t-1}		NTF^i_{t-1}		
Corporations							
R_t	0.0006	(0.0016)	-0.1767***	(0.0513)	-0.0318***	(0.0105)	0.0312
NTF^C_t	0.0098	(0.0060)	-0.4247**	(0.1884)	0.6526***	(0.0388)	0.4603
Security firms							
R_t	-0.0028**	(0.0013)	-0.2819***	(0.0421)	-1.3271***	(0.0985)	0.3102
NTF^S_t	-0.0013**	(0.0006)	-0.0043	(0.0202)	0.3630***	(0.0474)	0.1303
Individuals							
R_t	-0.0043***	(0.0013)	-0.2776***	(0.0404)	-0.0894***	(0.0059)	0.3551
NTF^I_t	-0.0346***	(0.0110)	-0.0858	(0.3271)	0.2877***	(0.0483)	0.0807
Foreigners							
R_t	-0.0026*	(0.0014)	-0.2472***	(0.0451)	0.0558***	(0.0055)	0.2055
NTF^F_t	0.0257**	(0.0125)	0.1187	(0.3784)	0.4216***	(0.0462)	0.1763

Significance at the 1%, 5%, 10% levels is indicated respectively by ***, **, *.

Table 4.5: VAR estimates: Dependent variables include adjusted trading shares and returns

Dep. Var.	Parameters (Std. Err.)						Adjusted R^2
	Const.		R_{t-1}		$\hat{S}^i_{t-1}$		
Corporations							
R_t	-0.0395***	(0.0122)	-0.1192**	(0.0481)	0.0394***	(0.0121)	0.0326
$\hat{S}^C_t$	0.8602***	(0.0493)	-0.4125**	(0.1935)	0.1430***	(0.0487)	0.0248
Security firms							
R_t	-0.0555***	(0.0166)	-0.1633***	(0.0504)	0.0555***	(0.0165)	0.0342
$\hat{S}^S_t$	0.5759***	(0.0470)	0.0046	(0.1430)	0.4242***	(0.0468)	0.1760
Individuals							
R_t	-0.0931***	(0.0147)	-0.2376***	(0.0504)	0.0928***	(0.0145)	0.0966
$\hat{S}^I_t$	0.5221***	(0.0475)	-0.0803	(0.1633)	0.4799***	(0.0471)	0.2185
Foreigners							
R_t	0.1602***	(0.0291)	-0.2112***	(0.0503)	-0.1597***	(0.0289)	0.0757
$\hat{S}^F_t$	0.5256***	(0.0468)	0.0401	(0.0809)	0.4759***	(0.0466)	0.2152

Significance at the 1%, 5%, 10% levels is indicated respectively by ***, **, *.

4.4 Empirical Study: Volatility and Heterogeneous Trading behavior

4.4.1 Contemporaneous Correlation

The relationships between volatility and trading activity have been examined empirically for a long time. The result is that there is a positive contemporaneous correlation between volume and volatility. In other words, when trading activity is large, volatility is also large. We develop the study of a volume-volatility relation by entering trading activities by different investor groups. In this section, we estimate the contemporaneous correlations between volatility and trading behavior of different investor groups. Second, we estimate dynamic relation of volatility with trading behavior of foreign investors.

At first, we examine the contemporaneous correlation between volatility and trading activity of foreign investors. In order to estimate the correlation between those variables, we employ a simple model of regression:

$$\log h_t = \phi + \theta X_t^F + \psi \log h_{t-1} + \delta \hat{V}_t + \eta_t. \tag{4.6}$$

where h_t is market volatility at time t estimated by RV_t, X_t^F is a variables that represents a trading activity of foreigners, $\hat{V}_t$ is an adjusted trading volume and η_t is residuals. We adopts net trading flows NTF_t^F and trading shares $\hat{S}_t^F$ as trading activities of foreign investors. As studied in existing literature, volatility is correlated with the trading volume and the past volatility, thus we include the trading value and the lagged volatility as control variables.

The estimated parameters of regressions are reported in Table 4.6. First, the coefficient of net trading flows of foreigners is negative and statistically significant. Volatility is low when net trading flows of foreigners are positive, that is, when foreigners are net buyers. According to the result of the previous section, foreigners buy stocks on balance when stock prices rise. Therefore, volatility falls during the periods of rises in prices.

Second, the coefficient of trading shares of foreigners is positive and statistically significant. This result suggests that volatility is high when trading shares of foreigners increase, that is, when foreigners trade stocks more actively. Contemporaneous correlation between returns and trading shares shows that the share of foreigners increases when stock prices fall. Therefore, volatility rises during the periods of falls in prices.

Table 4.6: Estimated parameters of the contemporaneous relation between volatility and foreign investors.
Dependent variable is logarithm of weekly realized volatility. Explanatory variables are a lagged dependent variable, an adjusted trading volume, and trading activity of foreigners: a net trading flow and a trading share. Newey-West corrected standard errors are reported in parenthesis below the coefficients. Data cover February 2008 to February 2016. (421 observations)

Variable	Coefficient (Std. Err.)	
Intercept	-3.0857***	-4.7849***
	(0.2238)	(0.4524)
Lagged log volatility	0.4163***	0.4476***
	(0.0432)	(0.0424)
Trading volume	0.3882***	0.2841***
	(0.1060)	(0.1055)
Net trading flow of foreigners	-0.4402***	
	(0.0904)	
Trading share of foreigners		1.9236***
		(0.0424)
Adjusted R^2	0.2554	0.2556

Significance at the 1%, 5%, 10% levels is indicated respectively by ***, **, *.

4.4.2 Volatility Dynamics

In this subsection, we estimate dynamics relation between volatility and trading activities of foreigners. Empirical studies of volatility dynamics have developed the models focusing only on return and volatility dynamics such as GARCH and SV models (Engle, 2004; Taylor, 2011). In addition, for the purpose of studying the relationships between volatility and trading activities, researchers have developed different specifications of volatility dynamics (for example, Schwert, 1989; Andersen, 1996; Avramov, Chordia, and Goyal, 2006). We investigate the volatility dynamics by entering the past trading activity of foreigners into volatility equations.

In addition, we also consider the asymmetric volatility effects. Over the past several decades researchers have documented strong evidence that volatility is asymmetric in equity market: negative returns are generally associated with upward revisions of the conditional volatility while positive returns are associated with smaller upward or even downward revisions of the conditional volatility. Nelson (1991) constructs exponential GARCH (or EGARCH) model to capture a such negative relation between past return and current volatility. We follow volatility equations with asymmetric relationship between market return and volatility by following the model of Avramov et al. (2006).

At first, we explain the general form which includes measures of trading behavior of foreign investors. It should be noted that each trading behavior of different investor groups is correlated with each other, and thus, multicollinearity problem occurs if we include all trading flow variables in regression equations. Therefore, we focus on the behavior of foreign investors in this section.

The weekly aggregate return is first regressed on its own first lags using the specification

$$R_t = \alpha + \beta R_{t-1} + \gamma X_t^F + u_t \tag{4.7}$$

where R_t is the market return on period t and Z_t^F is the measure of trading activity by foreigners: net trading flow or share of trading volume. h_t is the conditional volatility and u_t is assumed to be a error term with zero mean and variance h_t^2. Return equation 4.7 means that current return is decomposed into the expected return and the unexpected error term.

Therefore, the conditional volatility is assumed to evolve in the following regression:

$$\log h_t = \phi + \psi \log h_{t-1} + \rho_1 z_{t-1} + \rho_2 |z_{t-1}| + \delta_1 \hat{V}_t + \delta_2 X_{t-1}^F + \eta_t.$$

where $z_t \equiv u_t/h_t$ is the standardized residual, $\hat{V}_t$ is normalized trading volume and η_t is an error term. As noted above, volatility is related to trading volume, we enter the normalized trading volume into the volatility equation. The coefficients ρ_1 and ρ_2 capture the effect of asymmetric volatility. Specifically, a negative ρ_1 suggests that a positive lagged unexpected return reduces volatility, but a negative lagged unexpected return increases volatility. We estimate h_t by RV_t defined in the previous section.

The main purpose of this paper is to examine the relationship of heterogeneous behavior of different investors groups. First, we estimate the relation of net trading flows. Accordingly, return and volatility equations are expressed by

$$R_t = \alpha + \beta R_{t-1} + \gamma NTF_t^F + u_t, \qquad u_t \sim (0, h_t^2) \tag{Model 1}$$

and

$$\log(h_t) = \phi + \psi \log(h_{t-1}) + \rho_1 z_{t-1} + \rho_2 |z_{t-1}| + \delta_1 \hat{V}_t + \delta_2 NTF_{t-1}^F + \eta_t. \tag{Model 1}$$

Table 4.7 shows the estimation results of model 1. Standard errors reported in the parenthesis are corrected by using heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators (Newey and West, 1987, 1994).

Estimated parameters of model 1 show that market volatility is negatively correlated with net trading flows of foreign investors ($\delta_2 < 0$). The coefficient of first lagged net trading flow of foreign investors is negative and statistically significant. In other words, after foreign investors are net buyers volatility decreases, and vice versa. In addition, the coefficients of lagged standardized residuals are statistically insignificant. This result indicates that we cannot reject the hypothesis that $\rho_1 = 0$ or $\rho_2 = 0$, respectively. Note that NTF_t^F in the return equation of model 1 orthogonalizes residuals and net trading flows of foreigners in the volatility equation. The results in the existing literature of the asymmetric volatility effect have documented that current volatility is negatively associated with past returns: positive returns lower subsequent volatility while negative returns heighten subsequent volatility. The results shown in table 4.7 suggest that an uncorrelated component of returns with trading flows of foreigners is not correlated with subsequent volatility. Accordingly, the information that results in affecting the subsequent volatility is incorporated with net trading flows of foreigners.

Next, we estimate the effect of the share of foreign investors in trading volume.

Table 4.7: Estimated parameters of the weekly asymmetric volatility models 1.

Variable	Coefficient (Std. Err.)
Return	
Intercept	-0.0017
	(0.0016)
Lagged return	-0.1600***
	(0.0467)
Net trading flow of foreigners	0.0358***
	(0.0057)
Adjusted R^2	0.2229
Volatility	
Intercept	-2.9624***
	(0.3719)
Lagged log volatility	0.4543***
	(0.0740)
Lagged std. residual	0.0046
	(0.0084)
Absolute value of lagged std. residual	0.0252
	(0.0155)
Trading volume	0.3761***
	(0.1404)
Net trading flow of foreigners	-0.3657***
	(0.0899)
Adjusted R^2	0.2641

Note: In return equation, the dependent variable is the current return of TOPIX, and explanatory variables include first lagged return and current net trading flow of foreigners. In volatility equation of model 1, the dependent variable is the logarithm of realized standard deviations of TOPIX returns in a week: weekly realized volatility. The explanatory variables include the lagged dependent variable, lagged standardized residuals, lagged absolute standardized residuals, contemporaneous detrended trading volume and first-lagged net trading flows of foreign investors. Newey-West corrected standard errors are reported in parenthesis below the coefficients. Data cover February 2008 to February 2016 (421 observations). Significance at the 1%, 5%, 10% levels is indicated respectively by ***, **, *.

Return evolves as

$$R_t = \alpha + \beta R_{t-1} + \gamma \hat{S}_t^F + u_t, \qquad u_t \sim (0, h_t^2) \tag{4.8}$$

and

$$\log h_t = \phi + \psi \log h_{t-1} + \rho_1 z_{t-1} + \rho_2 |z_{t-1}| + \delta_1 \hat{V}_t + \delta_2 \hat{S}_{t-1}^F + \eta_t. \tag{4.9}$$

Table 4.8 shows the estimated parameters of model 2.

Estimated parameters of model 2 show that market volatility is positively but insignificantly correlated with trading shares of foreign investors. The coefficient of first lagged trading shares of foreign investors is statistically insignificant. Accordingly, we cannot reject the hypothesis that trading share of foreigners affect subsequent market volatility. In addition, the coefficient of lagged standardized residual is statistically insignificant but one of its absolute value is statistically significant. This result ($\rho_1 = 0$) indicates that there is no asymmetry in the relation between return and volatility. As noted above, $\hat{S}_t^F$ in the return equation of model 2 orthogonalizes residuals and trading shares of foreigners in the volatility equation. The results shown in table 4.8 suggest that signs of an uncorrelated component of returns with trading shares of foreigners are not correlated with subsequent volatility ($\rho_1 = 0$), while magnitudes are positively correlated subsequent volatility ($\rho_2 > 0$).

4.4.3 Discussion

In the previous subsections, we examine the relationship between trading behavior and market volatility. We find contemporaneous correlations between volatility and trading activity by foreigners. The net trading flows are negatively correlated with current market volatility, while the trading shares are positively correlated with volatility. On the other hand, while net trading flows of foreign investors have a negative relation with the subsequent volatility, the trading share of them have no correlation with the subsequent volatility.

Our study is motivated by the empirical facts about heterogeneity in different investor behavior and theoretical predictions about the volatility amplification because of trend-chasing trading patterns. In our results, foreign investors are trend-chasers in the sense that they purchase stock on balance when stock prices increase. However, both current and past net trading flows of foreigners are negatively correlated with market volatility. This is not consistent with the story that

Table 4.8: Estimated parameters of the weekly asymmetric volatility models 2.

Variable	Coefficient (Std. Err.)
Return	
Intercept	0.2216***
	(0.0263)
Lagged return	-0.1705***
	(0.0456)
Trading share of Foreigners	-0.2210***
	(0.0262)
Adjusted R^2	0.1532
Volatility	
Intercept	-3.1641***
	(0.7521)
Lagged log variance	0.4845***
	(0.0871)
Lagged std. residual	-0.0053
	(0.0080)
Absolute value of lagged std. residual	0.0351**
	(0.0163)
Trading volume	0.2966**
	(0.1423)
Trading share of foreigners	0.3883
	(0.4563)
Adjusted R^2	0.2236

Note: In return equation, the dependent variable is the current return of TOPIX, and explanatory variables include first lagged return and current net trading flow of foreigners. In volatility equation of model 1, the dependent variable is the logarithm of realized standard deviations of TOPIX returns in a week: weekly realized volatility. The explanatory variables include the lagged dependent variable, lagged standardized residuals, lagged absolute standardized residuals, contemporaneous detrended trading volume and first-lagged trading share of foreign investors. Newey-West corrected standard errors are reported in parenthesis below the coefficients. Data cover February 2008 to February 2016 (421 observations). Significance at the 1%, 5%, 10% levels is indicated respectively by ***, **, *.

trend-chasing behavior amplify volatility.

Avramov et al. (2006) decompose sell trades into contrarian and herding trades and find that contrarian sell trades decrease volatility of daily individual stocks while herding sell trades increase volatility. The authors provide an information-based explanation suggesting that contrarian trades are informed trades that stabilize prices while herding is driven by uninformed investors that increase volatility. While it is difficult to find out whether foreigners are informed or uninformed, we evaluate the relative market timing ability of the investor groups over the entire period by using the cumulative performance measure defined by Kamesaka et al. (2003). Figure 4.13 shows the cumulative performance of different investor groups calculated by

$$\text{Cumulative Performance} = \sum_{t=1}^{T} (\text{Purchases}_{t-1} - \text{Sales}_{t-1}) R_t$$

Cumulative performances of domestic investor groups are overwhelmed by foreign investors. This suggests that the performance of trend-chasing trades by foreign investors is not inferior to other investor types.

Foreigners trade stocks intensively when stock prices decline. At the same periods, they tend to sell stocks on balance. Accordingly, there is an asymmetry in the trading behavior of foreigners: When they sell stocks, they intensively trade stocks relative to other investors. It is possible to explain that they sell stocks rapidly and frequently to avoid losses due to price decline and frequent trading results in high volatility.

Trading frequency is also a key when investigating volatility. Jones, Kaul, and Lipson (1994) investigate the relation between transaction size, trading frequency and volatility and conclude that trading frequency itself generates volatility. Dufour and Engle (2000) find that as the waiting time between transactions decreases, the price impact of trades increase because of reduced market liquidity. Zhang (2010) shows high-frequency trading is positively correlated with stock volatility. Fluctuations of trading frequency by heterogeneous investors can generate imbalances of demand and supply of liquidity (Bae et al., 2008). The resulting fluctuations of market liquidity can generate market volatility.

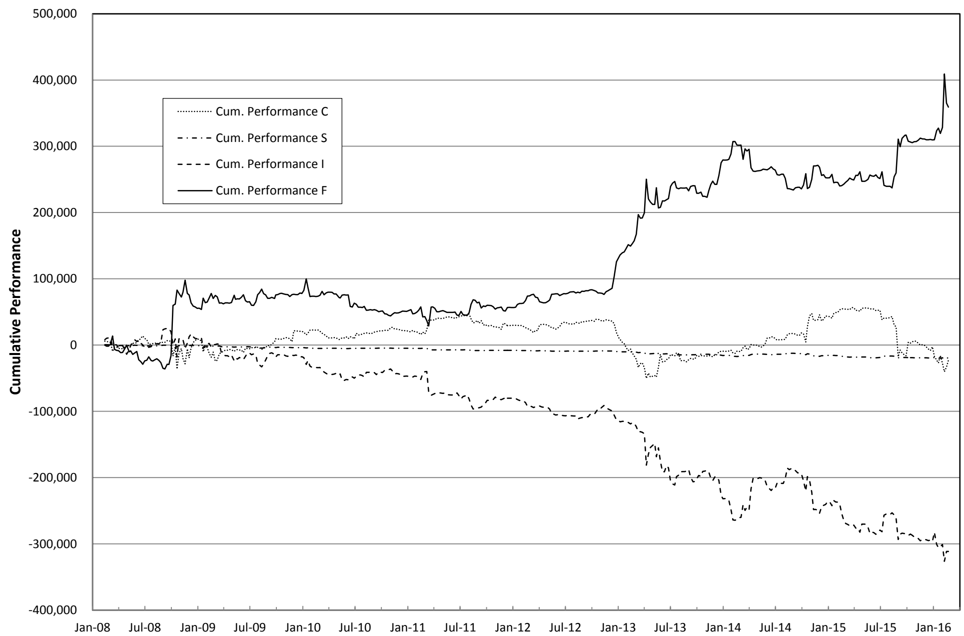


Figure 4.13: Cumulative performance of different investor groups in the first section of Tokyo Stock Exchange: February 2008 through February 2016. Investor types include foreign investors, individuals, security firms and institutions.

4.5 Conclusion

In this paper, we investigated the relationship between trading behavior of different investor types and market volatility. First, we examine the relationship between market returns and trading activities of different investor types. As the existing literature, we found that different trader types have different trading patterns. Domestic investors like individuals tend to be net-sellers when price increases, while foreign investors tend to be net-buyers when price increases. Trading shares are different from net trading flows. When returns are positive, shares of domestic investors increase. The trading share of foreign investors is negatively correlated with market returns. Thus, we conclude that the trading by foreign investors is intensive when price declines. We also employ the VAR model to examine the dynamic relation between return and trading activities. We found that all trading activities are positively autocorrelated.

In the analysis of volatility, we investigated the contemporaneous relation between volatility and foreigners' trading activity. Empirical results show that the trading share of foreign investors is positively correlated with market volatility while net trading flows are negatively associated with market volatility. Both results suggests that volatility rises during periods of falls in prices.

We also investigate the dynamic relation of volatility with trading activity of foreigners. By regressing returns on trading activity, we generated residuals which are orthogonal to trading activity of foreigners. We examine whether the asymmetric volatility effect exists. The result shows that there is no correlations between volatility and signs of past residuals, that is, the asymmetric volatility effect does not stem from uncorrelated components of return with trading activity.

Our study is motivated by the empirical facts about heterogeneity in different investor behavior and theoretical predictions about the volatility amplification because of trend-chasing trading patterns. In our results, foreign investors are trend-chasers in the sense that they purchase stock on balance when stock prices increase. However, both current and past net trading flows of foreigners are negatively correlated with market volatility. This is not consistent with the story that trend-chasing behavior amplify volatility.

While it is difficult to find out whether foreigners are informed or uninformed, we evaluate the relative market timing ability of the investor groups over the entire period by using the cumulative performance measure. We found cumulative performances of domestic investor groups are overwhelmed by foreign investors. This suggests that the performance of trend-chasing trades by foreign investors is not inferior to other investor types.

According to the results in this study, foreigners trade stocks intensively when stock prices decline.and, at the same periods, they tend to sell stocks on balance. Accordingly, there is an asymmetry in the trading behavior of foreigners: When they sell stocks, they intensively trade stocks relative to other investors. It is possible to explain that they sell stocks rapidly and frequently to avoid losses due to price decline and frequent trading results in high volatility. Existing literature of the volatility-volume relation have documented that trading frequency generates volatility: high-frequency trading is positively correlated with market volatility. The relation between volatility and trade frequency may result from the fluctuation of market liquidity.

Chapter 5

Conclusion

In this thesis, we investigate the relationship between heterogeneity of investors and asset prices. The importance of heterogeneity of investors in the functioning of asset markets have been recognized by financial economists. If there was no heterogeneity, there would be no trade. We have several types of heterogeneity of investors: expectations, risk aversion, information and so forth. We focus on trading volume, funding structure, trading behaviors of different investor groups and volatility.

In Chapter 2, we empirically investigate the relationship between measures of trading activity, return, and bull-bear market cycles in Japanese stock market. Trading activities are measured by trading volume, trading value and market turnover. At first, using two-state Markov switching model, we identify two regimes of bull market and bear market: We define the state of high mean and low volatility as bull market, and the state of low mean and high volatility as bear market.

Next, we estimate the relation between return and measures of trading activities by using the two-state bivariate Markov switching model. We found that trading activity has positive relation with past return during bull markets while small relation with past return during bear markets. We can interpret the findings as follows: In the former regime, investors react the past return because the stock performance affects their beliefs and the resulting changes in beliefs induce trades. On the other hand, the past return has no influences on investors' beliefs because investors assign little weight on the past return when they revise their beliefs under more uncertain circumstances. This differences of market environment can affect belief revision processes through the accuracy of information or confidence of investors.

The results show that the variance of trading activity at bull state is higher than bear state. It means that trading volume fluctuates wildly at the same time when it is affected by past returns strongly. We interpreted the coincidence as the following: Trading volume is generated by heterogeneity of investors such as disagreement and belief revisions. When investors are confident of the accuracy of their private information, they revise their beliefs based on the information. Thus, the information arrivals can change the degree of disagreement across investors over time. A revision of a belief induces a change in asset holdings, and it causes trading with other market participants who also try to change their positions. If the information arrival induces large disagreement, it generates large trading volume, and vise versa. To the contrary, they revise their beliefs less actively when they are uncertain about their private information. In this case, the resulting changes of disagreement are small and the variation of trading volume is also small. Therefore, the variance of error term is large in the regime in which the coefficient of past returns is large.

An important explanation is overconfidence of investors. During the periods of good performance of asset like bull market, investors become confident of their investment skills. This behavioral assumption generates the positive correlation between trading volume and past return. Of course, there exists sophisticated investors who are not overconfident in the market. We can speculate that the fraction of overconfidence investors can change and its impact on the return volatility also can change, thus the interaction between investors behavior and market environment generates bull-bear market cycles.

Chapter 3 presents price impact of short-term investors who face liquidity shocks. We investigate the model where short and long horizon investors trade stocks. Short-term investor faces the risk of exogenously forced liquidation, and the occurrences of liquidity shocks are correlated across short-term investors. This results in the volatility is experienced in the stocks which are held by mostly short-term investors.

Chapter 3 presents the relationship between stock return dynamics and trading behaviors of different investor types in the first section of Tokyo Stock Exchange. Investor types include brokered trading by corporations, financial firms, individuals and foreigners.

First, we examine the relationship between market returns and trading activities of different investor types. We start investigating whether different trading groups have different trading patterns. We define the investor behaviors as net trading flows and trading fractions in the total trading value at each period. As the existing literature, we found that different trader types have different trading patterns. Domestic investors like individuals tend to be net-sellers when price increases, while foreign investors tend to be net-buyers when price increases. Trading shares are different from net trading flows. When returns are positive, shares of domestic investors increase. The trading share of foreign investors is negatively correlated with market returns. Thus, we conclude that the trading by foreign investors is intensive when price declines. We also employ the VAR model to examine the dynamic relation between return and trading activities. We found that all trading activities are positively autocorrelated.

In the analysis of volatility, we investigated the contemporaneous relation between volatility and foreigners' trading activity. Empirical results show that the trading share of foreign investors is positively correlated with market volatility while net trading flows are negatively associated with market volatility. Both results suggests that volatility rises during periods of falls in prices.

We also investigate the dynamic relation of volatility with trading activity of foreigners. By regressing returns on trading activity, we generated residuals which are orthogonal to trading activity of foreigners. We examine whether the asymmetric volatility effect exists. The result shows that there is no correlations between volatility and signs of past residuals, that is, the asymmetric volatility effect does not stem from uncorrelated components of return with trading activity.

Our study is motivated by the empirical facts about heterogeneity in different investor behaviors and theoretical predictions about the volatility amplification because of trend-chasing trading patterns. In our results, foreign investors are trend-chasers in the sense that they purchase stock on balance when stock prices increase. However, both current and past net trading flows of foreigners are negatively correlated with market volatility. This is not consistent with the story that trend-chasing behaviors amplify volatility.

According to the results in this study, foreigners trade stocks intensively when stock prices decline.and, at the same periods, they tend to sell stocks on balance. Accordingly, there is an asymmetry in the trading behaviors of foreigners: When they sell stocks, they intensively trade stocks relative to other investors. It is possible to explain that they sell stocks rapidly and frequently to avoid losses due to price decline and frequent trading results in high volatility. Existing literature of the volatility-volume relation have documented that trading frequency generates volatility: high-frequency trading is positively correlated with market volatility. The relation between volatility and trade frequency may result from the fluctuation of market liquidity.

Heterogeneous investors are one of the most important topics in financial economics. I believe that the research program of heterogeneous investors can contribute the understanding of futures of financial markets such as trading volume, bubbles and crashes and volatility dynamics.

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