# Incentives and Imperfect Learning in Financial Markets

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# Declaration of Originality

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This thesis is dedicated to my parents with love and admiration.

献给我的父亲和母亲。

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# Chapter 1

# Introduction

## 1.1 Introduction

The principal functions of financial markets include channeling capital from lenders to borrowers, producing and disseminating information and pooling risks among market participants. The acquisition and dissemination of information is at the centre of all financial activities as information is inevitably involved in every trade and it plays a key role in price determination.

The actual data generating process of future cashflows are usually uncertain. Investors must learn about the unknown process using all available information. Bayes' rule describes a rational agent's belief updating process after a piece of new information is received, which is the cornerstone of learning in finance literature. Under Bayes' rule, the posterior belief is a precision-weighted average of the prior mean and the average value of the new signals. Moreover, the impacts of unanticipated information on asset price depends on the relative precision of investors prior belief and the new signal.(Hautsch and Hess [2007] provides detailed analysis on Bayesian learning.) Due to learning uncertainty of the economic parameters declines over time. Investors in the market trade upon their updated beliefs. Through this Bayesian learning mechanism new information can be reflected in asset prices, which fluctuate over time in response to the unexpected component of news. Ideally, market prices should provide accurate signals for resources allocation.

The efficient market hypothesis by Malkiel and Fama [1970] is built on the premise that publicly available information transmits to economic agents instantaneously and is incorporated into asset prices accurately. Malkiel and Fama [1970] also provide compelling evidence to support their argument that asset prices adjust rapidly in response to new information by examining the price reaction to mergers, stock-splits and other corporate events. In an informationally efficient market, all known information is already reflected in the current prices. Since new information is ex ante unpredictable, the future price changes must be also unpredictable. Therefore, a stock price series can be characterized by a random walk, which means that any future price movements are only random departures from the current price level.

However, this perfect-information assumption does not always hold in reality for at least the following two reasons. Firstly, obtaining and processing information can be very costly, depending on the nature of the information, which might result in imperfect learning among agents. Secondly, information asymmetry is ubiquitous in financial markets. In the presence of limits to arbitrage, the privately possessed information might not be fully reflected in security prices. Kyle [1985] develops a seminal auction equilibrium model to explain how asset prices are determined in the presence of private information. In his sequential auction model an insider investor trades on his private information while other investors trade on noise. His model suggests that the insider's information is incorporated into prices only gradually and the existence of noise traders helps improve the market liquidity in meaningful ways. Therefore, due to these informational frictions, security prices are not always consistent with 'fundamentals' and the past asset returns in some cases have predictive power for future returns. For instance, stock prices are found to display a positive serial correlation in the short run, which is the well-known momentum effect. In addition, Campbell and Shiller [1998] document that the historical P/E ratios explained around 40 % of the variance of future returns in US stock markets, which suggests that equity returns are predictable to a large extent. Moreover, these predictable patterns can generate abnormal risk adjusted returns. The most notable example is the puzzling price drift after firms' earnings announcements. By buying stocks with good earnings news and short-selling stocks with adverse earnings news, investors

can earn substantial excess returns, which is obviously hard to reconcile with the efficient market theory. Ball and Brown [1968] and Chan, Jegadeesh, and Lakonishok [1996] provide a in-depth analysis on this topic. Grossman and Stiglitz [1980] even argue that there would be no financial incentives to acquire information if all information was already fully reflected in asset prices. Therefore, the conventional models built upon frictionless markets and perfect information assumptions are not adequate to capture the complexity of rationality in the real financial world.

## 1.2 Imperfect Learning

Learning helps us better understand various market anomalies documented in the finance literature. For instance, Pastor and Veronesi [2009] show that investors learn about future dividends gradually over time, during which uncertainty surrounding the growth rate of a firm increases the firm's M/B ratio. The higher the uncertainty, the higher the price. Hence, they argue that high-tech stocks were not necessarily overpriced before the bursting of the Internet Bubble as the future profitability of those firms were highly uncertain. Moreover, they suggest that the learning process also explains why young firms are highly valued and their returns exhibit high volatility.

Nevertheless, learning in financial markets is not always perfect. When rational investors try to make best use of available information, they might be subject to some learning constraints, causing asset prices to deviate from their true values. Hence, it is of particular importance to study the potential learning biases caused by those constraints and their economic consequences. One of the factors which might hinder investors from learning properly is that information acquisition can be very costly sometimes. When the marginal cost of processing information exceeds the marginal benefits of acting on the information, a group of investors might choose to follow other investors instead of learning by themselves. The phenomenon of relying on other agents' actions to form one's own beliefs is called 'information cascades', under which individuals would rationally take identical actions even if they have different private signals. Since followers do not trade on their own information, their private information is not revealed

in market prices. Welch [1992] develops a sequential trading model to rationalize some investors' imitation behavior. Alevy, Haigh, and List [2007] 's field experiment on market professionals' trading behavior lend support to the 'information cascades' hypothesis.

Learning is undoubtedly facilitated by media, professional financial analysts and the large amount of financial data thanks to new technologies. At the same time, however, investors are more likely to suffer from information overload problem than before, which makes them selective in learning new information. The *Rational Inattention* theory has gained prominence during the past two decades as it rationalizes the imperfect learning behaviors of economic agents with limited information processing capacity. In the extant models of rational inattention, agents are still rational in that they optimally neglect certain information to maximize their expected utilities. Sims [2003] argues that the idea of limited attention is intuitively appealing as it can explain a wide range of anomalies using a relatively simple mechanism. For instance, it can be used to explain much of the investors' inertia behavior in financial markets. Also, Corwin and Coughenour [2008] find that limited attention significantly affects liquidity provision in security markets as market specialists pay more attention to their most active stocks, causing insufficient price improvement and increased transaction costs to other stocks. Huang, Wei, and Yan [2007] demonstrate that costly information acquisition makes investor inattentive to certain news and this type of inattention serves to explain the under-diversification of investors' portfolio choice. Rational Inattention also has plentiful implications for macroeconomic research. Sims [2005] provides us with some useful insights. For instance, he discusses a central bank's information disclosure policy and disputes the point of view that a detailed report will cause more overreaction than a brief summary that contains only the heavily filtered view of the Fed. He argues that when the central bank provides more information, investors would seek various sources for filtered signals and the noises in those signals might cancel out. Hence, a transparent monetary policy does not necessarily lead to more market fluctuations even if investors have limited computational capacity.

In the finance literature, imperfect learning arises in myriad settings. Non-Bayesian learning, learning with incomplete information and higher order beliefs,

among others, are also examples of departures from the rational and perfect learning framework.[1] Pastor and Veronesi [2009] provide a comprehensive analysis on this topic.

## 1.3 Incentive Issues

The study of incentive structures is the key to understanding the decision-making process of economic agents. An incentive is something which motivates a self-interested agent to do what he is expected to do in the forms of fines or rewards. In financial markets, various incentive contracts are designed to promote agents' effort and to ensure they act in the interest of contract suppliers. Moreover, one of the major roles of government in regulating the financial sector is to address the underlying incentive inefficiency and align market participants' private motives with public interest.

As mentioned earlier, the central role of financial markets is to transfer capital from lenders to borrowers. In the presence of information asymmetries and inappropriate incentive contracts, however, financial intermediaries might not necessarily channel the scarce resources to the economic activities which yield the highest returns as information asymmetry causes misplaced incentives. For instance, through relationship banking, banks play an indispensable role in gathering information, screening loan applicants and monitoring borrowers after loans are issued. Yet, they do not always act for the interest of investors as investors are not able to observe the true value of the loans or monitor banks' actions. At the same time, financial innovation significantly contributed to the rise of information asymmetries as many financial instruments are highly complex and nontransparent, which aggravates the perverse incentives.

The misplaced incentives can be very powerful and result in unintended consequences. A large body of research suggests that severely distorted incentives significantly contributed to the US sub-prime mortgage crisis. Both the US government and financial institutions played major roles in fostering the crisis. In the pre-crisis period, the US government issued a series of policies to promote home

[1] See Gervais and Odean [2001] for non-Bayesian learning, Feldman [2007] for incomplete information equilibria and Allen, Morris, and Shin [2006] for higher order beliefs.

ownership and encouraged sub-primer borrowers to purchase their own properties by taking a huge amount of loans, sowing the seeds of the crisis.

Distorted incentives also plague the hedge fund industry. As we know, hedge funds are exempt from most of the reporting and regulatory requirements which are imposed on mutual funds. Since they operate in a largely opaque manner, a central question surrounding hedge fund management is if hedge fund managers' risk taking incentive is in line with investors' interest. Most of the work in this genre is concentrated on the option-like feature of the High-Water-Mark(HWM) provision and documents a bell-shaped risk-performance pattern. Intuitively speaking, any convex compensation scheme would induce high risk taking as managers can benefit from increased underlying volatility, and this high-risk propensity should be most pronounced near the exercise price of the option. Hodder and Jackwerth [2007] argue that hedge fund managers would substantially increase risk when the fund value is somewhat below HWM in order to increase the chance of finishing the option in the money. Buraschi, Kosowski, and Sritrakul [2013] also find a similar hump-shaped risk taking pattern based on a large set of hedge fund data. Such risk shifting pattern can be detrimental to the interests of investors.

## 1.4 Outline of the Thesis

This thesis aims to explore the impacts of investors' imperfect learning behavior on asset prices and the economic consequences of misaligned incentives of financial intermediaries in a world with asymmetric information. Moreover, the next three chapters are all motivated by some well known phenomena on the recent financial crisis. For instance, asset prices tend to move very closely during crisis periods despite the low correlations in their fundamentals.(See Buraschi, Trojani, and Vedolin [2013], Peng and Xiong [2006] and Didier, Love, and Martnez Pera [2012] for detailed discussion.) To account for this anomaly, Peng and Xiong [2006] put forward the 'catergory-learning' behavior model and point out that when attention constraint is binding, rational agents should devote more attention to market-level information than to firm-level information. The second chapter of the thesis empirically tests if investors indeed exhibit this type

of learning propensity, how it affects asset prices and moreover how it can be related to the well-documented phenomenon of underreaction to earnings news. To the best of my knowledge, it is the first study on investors' category-learning behavior in the context of earnings announcements.

Specifically, we conduct an event study to quantify the extent to which investors tend to be distracted away from firm's earnings news by market-level shocks. Our analysis also shows that market state, which determines the level of attention that investors pay to the stock market, also has impacts on the magnitude of post-earnings announcement drift. Moreover, our preliminary results on the timing of earnings announcements uncover some interesting facts regarding firm managers' reporting choice, which contributes to the growing literature on managerial strategy of corporate information disclosure.

The third chapter of the thesis focuses on the origin of the recent crisis and provides a rational expectations model to show the mechanism through which securitization could lead to deterioration in banks' asset quality. Securitization is the financial practice of selling various types of contractual debt to the secondary loan market investors in the form of pass-through securities. It helps banks convert illiquid assets into liquid assets. It also marks the transition of banks from 'originate-to-hold' to 'originate-to-distribute' in their lending business. The rapid expansion of subprime mortgage market in the past decade was largely facilitated by the development of mortgage-backed securities(MBS). According to Keys, Mukherjee, Seru, and Vig [2010], mortgage-based securities were worth 3.6 trillion dollars in year 2006 and accounted for 60% of outstanding mortgage debt in the U.S. However, the quality of mortgage loans monotonically declined for six consecutive years before the outbreak of the credit crunch.(See Demyanyk and Van Hemert [2011] for example) Figure 1 depicts the rising default rate of mortgages between year 2001 to year 2007. (Source: Figure 1 in Demyanyk and Van Hemert [2011]) .

Securitization market was at the epicentre of the 2007-2008 crisis beyond dispute. The origin of the crisis is believed to be the sharp rise in the US market mortgage default rates, which triggered a sudden liquidity dry-up in the money market, driving many financial institutions into insolvency.(See Brunnermeier [2009] and Gorton and Metrick [2012].) Since the collapse of secondary loan mar-

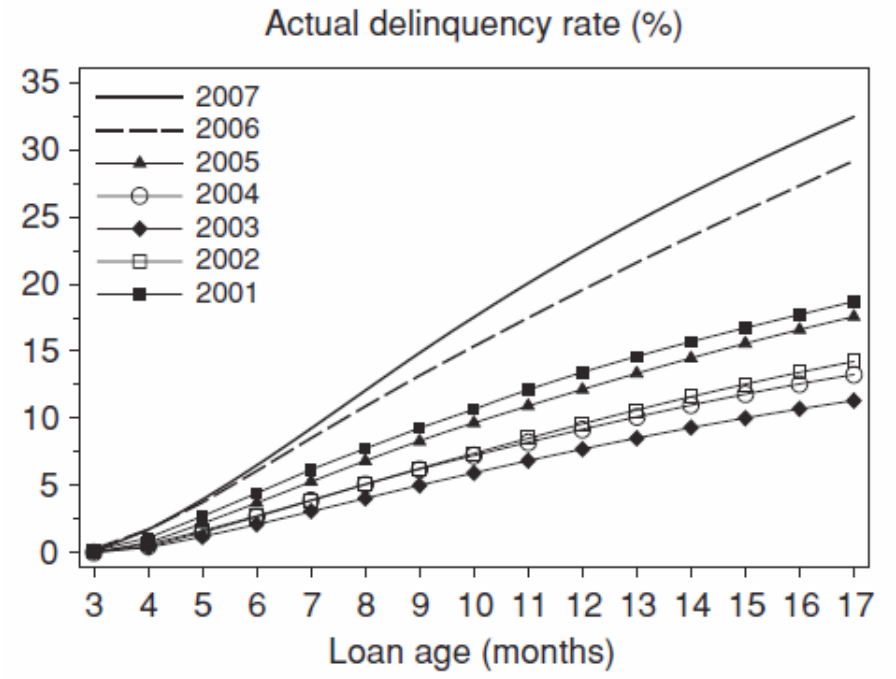



Figure 1.1: Actual delinquency rate of mortgage loans between year 2001 and 2007 in the US

ket in 2007, critiques of the securitization practice have gained great prominence. Due to information asymmetry, loan purchasers cannot observe the quality of securitized loans. A number of empirical papers show that securitization seems to have distorted loan originators' incentives. Keys, Mukherjee, Seru, and Vig [2010] find that securitization significantly reduced banks' screening standards and their incentive to monitor borrowers afterwards. Berndt and Gupta [2009] document that firms with loans traded in the secondary loan market significantly underperform their peers by 9% risk-adjusted returns in the stock market every year. They argue that this is because investors in the stock market expect banks to sell bad-quality loans.

Our equilibrium model shows that the originate-to-distribute practice can largely increase the lending capacity of the banking sector as banks have the opportunity to reallocate their resources and outsiders get to enjoy more investment opportunities. Moreover, we provide theoretical explanations of why

the securitization practice inevitably causes deterioration in banks' asset quality. The outcome of the model also suggests the channels through which regulators can uplift banks' optimal lending standards and market price of securitized assets by imposing loan sale limits.

The fourth chapter of the thesis studies the risk taking behavior of hedge fund managers in the presence of various compensation incentives. Although hedge funds did not play a major role in the recent financial crisis, they precipitated the crisis in certain ways. Before the collapse of the subprime mortgage market in 2007, hedge funds held around 47 % of the 3-trillion-dollar worth of CDOs while the banks held only 25 % and other financial institutions held 28 %.[1] Hedge funds that aim to meet high targeted returns usually adopt aggressive trading strategies and try to magnify the returns using a high degree of leverage. By virtue of leverage, a fund could buy more CDOs than it could with its own capital, which drove down subprime interest rates further and exacerbating the problem. Moreover, Chan, Getmansky, Haas, and Lo [2005], among others, suggest that hedge funds pose systematic risk to the whole financial system. They argue that the risk exposures of funds exert a material impact on the banking sector, which might create a new source of systematic risks.

In our paper, we investigate which incentives the hedge fund managers are subject to when making risk taking decisions in the context of hedge fund tournaments. In particular, we attempt to bridge the gap in the literature by introducing the money flow concern into hedge fund manager's objective function. Several papers on the empirical relationship between fund flow and fund's relative performance all suggest that hedge funds exhibit a concave fundflow-(relative) performance relation.(See Getmansky [2012] , Chen [2011] and Goetzmann, Ingersoll, and Ross [2003].) Based on Taylor [2003]'s two-period model of mutual fund tournament, we add the component of management fee from new flows to the managers' compensation and derive the optimal risk level which maximizes risk averse managers' expected utility. Following Hodder and Jackwerth [2007], we numerically solve the model and obtain some interesting results regarding managers' optimal risk choice in various scenarios. Our study contributes to a

[1]Statistics are obtained from the article 'The real role of hedge funds in the crisis' on Financial Times.

substantial body of literature on hedge funds' risk taking decisions by examining the combined effects of hedge fund managers' tournament concern, incentive contract and liquidation threat. Compared with existing work, our paper provides a richer set of predictions on managerial risk-shifting choices. (Chapter 3 is a joint work with Dr Xuewen Liu and Dr Tianxi Wang and Chapter 4 is a joint work with Lei Ding, a PhD candidate at Imperial College Business School.)

# Chapter 2

# Category-learning with Limited Attention and Under-reaction to Earnings Announcements

**Summary**

It has been documented that investors have limited attention and tend to under-react to new information when they have attention constraints. If we classify information into market level and firm specific level, rational investors should pay more attention to market-level news as it helps reduce the uncertainty of the portfolios to a larger extent than firm level news. This chapter studies if investors indeed exhibit this type of category-learning behavior (market-level news is processed before firm-level news) in the context of earnings announcement and the main findings are the following: (1) Investors tend to be distracted away from firms' earnings news when there is a market-level shock, causing more pronounced under-reaction on earnings announcement day and stronger post-earnings-announcement drift(PEAD) afterwards; (2) After resolving market-wide uncertainty, investors shift their attention back to firm-level news quickly and the initial under-reaction is corrected within one month after announcements for our sample period; (3) Consistent with our inattention hypothesis, the 'PEAD' rolling portfolio yields substantially higher risk-adjusted abnormal returns in high-market-news months than other times; (4) Firm managers strate-

gically time their earnings announcements to avoid days which have at least one major macroeconomic announcement, especially when they have favorable news to release.

## 2.1 Introduction

In traditional asset pricing models, investors are assumed to be perfectly rational and have infinite capacity to process information. However, more and more psychological studies have demonstrated that as a cognitive resource, people's attention has its limit and with this constraint, people cannot perform multiple tasks at the same time. Therefore, in the past decade researchers began to take into account the limits of investors' attention capacity in their asset pricing models and a substantial body of studies support the notion that investors' attention constraint significantly affect their trading behavior as well as asset prices in financial markets. (Sims [2003], Huang, Wei, and Yan [2007] and Maćkowiak and Wiederholt [2010] provided detailed discussions on this topic.)

To explain the phenomenon of excess asset price comovements during financial crises, Peng and Xiong [2006] develop a rational expectations model with attention constraints to show why people prefer market information over firm information when they are unable to process both of them instantaneously and they call this learning preference as category-learning behavior. It is worth mentioning that investors who exhibit this learning propensity are still rational in that they update their beliefs based on Bayes rule and they optimally allocate less attention on firm-specific news to maximize their expected utility when their attention constraints are binding. Therefore, their category-learning propensity is not the consequence of any behavioral biases.

In addition, a bunch of empirical papers suggest that investors tend to be distracted by extraneous events due to limited attention. If inattentive investors only gradually learn about an event, and if market frictions, limits to arbitrage for example, prevent attentive investors from arbitrating away the mispricing, then asset returns will display continuations. If we combine limited attention with documented investors' behavioral biases, the consequences of investors' behavior could be reinforced by the attention constraint (See Dellavigna and Pollet

[2009] and Hirshleifer, Lim, and Teoh [2009]). Motivated by the existing studies, this paper aims to find out if investors indeed exhibit the 'category-learning' propensity and to what extent it exerts influence on asset prices.

In this paper, we test for this type of learning preference in the context of earnings announcements, as earnings announcements convey the most important information of firms and the announcements are made regularly on a quarterly basis. Dating back to Ball and Brown [1968], a great deal of papers find that investors tend to underreact to earnings news, leading to price drift after announcements. Although researchers have put forward various theories to explain this phenomenon, more and more people believe that the return continuation is due to people's initial underreaction. If category learning behavior is true, we should expect the under-reaction to be more pronounced when investors are distracted by market-level news.

Another important ingredient of our study is the aggregate level of attention investors can devote to the stock market. If investors' attention capacity is time-varying, then we shall expect to see the time-varying level of underreaction to firms' news as well. Karlsson, Loewenstein, and Seppi [2009] propose a *Selective Attention* model, in which they show that investor pay more attention to rising markets than to falling markets. The key assumption in their model is that investors derive utility not only from their final consumption but also from the changes in their financial wealth. To maximize their expected utilities, investors are predicted to "put their heads in the sands" to avoid further information after receiving bad news. According to their model, market state is the key determinant of the optimal amount of attention investors should pay to the news in the stock market.

Based on Peng and Xiong [2006] and Karlsson, Loewenstein, and Seppi [2009], we develop two *Rational Inattention* hypotheses as follows: (1) When market-level news and earnings announcements arrive in the market at the same time, people tend to process market information first. Underreaction to earnings announcement is therefore reinforced by the arrival of market information. (2) Underreaction to earnings announcements should be more severe in down markets than in up markets due to time-varying attention capacity. It is worth noting that these attention propositions do not result from investors' behavioral bias, as investors

are still rational in the sense that they use Bayesian law to update their beliefs, i.e., they correctly interpret the information they obtain. Also, they derive the optimal attention allocation by maximizing their expected utility.

Following the literature on investors' inattention and earnings announcements, we focus on investors' immediate reaction to earnings announcements and post-announcement response. If distraction hypothesis holds, distracting news should have opposite effects on the announcement day and for the post-announcement period. Specifically, we examine three important measures of people's reaction, namely abnormal trading volumes, cumulative abnormal returns and abnormal profits from 'PEAD' portfolio strategies based on market distraction effects. To capture market level shocks we use jump in VIX as a proxy as a rise of market-level uncertainty is characterised by a sharp increase in VIX. Following Cooper, Gutierrez, and Hameed [2004], we define a month/day as a up market if the most recent two years' cumulative market return is positive, and a down market if it is negative. By doing so, we can compare investors' reaction under different market conditions.

To test our hypotheses, we conduct both univariate tests and multivariate regression analyses. Firstly, all the trading days in our sample are sorted into ten deciles based on daily change in VIX and the top decile days are defined as *'high-market-news'* days. By analysing share turnover, abnormal trading volumes and abnormal log dollar trading volumes, we find that investors trade considerable less on earnings announcement stocks on high-market-news days than other days. Similar result is obtained when we compare Down markets and Up markets. More importantly, these patterns hold across different types of earnings news (good news and bad news). To control for other factors which might affect investors' responsiveness, we estimate the regression model of stocks' abnormal trading volumes on a market shock dummy, a market state dummy and the attention-related firm characteristics. The estimation result shows that market news and Down market state are both negatively associated with investors' immediate trading volumes. Secondly, after controlling for firm characteristics and calendar effects, the cumulative abnormal returns for the post-announcement window are significantly larger when announcements are made on 'high-market-news' days (or in Down markets) than other times. Specifically, the post-announcement

differential drift between good news and bad news is increased by 47.6% following high-market-news days. Similarly, the delayed response to earnings news is economically smaller by 30% in Up market than in Down market. Our results are robust to different criteria of choosing 'high-market-news' days and different definitions of market states. In addition, the estimated coefficients of the control variables support the inattention theory as firms which are more visible to investors enjoy more attention and thus suffer less from under-reaction on earnings announcement day and have smaller post-announcement price drift. To investigate how inattentive investors adjust their initial under-reaction over time, we analyze the cumulative abnormal returns over different post-announcement windows and find that distracted investors shift back to earnings news quickly after market-level shocks and the initial under-reaction caused by market-distracting news can be corrected within one month after announcements. In a related paper, Dellavigna and Pollet [2009] find that investors can be distracted by weekends and pay less attention to earnings news released on Fridays. They also find that the total cumulative abnormal returns tend to be surprisingly larger for those earnings announcements when they add up returns on and after announcement days. Consistent with their findings, our test result also suggests the price reaction to earnings news is magnified in the long run when investors are distracted initially.

To measure the economic importance of market distraction effects, we construct the classic 'PEAD' portfolio by buying the good-news stocks and selling the bad-news stocks and rebalance the portfolio at the end of every month. In the meantime, the monthly volatility of VIX is used to identify the most turmoil months during our sample period, based on the assumption that a highly volatile VIX indicates that investors update their beliefs of the aggregate market frequently in response to new information. We define the months with the largest volatility of VIX as 'high-market-news' months and expect that our 'PEAD' portfolio formed at the end of these months to deliver superior performance. After regressing the monthly returns of the portfolio on Fama-French and Momentum factors, we find that the risk-adjusted abnormal return is substantially higher for 'high-market-news' months compared with the rest of the sample period. Specifically, the alpha associated with the portfolio following high-market-news months

is 2.17% per month while it is only 1.45% for other times. In addition, we examine some other measures of portfolio performance (average monthly return and Sharpe ratio for example), similar findings are obtained. To address the liquidity issues raised by Sadka [2006] and others, we include different liquidity measures which are widely used in the literature in the regression models. Our results are highly robust.

Our study also contributes to the growing literature in managerial earnings management by linking the timing of announcements with investors' category learning preference. Specifically, we investigate if managers take into the account the market distraction effects caused by macro-economic announcements when they manage their earnings news release. The extant studies on the US macro announcements suggest that there are 7 macro indicators (CPI, Housing, Newhome, PPI, Trade imbalance, Unemployment and GDP final) which exert significant impacts on stock markets and other financial markets on their release days. We thus introduce a Macro-announcement dummy variable to study their impacts on the seasonal distribution of the number of earnings announcements. The regression analysis shows that after adjusted for seasonality, the daily number of earnings announcement is significantly decreased by 15% for Macro-announcement days. This tendency holds across all types of earnings news. Furthermore, it is most pronounced for managers with favourable news to release as we find that the release of macro indicators cause 27% reduction in the number of earnings announcements which have the highest earnings surprise.

To conclude, this paper provides the first direct evidence on investors' category-learning behavior and quantifies the magnitudes of its economic consequences on firms' earnings announcements and it also sheds light on the managerial strategy of corporate information disclosure. The rest of the paper is organized as follows. Section 2 introduces the related literature and the motivation of our study. Section 3 describes the main hypotheses, data and methodology of this paper. Section 4 presents the preliminary univariate tests. Section 5 contains multivariate regression analysis and economic interpretation of the estimation results. Section 6 shows the profitability of portfolio trading strategy based on market distraction effects. Section 7 investigates how the market distraction effects relates to managers' strategy in timing their earnings announcements. Section 8

provides concluding remarks.

## 2.2 Related Literature

An extensive body of studies on psychology have demonstrated that human brain has its limit, and people cannot deal with many tasks at the same time, especially those which require central cognitive processing of human brain. For example, Kahneman [1973] points out that due to limited attention, people have to allocate their cognitive resources to different tasks, and when they focus on one task, attention paid to other tasks decreases consequently. In addition, many experiments have been conducted to assess limitations on simultaneous cognition. Pashler and Johnston [1998] provide a review on these empirical findings. More importantly, Yantis [1998] suggests that people can use deliberate strategies and intentions to control their allocation of attention. [1] These psychological findings lend support to our *Rational Inattention* Hypothesis. In the context of financial markets, investors who are facing numerous information signals have to optimally allocate their attention using deliberate strategies. In particular, our study pertains to four strands of the literature in finance.

### 2.2.1 Rational Inattention

#### 2.2.1.1 Category Learning Behavior

Peng and Xiong [2006] present a rational expectation model to show that rational investor should allocate more attention to market-level information than industry and firm-level information when they are facing attention constraints. This type of category-learning behavior results from people's optimal attention allocation decision. In their model, each dividend process is determined by three independent factors: market, sector and firm-specific factors (denoted by $h_t$, $f_{i,t}$, and $g_{i,j,t}$

[1] They also distinguish between the 'goal-driven' and 'stimulus-driven' attention: the former is referred to as 'active' mode of attention, as it is directed by people's perceptual goals. In contrast, the latter is said to be 'passive', as it is captured by salient events or 'abrupt visual onsets'. Since this paper is to investigate the optimal choice of attention allocation, we will concentrate on the 'goal-driven' attention only, although the stimulus-driven attention is also interesting on its own right, and can be applied in explaining other aspects of investors' behavior.

respectively) and the representative investor who is assumed to hold a diversified portfolio needs to decide on the optimal consumption level to maximize her expected utility .

Investor's objective:

$$MaxE_t[\sum_{s=t}^{\infty} \delta^{s-t} u(c_s)] \tag{2.1}$$

Dividend process for firm i in sector j at time t:

$$d_{i,j,t} = h_t + f_{i,t} + g_{i,j,t}, i = 1, ..., m, j = 1, ..., n. \tag{2.2}$$

Investor cannot observe those fundamental factors, but she knows the distribution of the them and she can analyze different signals to form the posterior beliefs about those factors according to the Bayes rule before dividends are realized. By doing so, the investor obtains more accurate forecasts about future dividends, and then she can make more efficient decisions in choosing consumption level. They use $\kappa$ to denote the attention limit, and $\lambda_{h,t} \in [0, 1]$, $\lambda_{f,i,t} \in [0, 1]$ and $\lambda_{g,i,j,t} \in [0, 1]$ to stand for fractions of attention allocated to market, sector, and firm factors respectively. Accordingly, the attention constraint can be expressed as follows:

$$\lambda_{h,t} + \sum_{i=1}^{m} \lambda_{f,i,t} + \sum_{i=1}^{m} \sum_{j=1}^{n} \lambda_{g,i,j,t} \leq 1 \tag{2.3}$$

Where $n$ is the number of sectors and $m$ is the number of firms in each sector.

They show that when $m^2\sigma_h^2 > \sigma_f^2$ and $n^2\sigma_f^2 > \sigma_g^2$, the representative investor should pay more attention to the market information than the sector and firm information. They argue that this condition can be easily satisfied in reality. In the extreme case, when $\kappa < (m/\theta)log(n^2\sigma_f^2/\sigma_g^2)$, she should pay attention to the market and sector information only. Intuitively speaking, when holding a diversified portfolio, investors can benefit from devoting more attention to common factors (i.e., market and sector), because learning these common factors can reduce the uncertainty of the portfolio to a larger extent than the firm-specific factor. Hence, an investor with attention-constraint should learn more category information than firm-level information, and "the degree of categorization de-

pends on her attention constraints" (Peng and Xiong [2006]). [1]

In addition, Peng, Xiong, and Bollerslev [2007] provide empirical evidence that "market volatility and the comovement of individual stocks with the market increase contemporaneously with the arrival of market-wide macroeconomic shocks, but decrease significantly in the following five trading days". Their finding supports the category-learning-behavior hypothesis as it shows the time-varying process of investors' attention allocation. However, they do not examine category-learning behavior directly through investors' reaction to firm-level news and the consequences of time-varying attention allocation has not been fully investigated. To overcome these limitations, our paper aims to find out whether the arrival of market information distracts investors from firm-specific information, and the outcomes of this attention-shifting process.

#### 2.2.1.2 'Ostrich Effect'

Karlsson, Loewenstein, and Seppi [2009] point out that conventionally investors are assumed to derive utility from the real cashflows from their investment, which means they care about the value of the assets only when they liquidate them and consume the proceeds. However, this assumption contradicts with our daily experience- people's utility level can be easily affected by the changes in their financial wealth. They take this psychological impact of new information on utility into account and propose a novel model of *Selective Attention* towards information, in which rational investors decide if they should obtain new information about the value of their investments or not.

In their model, investors receive information about the aggregate market before they decide whether to learn new information about their portfolios. The main prediction of their model is so-called *'Ostrich Effect'*- Given a series of bad news, rational investors would optimally choose not to learn additional information to avoid further disappointing news. On the other hand, given good news, investors would want to have further information to confirm the value of their

[1] They also combine this category-learning behavior with investors' overconfidence bias to show that when people process more market information and then overreact to this common factor, return correlation of stocks is higher than that of the fundamentals, causing excessive asset price comovements.

portfolios. They conclude that in up markets, people may check the value of their portfolios more frequently than is required for decision-making, while in downturns, information-averse investors would give up portfolio rebalancing opportunities by not attending to new information. This *'Ostrich Effect'* hypothesis is consistent with investor rationality because investors shield themselves from new information to maximize their utility. Their key assumption that investors can derive utility from information is also justified by prior research.[1] They also analyze accounts data of investors in Sweden and the US, and find that investors monitor their portfolios online much more frequently when stock market is rising than when it is falling. The negative relationship between account look-up and past market returns supports their *'Ostrich Effect'* hypothesis. [2]

### 2.2.2 Under-reaction to Earnings Announcements and Distraction Effects

Ball and Brown [1968] was the first to notice that the cumulative abnormal returns after announcements keep going up for positive-news stocks and down for negative-news stocks. This type of return continuation is also known as post-earnings-announcement drift anomaly (PEAD). Chan, Jegadeesh, and Lakonishok [1996] analyze the profitability of rolling trading strategies based on PEAD, which is refered to as 'Earnings Momentum' strategy in their article. They confirm that there is delayed reaction of stock prices to earnings news. A large number of explanations have been put forward to account for this market anomaly and most of them resort to investors' behavioral biases. In general, more and more researchers believe that this drift is due to investors' underreaction to the information content of earnings announcements, and the extent of underreaction depends on the type of the announcements and the characteristics of the firms. For example, Bernard and Thomas [1989] investigate the returns serial correlations, and suggest that investors underestimate the implications of cur-

[1] Barberis, Huang, and Santos [2001] argue that by assuming that investors utility depends on the value of their financial wealth, their model offers an intuitive and parsimonious explanation for the equity premium puzzle.

[2] Based on Karlsson, Loewenstein, and Seppi [2009]'s model, Hou, Peng, and Xiong [2008] empirically test if the 'PEAD' portfolio and 'Momentum' portfolio is affected by market states.

rent earnings for future earnings. Mendenhall [2004] provides empirical evidence in favor of this explanation by examining the relationship between the stocks' arbitrage risk and the post-announcement drifts.

During the past decade, a bunch of papers provide empirical evidence that investors have limited attention and they can be distracted by some salient or unexpected events. Moreover, this distraction effect has significant influence on financial markets. In the literature, trading volume, number of analysts, and media coverage are the most widely used proxies of investors' attention. For instance, Barber and Odean [2008] argue that investors are more likely to be attention constrained when they buy stocks rather than sell stocks, because many of them are subject to short-selling constraints and can only sell the stocks they already hold. Their results show that compared to institutional investors, individual investors are net buyers of attention grabbing stocks, and their buying behavior is more heavily influenced by attention constraint than selling behavior is. Corwin and Coughenour [2008] investigate the impacts of specialists' limited attention on security markets. They find that specialists tend to exert more effort toward their most active stocks during periods of high activity, resulting in insufficient price improvement and increased transaction costs for the remaining stocks. Thus, the allocation of effort subject to specialists' limited attention significantly affect liquidity provision in stock markets. More specifically, the rate and magnitude of price improvement for a stock is negatively related to specialist's attention paid to other stocks in the same trading panel, and these effects of limited attention are most pronounced for the least active stocks and are robust to different econometric techniques. Peress [2008] uses media coverage to proxy for market participants' attention and examine if post-earnings-announcement drift can be related to investors' attention level. Specifically, he calculates the number of Wall Street Journal articles which mention the earnings news to measure how much attention the market as a whole pays to the announcement. His main finding is that stocks with more intensive media coverage enjoys stronger price reaction on earnings announcement day and weaker subsequent drift. Gilbert, Kogan, Lochstoer, and Ozyildirim [2012] focus on the US leading economics index (LEI) to study if investors react to stale information, as the constituents of the index are released before the index itself and the method used to construct the index is

publicly available. They find that the release of LEI has a statistically and economically significant impact on market returns, volatility and trading volumes. Moreover, they show that a trading strategy which trades in the direction of the announcement before its release and trades in the opposite direction after its release yields a 8% annual return. Hence, they conclude that some inattentive investors would react to the repackaging of stale information, causing temporary yet significant mispricing.

In the literature, the most related papers to ours are Dellavigna and Pollet [2009] and Hirshleifer, Lim, and Teoh [2009]. They both conduct event study and choose *Earnings Announcements* to examine the economic consequences of investors' limited attention. Specifically, Dellavigna and Pollet [2009] test the hypothesis that investors tend to pay less attention to stock markets on Friday as they are distracted by the upcoming weekends and the earnings news released on Fridays thus experience more pronounced under-reaction than other week days. They find that weekends distraction effect is statistically significant as Friday announcements on average have a 15% lower immediate response and a 70% percent stronger delayed response. Moreover, a trading strategy to exploit the different responses to Friday announcements and to other weekday announcement earns 4% abnormal returns per month. Similarly, Hirshleifer, Lim, and Teoh [2009] directly test the distraction effects of competing earnings news from other firms in the market. They propose a distraction hypothesis that extraneous earnings news prevent investors from reacting promptly to the information content of a given firms' announcement. In particular, they sort trading days into 10 deciles every quarter based on the total number of earnings announcements on each day and define the top decile as 'high-news-days' and the bottom decile as 'low-news-days'. By examining abnormal returns, abnormal trading volumes and post-announcement drift, they find that underreaction to earnings news is more sever when the distraction from extraneous news is higher. Their empirical results show that the number of earnings announcements from competing firms has significant impact on the investors' response coefficient to earnings announcements. A greater number of earnings announcements is positively related to a weaker price and trading volume reaction to a given earnings announcement, and a larger post-announcement drift. The findings of these two papers are consistent

with the notion that attention constraints cause stronger market under-reaction to earnings news, which can explain part of the PEAD anomaly.

### 2.2.3 Earnings Management and Timing of Announcements

Earnings has been considered the most important signal of a company's performance to investors. Earnings management is a common practice among managers who often manipulate earnings by moving income between different periods. For example, Degeorge, Patel, and Zeckhauser [1999] provide empirical evidence that earnings threshold induces different types of earnings management behaviors and among the three thresholds they propose in their model, the positive profit threshold plays a crucial and predominant role in manager's reporting decision. In particular, managers have a strong incentive to adjusted upward earnings when they are slightly below thresholds.

In addition, timing of announcement is also crucial to managers. For instance, Aboody and Kasznik [2000] focus on scheduled CEO option awards and they find that manager have a strong tendency to release bad news before option awards and good news after option awards as the exercise price of the option is usually equal to the stock price on the award day. Penman [1987] is one of the earliest work on the distribution and seasonality of earnings news. It documents that earnings report arriving during the second half-month periods tend to carry bad news and during the week, Mondays and Fridays on average have more bad earnings news compared with other week days. The author claims that the seasonality of earnings news can serve to explain the seasonality in market returns. Begley and Fischer [1998] also study the relation between the delay of earnings announcements and the content of earnings news (bad news or good news). They confirm the hypothesis of good news early and bad news late. These papers all suggest that managers in reality strategically decide on when to disclose firm information to the public for the purpose of maximizing shareholders' or their own interest.

### 2.2.4 Macroeconomic Announcements

In the last section of our paper, we link the major macro announcements with the distribution of earnings news to see if the firm managers' earnings disclosure decision is subject to the release of market aggregate information.

Mitchell and Mulherin [1994] is one of the first to study the impacts of public information on the aggregate stock market. They find that stock market activities are positively related to the daily number of Dow Jones news announcements. In addition, they proxy the importance of news by the size of New York Times headlines, and find it to be positively related to both market returns and market trading volumes.

The US scheduled macroeconomic announcements have received great research interest as they are considered to carry the most fundamental information on the economy and help market participant adjust their expectations of the future. Flannery and Protopapadakis [2002] utilize a GARCH model to study the relation between conditional volatility of daily equity returns and 17 US monthly macroeconomic announcements. They identify three nominal variables: PPI, CPI and Monetary Supply, and three real variables: Unemployment, Balance of Trade, and Housing Starts, as risk factors which exert influences on both the level and the volatility of stock returns. In addition, Andersen, Bollerslev, Diebold, and Vega [2007] employ a high-frequency dataset to study how the US, German and British investors react to US macro announcements in stock, bond and foreign exchange markets. They find interactions across different countries and different markets surrounding US macro announcements. Specifically, they identify the conditional mean jumps caused by macro announcements and suggest that these target markets are all closely linked to economic fundamentals.

## 2.3 Hypotheses, Data and Methodology

### 2.3.1 Main Hypotheses

Based on Peng and Xiong [2006] and Karlsson, Loewenstein, and Seppi [2009], I develop two *'Rational Inattention'* hypotheses:

**Hypothesis 1** *When market news and earnings announcements arrive in the market at the same time, people tend to process market information first. Underreaction to earnings announcement is therefore reinforced by the arrival of market-level information.*

**Hypothesis 2** *Since people in general pay more attention to rising markets' news than to falling markets' news, under-reaction to earnings announcements should be more severe in Down markets than in Up markets.*

The first hypothesis is related to investors' category-learning behavior and the second hypothesis is related to the aggregate level of attention investors pay to the new information in the capital market.

### 2.3.2 Data Description

We obtain the data from the following sources: market returns, stock returns, prices, trading volumes, and other fundamental data of all the common stocks listed on NYSE, AMSE and NASDAQ between January 2001 and December 2010 are obtained from CRSP and Compustat. Analysts' forecasted earnings, actual earnings, actual earnings announcement dates and number of analysts reporting forecasts are obtained from database I/B/E/S. Daily VIX and VOX data between year 1986 and 2010 are obtained from Chicago Board Options Exchange. Monthly data of Fama-French three factors, Momentum factor, Sadka's liquidity factors and Pastor-Stambough's liquidity factors are obtained from WRDS. Breakpoints of the 25 size and book-to-market portfolios are obtained from Kenneth French's website. Institutional Ownership, the percentage of stock shares owned by institutions, is obtained from Thomson Reuters 13F filings. Announcement dates of Housing Starts and New Home Sales are obtained from US Census Bureau. Announcement dates of PPI, CPI and Unemployment rates are obtained from US Bureau of Labor Statistics. Announcement dates of GDP and Trade Balance are obtained from US Bureau of Economic Analysis.

In addition, the following criteria are applied in filtering data:

1. Our sample is restricted to common stocks listed on NYSE, AMEX and NASDAQ (with share code 10 or 11 from the CRSP database)

2. Stocks are excluded from the sample if their prices are once below 1 dollar.

3. When merged with the fundamental data from Compustat, the unmatched stocks are dropped from the sample.

4. Stocks with non-positive total assets or total liabilities are dropped from the sample.

5. We only use median forecasted earnings which are released within 60 days before announcement to exclude stale forecasts.

6. When a firm announced two quarters' earnings on the same day, we only use the latest quarter's earnings data to compute earnings surprise.

7. Observations with actual earnings or forecasted earnings higher than the stock price are eliminated.

### 2.3.3 Methodology

Following Dellavigna and Pollet [2009] and Hirshleifer, Lim, and Teoh [2009], We investigate investors' reaction by examining abnormal trading volumes, abnormal stock returns and the profitability of trading strategies based on post-earnings announcement drift. Specifically, comparative statistics on investors' reaction to earnings news are analysed under different market conditions and multivariate regression estimations are conducted to further examine the significance and magnitude of the market distraction effect after we control for other possible factors which might be related to investors' responsiveness. In addition, we also study if firm managers are aware of the distracting effects of market-level news and strategically time their earnings announcements accordingly. Detailed tests procedures are presented in the following sections.

## 2.4 Univariate Tests of Market Distraction Effects

### 2.4.1 Abnormal Trading Volume

Prior studies have provided ample evidence of the link between trading volumes and investors' attention. For instance, Barber and Odean [2008] argue that compared with firm size, media coverage and analysts' report, trading volume is a more direct measure of attention investors actually pay to a stock through their trading activities, and the daily abnormal trading volume reflects the change in investors' attention level. Moreover, Chordia and Swaminathan [2000] find that high-volume-stocks respond more quickly to news than low-trading-volume stocks after they control for the size factor. Following existing papers, we adopt trading volumes to measure how much attention investors actually devote to stocks.

In the following test, we use three measures of trading volumes: Share Turnover, Abnormal Trading Volume and Abnormal Log Dollar Volume. *Share Turnover* is the number of shares traded over certain period divided by shares outstanding. It is one of the most common ways to measure trading volume.[1] *Abnormal trading volume* for individual stock at announcement day is defined as the difference between the daily number of shares traded at announcement and the average daily number of shares traded over the preceding 30 days divided by their sum. Dollar volume is the product of stock price and its trading volume. *Abnormal log dollar volume* is computed as the difference of log dollar volume between announcement window and the pre-announcement window [-40,-11] divided by their sum.

$$DVOL[0,1] = \frac{\frac{1}{2}\sum_{t=0}^{1} log(DollarVol_t + 1) - \frac{1}{30}\sum_{t=-11}^{-40} log(DollarVol_t + 1)}{\frac{1}{2}\sum_{t=0}^{1} log(DollarVol_t + 1) + \frac{1}{30}\sum_{t=-11}^{-40} log(DollarVol_t + 1)} \tag{2.4}$$

where $DollarVol_t$ is dollar volume traded on day t. $[0,1]$ indicates the trading days relative to announcement date, where 0 stands for the announcement day and 1 stands for the day after announcement. Similarly, we define the average

[1] See Lo and Wang(2009) for detailed discussion.

Table 2.1: Trading Volume Response to Earnings Announcements

This table compares different measures of trading volume response of investors to firms with earnings announcements and to firms without earnings announcements. Trading days with no earnings announcements are excluded from our sample. Average turnover is the shares traded on announcement day divided by shares outstanding. The abnormal trading volume VOL is the difference between the daily number of shares traded at announcement (or post announcement) and the average daily number of shares traded over the preceding 30 days divided by their sum. DVOL is the difference of log dollar volume between announcement window (or post announcement window) and the pre-announcement window divided by their sum.

| | Immediate Reaction | | | Post Reaction | | Firms | Days |
|---|---|---|---|---|---|---|---|
| | DVOL[0,1] | VOL[0,1] | Turnover | DVOL[2,31] | VOL[2,31] | | |
| *Announcement Firms* | 59.98% | 22.53% | 1.73% | 4.93% | 1.89% | 48 | 2457 |
| *Other Firms* | -0.33% | -7.28% | 0.83% | 0.80% | 0.51% | 3909 | 2457 |
| *Difference* | **60.32%*** ** | **29.81%*** ** | **0.91%*** ** | **4.13%*** ** | **1.38%*** ** | | |

abnormal trading volume for post-announcement window $[2, i]$ as:

$$DVOL[2,i] = \frac{\frac{1}{i-1}\sum_{t=2}^{i} log(DollarVol_t + 1) - \frac{1}{30}\sum_{t=-11}^{-40} log(DollarVol_t + 1)}{\frac{1}{i-1}\sum_{t=2}^{i} log(DollarVol_t + 1) + \frac{1}{30}\sum_{t=-11}^{-40} log(DollarVol_t + 1)} \tag{2.5}$$

First of all, stocks are assigned into two groups on a daily basis: Announcement Group and No-announcement Group, and then the average share turnover, average abnormal trading volume and average abnormal log dollar volume are computed for each group. Table 1 summarizes the statistics of the three trading volume measures. The sample period is from January 2001 to December 2010.

Table 2.1 shows that: (1) on average, firms with earnings announcements have much higher share turnover than firms without earnings announcements and the difference between these two groups is highly significant. (2) $VOL[0,1]$ and $DVOL[0,1]$ also measure the immediate response to earnings announcements and the comparison between these two stock groups reveals the attention-shifting process: since people pay more attention to earnings-announcement firms, those firms' trading volume soar up over announcement window(day 0 and day1). In contrast, stocks with no earnings announcement receive less attention than before and their trading volume plunge consequently, which is shown by the negative $VOL[0,1]$ and $DVOL[0,1]$. (3) Post-announcement response $DVOL[2,31]$ and $VOL[2,31]$ (abnormal trading volume over post-announcement window (day 2 to

day 31)) suggests that people do not shift their attention back immediately after earnings news, which is consistent with the notion that it takes time for people to process new information.

### 2.4.2 Jump in VIX: The Proxy of Market-level Shock

In this paper, we use the change in the index VIX to proxy for market-level news. According to Chicago Board Option Exchange, VIX is the weighted average of the implied volatilities of various S&P 500 options and it reflects investors' expectation of future market volatility. Therefore, we should expect the level of VIX to fluctuate as investors receive new information about the market and update their expectations accordingly. We believe that change in VIX is better than other proxies as it is a relatively clean measure of market-level news while other measures including market aggregate trading volumes, market returns and market actual volatilities are the consequences of market participants' reaction to news.

In particular, we use a jump in VIX as an indicator of a market-level shock. We focus on positive changes in VIX as they are usually associated with bad macro news and bad news should be more distracting than good news. Changes in VIX ($\Delta VIX$) are calculated on a daily basis for our sample dated from year 2001 to 2010. Trading days are sorted according to change in VIX and the days with the top 10% highest change in VIX are labelled as 'high-market-news' days and the days with smallest change in VIX as 'low-market-news' days. Days when stock market is closed and days which have no earnings announcements are excluded from the sample. Summary statistics of change in VIX are presented in panel A of Table 2.2.

Panel B of Table 2.2 examines three different measures of trading volumes of stocks with earnings news and of stocks without earnings news. By comparing high-market-news days and low-market-news days, we can see that investors react less to earnings announcements when there is a market-level shock, as the average share turnover, average abnormal trading volume and abnormal log dollar volumes for announcement firms are all lower than low-market-news days. Moreover, the spread between announcement firms and no-announcement firms

shrinks in the presence of market-level shocks. To investigate if this spread is statistically significant, we estimate the following regression using only observations from high-market-news days and low-market-news days.

$$DVOL[0,1] = \alpha_0 + \alpha_1 Announcement + \alpha_2 Shock + \alpha_3 (Announcement \times Shock) \tag{2.6}$$

where *Announcement* is an indicator variable which is equal to 1 for announcement firms and 0 for no-announcement firms, and *Shock* is an indicator variable which equals 1 for high-market-news days and 0 for low-market-news days. Hence, $\alpha_3$ captures the spread of the difference of abnormal trading volumes between high-market-news days and low-market-news days. The estimated $\alpha_3$ is shown in the bottom row labeled as 'DID' (Difference in Difference) for different measures of trading volumes. Except for turnover, the 'DID' is highly significant for the other measures. To exclude the distraction effects of other firms' earnings announcements documented by Hirshleifer, Lim, and Teoh [2009], the average number of stocks with earnings announcements under different market conditions are also calculated. Since there are more firms releasing earnings news on low-market-news days than on high-market-news days in our sample (55 vs. 47), we can rule out the alternative explanation that investors are distracted because of too much firm-level information.

Another variable of interest in our study is *Market State*, which is related to market participants' aggregate attention level. Following Cooper, Gutierrez, and Hameed [2004] and Hou, Peng, and Xiong [2008], we calculate the past two years' cumulated S&P 500 returns for each month, and define the trading days as *Up market* if the past cumulated market return is positive or *Down market* if it is negative.[1] We compare investors' reaction to earnings announcements under different market conditions. Table 2.3 shows that in Up markets when investors are more attentive to new information, stocks with earnings announcements have higher abnormal trading volumes compared with Down markets. For example, the average abnormal log dollar trading volume of announcement stocks

[1]We also use the past three years' and one year's cumulative return to measure market states. The findings of this paper are robust to different definitions of market states.

Table 2.2: Trading Volume Response and Market Shock

Panel A of this table presents the summary statistics of change in VIX, the proxy of market news. Trading days with no earnings announcements are excluded from the sample. High-Market-News are the trading days which have the top 10% highest change in VIX and Low-Market-News are the trading days which have the smallest change in VIX. Panel B compares the abnormal trading volumes between firms with earnings announcements and firms without earnings announcements. Investors' immediate reaction is measured by Abnormal Log Dollar Trading Volume $DVOL[0,1]$ and Abnormal Trading Volume $VOL[0,1]$ over announcement window (day 0 and day1) and Share Turnover on announcement day. The bottom row of the table shows the spread of difference in investors' immediate reaction to earnings news between High-Market-News days and Low-Market-News days. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A. Change in VIX

| | | | | | Percentiles | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev | No. >=0 | No. < 0 | P10 | Median | P90 | No. obs |
| ΔVIX | -0.0048 | 1.79 | 1130 | 1313 | -1.51 | -0.09 | 1.63 | 2443 |

Panel B. Trading Volume Response

| | | Immediate Reaction | | | | |
|---|---|---|---|---|---|---|
| | | DVOL[0,1] | VOL[0,1] | Turnover | No. Firms | No. days |
| *Low-Market-News* | Announcement Firms | 65.37% | 23.90% | 1.77% | 55 | 238 |
| | Other Firms | 2.40% | -7.35% | 0.82% | 3917 | |
| *Difference* | | **62.97%*** ** | **31.25%*** ** | **0.95%*** ** | | |
| *High-Market-News* | Announcement Firms | 51.03% | 22.02% | 1.74% | 47 | 245 |
| | Other Firms | -1.60% | -4.45% | 0.89% | 3870 | |
| *Difference* | | **52.63%*** ** | **26.47%*** ** | **0.85%*** ** | | |
| *DID* | | **10.34%*** ** | **4.79%*** ** | **0.10%** | | |

in Up markets is 61.53%, which is higher than 57.96% in Down markets. More importantly, the difference in abnormal trading volumes between announcement group and no-announcement group is significantly larger in Up markets than in Down markets as the estimated 'DID' is highly significant for each trading volume measure, and the results are not driven by the distraction effects of competing announcements.

To examine the impacts of earnings news content on investors' trading behavior, we assign earnings news into different groups based on their *Earnings Surprise*, which is measured by analysts' *Forecast Error* :

$$FE = (E_{iq} - F_{iq})/P_{iq} \tag{2.7}$$

where $E_{iq}$ is the actual earnings per share, $F_{iq}$is the median forecasted earnings

Table 2.3: Trading Volume Response and Market States

Market states are identified through the past two years' cumulative market returns. Trading days with positive cumulated returns are labeled as Up Market while trading days with negative cumulated returns are labeled as Down Market. This tables compares investors' responses to earnings news under different market states. Investors' immediate reaction is measured by Abnormal Log Dollar Trading Volume $DVOL[0,1]$ and Abnormal Trading Volume $VOL[0,1]$ over announcement window (day 0 and day1) and Share Turnover on announcement day. The bottom row of the table shows the spread of difference in investors' immediate reaction to earnings news between Up markets and Down markets. Sample period is from January 2001 to December 2010. Trading days with no earnings announcements are excluded from the sample. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| | | Immediate Reaction | | | | |
|---|---|---|---|---|---|---|
| | | DVOL[0,1] | VOL[0,1] | Turnover | No. Firms | No. days |
| *Up Market* | Announcement Firms | 61.53% | 23.82% | 1.79% | 50 | 1350 |
| | Other Firms | -1.26% | -7.24% | 0.82% | 4004 | |
| *Difference* | | **62.79%*** ** | **31.06%*** ** | **0.97%*** ** | | |
| *Down Market* | Announcement Firms | 57.96% | 20.86% | 1.66% | 47 | 1093 |
| | Other Firms | 0.87% | -7.33% | 0.81% | 3791 | |
| *Difference* | | **57.09%*** ** | **28.19%*** ** | **0.85%*** ** | | |
| *DID* | | **5.70%*** ** | **2.87%*** ** | **0.12%*** ** | | |

from analysts and $P_{iq}$ is the announcement month-end price of the stock.

To avoid stale forecasts, we only use the latest estimates on IBES summary statistics tape for each announcement. Also, observations with actual earnings or forecast higher than the stock price are dropped from the sample to mitigate potential data error, and stocks with prices lower than 1 dollar are excluded from the sample as well. When forecast errors is positive, an earnings announcement is regarded as good news. Otherwise, it is bad news. Based on forecast errors/earnings surprise, we rank announcements at the end of each calendar quarter, and assign them into ten deciles. Decile 1 consists of stocks with the lowest (negative) earnings surprise, while decile 10 consists of stocks with the highest (positive) earnings surprise.

Table 2.4 compares abnormal log dollar trading volumes in response to earnings announcements under different market conditions. Panel A shows that stocks with earnings news experience lower abnormal trading volumes on high-market-news days than on low-market-news days and this pattern holds across different types of earnings news. Except for FE3 and FE7, the difference in abnormal trading volumes $\Delta DVOL[0,1]$ is highly significant. In addition, Panel B reveals

Table 2.4: Abnormal Log Dollar Trading Volume and Earnings Surprise

DVOL[0,1] is the abnormal log dollar volume over the announcement window (day 0 to day 1). Forecast error is the difference between actual earnings per share and analysts' forecast divided by month-end stock price, which is used to measure Earnings Surprise. Earnings announcements in the sample are ranked according to forecast error every quarter. FE10 presents the stocks with the highest earnings surprise and FE1 are stocks with the lowest earnings surprise. High-Market-News are the trading days which have the top 10% highest change in VIX and Low-Market-News are the trading days which have the smallest change in VIX. Trading days with positive two years' cumulated returns are labeled as Up Market while trading days with negative cumulated returns are labeled as Down Market. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Abnormal Trading Volume and Market-level Shock | | | | | | |
|---|---|---|---|---|---|---|
| | Low-Market-News | | High-Market-News | | Difference | |
| | DVOL[0,1] | *Forecast Error* | DVOL[0,1] | *Forecast Error* | Δ DVOL[0,1] | No.obs |
| FE 1 | 63.75% | *-3.66%* | 39.46% | *-6.54%* | **24.29%*** ** | 2293 |
| FE 2 | 59.40% | *-0.35%* | 49.56% | *-0.68%* | **9.84%*** | 2142 |
| FE 3 | 59.58% | *-0.10%* | 52.19% | *-0.19%* | 7.39% | 2147 |
| FE 4 | 58.44% | *-0.01%* | 47.06% | *-0.04%* | **11.38%** ** | 2225 |
| FE 5 | 62.27% | *0.02%* | 52.14% | *0.01%* | **10.13%** ** | 2206 |
| FE 6 | 64.35% | *0.06%* | 57.90% | *0.06%* | **6.45%*** | 2174 |
| FE 7 | 64.89% | *0.11%* | 58.25% | *0.14%* | 6.64% | 2189 |
| FE 8 | 71.19% | *0.19%* | 57.60% | *0.25%* | **13.59%*** ** | 2187 |
| FE 9 | 76.09% | *0.36%* | 57.70% | *0.48%* | **18.39%*** ** | 2251 |
| FE 10 | 76.19% | *1.76%* | 54.24% | *2.68%* | **21.95%*** ** | 2311 |
| Panel B. Anormal Trading Volume and Market States | | | | | | |
| | Up Market | | Down Market | | Difference | |
| | DVOL[0,1] | *Forecast Error* | DVOL[0,1] | *Forecast Error* | DVOL[0,1] | No.obs |
| FE 1 | 54.56% | *-4.12%* | 50.33% | *-6.00%* | **4.23%*** | 10128 |
| FE 2 | 57.16% | *-0.37%* | 51.07% | *-0.57%* | **6.09%*** ** | 10352 |
| FE 3 | 56.39% | *-0.11%* | 52.30% | *-0.14%* | **4.09%** ** | 10530 |
| FE 4 | 55.87% | *-0.02%* | 53.48% | *-0.02%* | 2.39% | 10741 |
| FE 5 | 57.53% | *0.01%* | 55.38% | *0.03%* | 2.15% | 10781 |
| FE 6 | 63.03% | *0.05%* | 60.09% | *0.09%* | **2.94%*** | 10821 |
| FE 7 | 65.65% | *0.09%* | 62.56% | *0.16%* | **3.09%*** | 10727 |
| FE 8 | 68.88% | *0.17%* | 63.04% | *0.29%* | **5.84%*** ** | 10623 |
| FE 9 | 70.35% | *0.33%* | 67.10% | *0.55%* | 3.25% | 10556 |
| FE 10 | 68.44% | *1.74%* | 68.51% | *2.87%* | -0.07% | 10444 |

that investors trade relatively less on earnings news in Down markets compared with Up markets.

## 2.5 Multivariate Tests: Regression Analysis

### 2.5.1 Abnormal Trading Volume at Announcement $DVOL[0,1]$

Our market distraction hypothesis posits that market-level news will distract investors and thus reduce investors' trading volume response. In this section, we perform regression analysis of the abnormal trading volume $DVOL[0,1]$ over the announcement window (day 0 and day1) while controlling for other possible sources of variation in investors' response to see if the market distraction effect is still statistically significant.

In particular, the following factors are included in our control variable set, as they have been documented to affect investors' attention and(or) investors' reaction to earnings news: (1) Firm Size. Stocks in the sample are sorted based on their market capitalization and assigned into one of the ten *Size* deciles; (2) B/M (book-to-market ratio) deciles; Glamour stocks should be more-attention grabbling than value stocks.[1] (3) Friday dummy. Dellavigna and Pollet [2009] show that people tend to pay less attention to stock markets on Fridays as they are distracted by weekends, causing more pronounced under-reaction to earnings news on Fridays. (4) Number of analysts following the stock. Stocks with more analysts following should enjoy more attention from market participants and thus suffer less from investors' under-reaction. Analysts' data is obtained from I/B/E/S. (5) Share Turnover, which is the average monthly share trading volume divided by the average number of shares outstanding over the past 12 months before the announcement. This is also a proxy for investors' attention paid to a stock at normal times. (6) Number of competing announcements. According to Hirshleifer and Teoh [2003], other earnings announcements would significantly distract investors' attention, leading to more severe under-reaction. For each calendar quarter, we rank trading days based on the number of earnings announcements made on each day and assign trading days into ten deciles. Decile 10 indicates high distraction from competing firm's announcements; decile 1 means low distraction from other firms. (7) Institutional Ownership, which is the percentage of shares owned by

[1] Market capitalization is the number of ordinary shares multiplied by the month-end stock price; Book equity is computed according to the formula: $BE = TotalAsset - TotalLiability + DeferredTaxes - PreferredStockCapital$

financial institutions. Individual investors and institutional investors are found to have different levels of attention constraints and individual investors are documented to be more likely to buy attention-grabbing stocks. Moreover, Hirshleifer, Myers, Myers, and Teoh [2008] find that individual investors cause stronger post-earnings announcement drift. (8) Age, which is measured by the number of years elapsed since the firm first appears in CRSP. Older firms are supposed to be more attention-grabbing than younger firms (See Barber and Odean [2008]). (9) Indicator variables for months to control for the different responses to earnings news across quarters and within a quarter.

In this section, we focus on the earnings news with the biggest or lowest earnings surprise (FE1 and FE10). As analyzed before, the spread in abnormal trading volumes between announcement firms and no-announcement firms shrinks in the presence of market-level shocks. To investigate if the decrease in the spread is still statistically significant when we control for firm characteristics, we estimate the following regression model using a *Marketshock* dummy (1 for a market shock and 0 otherwise) and an *Announcement* dummy(1 for announcement stocks and 0 otherwise). The variable of interest to us is the interaction term between the Announcement dummy and the Marketshock Dummy as it captures the difference of the spreads in abnormal trading volumes between high-market-news days and low-market-news days (which is also called Difference in Difference). The estimation results are summarized in Table 2.5. Dependent variable $DVOL[0,1]$ is shown under each column heading, and independent variables are listed in the first column of the table.

$$\begin{aligned} DVOL[0,1] = \beta_0 + \beta_1 Announcement + \beta_2 Marketshock + \beta_3 Announcement \times Marketshock \\ + \sum_{i=1}^{n} c_i Control_i + \sum_{i=1}^{n} d_i (Announcement \times Control_i) + \varepsilon \end{aligned} \tag{2.8}$$

As can be seen in the table, the coefficient estimate of the interaction term of Marketshock and Announcement dummy is significantly negative in all regression models, which supports our prediction that when there is a market-wide shock, investors' trading volume response is less sensitive to earnings news, causing a

Table 2.5: DID: Determinants of Trading Volume Response DVOL[0,1]

The dependent variable DVOL[0,1] is the abnormal log dollar volume over announcement window (day 0 and day 1). Announcement is an indicator variable, which is 1 for announcement stocks and 0 otherwise. Market Shock is an indicator variable, which is equal to 1 for high-market-news days and 0 otherwise. Up Market is an indicator variable for market state, which is equal to 1 for Up Market and 0 for Down Market. Acc. Market Returns is the past 2 years' accumulated market returns. Control variable set contains *Size* deciles, *B/M ratio* deciles, *Age*, average *Share turnover* of the past 12 months, log of (1+Number of *Analysts*), Deciles of the number of *Competing News*, *Friday* dummy, *IO(Institutional Ownership)*, market abnormal trading volume, and indicator variables for months. Panel A reports the results of market distraction effects while Panel B reports the estimated coefficients of attention-related control variables. Standard errors adjusted for heteroskedasticity and clustering of the announcement day are reported in parentheses. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Market Distraction Effects | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] |
| Announcements | **0.675*** ** | **0.968*** ** | **0.592*** ** | **0.895*** ** | **0.663*** ** | **0.950*** ** |
| | (0.0114) | (0.0727) | (0.0189) | (0.0725) | (0.0120) | (0.0722) |
| Announce x Marketshock | **-0.174*** ** | **-0.169*** ** | **-0.155*** ** | **-0.153*** ** | **-0.163*** ** | **-0.160*** ** |
| | (0.0428) | (0.0405) | (0.0406) | (0.0384) | (0.0398) | (0.0381) |
| Announce x Up Market | | | **0.148*** ** | **0.127*** ** | | |
| | | | (0.0224) | (0.0219) | | |
| Announce x Acc. Market Returns | | | | | **0.276*** ** | **0.241*** ** |
| | | | | | (0.0418) | (0.0422) |
| Controls | | X | | X | | X |
| Constant | -0.00199 | -0.0134 | -0.00935 | -0.0170 | -0.00426 | -0.0142 |
| | (0.00390) | (0.0195) | (0.00631) | (0.0203) | (0.00406) | (0.0197) |
| Observation | 6,326,470 | 6,288,933 | 6,326,470 | 6,288,933 | 6,326,470 | 6,288,933 |
| $R^2$ | 0.002 | 0.015 | 0.002 | 0.015 | 0.002 | 0.016 |
| Panel B. Coefficients of Control Variables | | | | | | |
| Announce x Size | | **-0.0516*** ** | | **-0.0457*** ** | | **-0.0461*** ** |
| | | (0.00645) | | (0.00657) | | (0.00654) |
| Announce x B/M | | -0.00172 | | 0.00336 | | 0.00418 |
| | | (0.00571) | | (0.00570) | | (0.00573) |
| Announce x Turnover | | **0.204*** ** | | **0.225*** ** | | **0.228*** ** |
| | | (0.0407) | | (0.0406) | | (0.0405) |
| Announce x Age | | **0.0375*** ** | | **0.0355*** ** | | **0.0353*** ** |
| | | (0.0104) | | (0.0103) | | (0.0103) |
| Announce x Competing News | | **-0.0567*** ** | | **-0.0559*** ** | | **-0.0560*** ** |
| | | (0.00667) | | (0.00660) | | (0.00658) |
| Announce x Friday | | **-0.176*** ** | | **-0.168*** ** | | **-0.169*** ** |
| | | (0.0369) | | (0.0372) | | (0.0369) |
| Announce x IO | | **0.247*** ** | | **0.188*** ** | | **0.189*** ** |
| | | (0.0330) | | (0.0342) | | (0.0338) |

smaller spread in abnormal trading volumes between announcement stocks and other stocks. In addition, following Cooper, Gutierrez, and Hameed [2004]'s

definition of market state, we use dummy variable $UpMarket$ to examine the ostrich effect. Specifically, $UpMarket$ is equal to 1 when the announcement is made in an Up market and 0 for a Down market. The interaction term between the Up market dummy and the Announcement dummy is added to regressions (3) and (4) in Table 2.5, and the positive coefficients suggest that when earnings news is released in a rising market, people tend to react more to it on the announcement day than in a falling market. To ensure the robustness of the result, we replace the $UpMarket$ dummy with the corresponding lagged cumulated market returns in regressions (5) and (6). The result is not qualitatively changed.

Except for the size factor, coefficient estimates on the other control variables are consistent with our inattention conjecture. For instance, the coefficient for the Friday dummy is negative, suggesting that investors pay less attention to news on Fridays, and those news receive weaker immediate trading response. Also, as documented in Hirshleifer, Lim, and Teoh [2009], announcements made on high-competing-news days have experience more severe under-reaction, which is confirmed by the negative coefficient of *Competing News* in our model. Besides, turnover, age and institutional ownership seem to have positive effects on investors' immediate response to earnings announcements as all the coefficient estimates on these control variables are significantly positive, which is also consistent with the attention story: attention grabbing stocks tend to receive stronger trading volume response than firms which are less salient.

To control for the possible non-linear effect of earnings surprise on trading volume, we use an indicator variable for Earnings Surprise, which is equal to 1 for top-decile stocks (good-news stocks) and 0 for bottom-decile stocks (bad-news stocks). W also include market's abnormal trading volume during the same period in the following regression model to control for the market-wide variation in trading volumes. Market abnormal trading volume for each day is defined as the average abnormal trading volume for all the stocks listed in CRSP. Test results are summarized in Table 2.6. Panel A reports the estimated coefficients of Market Shocks and Market States while Panel B lists the estimated coefficients of the attention-related control variables. Standard errors adjusted for heteroskedastic-

ity and clustering of the announcement day are shown in parentheses.

$$DVOL[0,1] = \beta_0 + \beta_1 TopDecile + \beta_2 Marketshock + \sum_{i=1}^{n} c_i Control_i + \varepsilon \quad (2.9)$$

The coefficient estimate of the Marketshock dummy variable is significantly negative in all regression models, which supports our prediction: when there is a market-wide shock, investors tend to distracted away from firm-level news. Therefore, investors' trading volume response is less sensitive to earnings news and the positive coefficient of the market state dummy suggests that when earnings news is released in rising markets, people tend to react more to it on the announcement day than in falling markets.

In addition, coefficient estimates on the control variables are in general consistent with our inattention conjecture. It is worth mentioning that our market distraction effect is economically comparable to the Friday effects documented by Dellavigna and Pollet [2009] as the arrival of a market shock is associated with a 15% reduction in the abnormal trading volume of announcement stocks while Fridays on average cause a 18% decrease. (The sensitivity is $1.02 - 0.15 \times 1 = 0.87$ when the dummy variable $Marketshock = 1$ and 1.02 when $Marketshock = 0$.)

### 2.5.2 Post-announcement Drift- $CAR[2, 61]$

Cumulative abnormal returns ($CAR$) after announcements is the most important measure of investors' delayed reaction to earnings news. In this paper, we define it as the sum of the daily abnormal returns over the post-announcement window. In the literature, three benchmark models are widely used to measure abnormal returns: (1) Market Model; (2) Fama-French or other asset pricing models; (3) Matched Portfolio's returns. Daniel, Grinblatt, Titman, and Wermers [1997] find that firms' characteristics can explain the cross-section of average returns better than estimated covariance. Hence, we follow their method to form the matched portfolio as the return benchmark for each stock.

Firstly, 25 Size-B/M portfolios are constructed using all the listed stocks on NYSE, AMEX and NASDAQ by sorting size and B/M independently, and then

Table 2.6: Determinants of Trading Volume Response DVOL[0,1]

The dependent variable DVOL[0,1] is the abnormal log dollar volume over announcement window (day 0 and day 1). Market Shock is an indicator variable, which is equal to 1 for high-market-news days and 0 otherwise. Up Market is an indicator variable for market state, which is equal to 1 for Up Market and 0 for Down Market. Acc. Market Returns is the past 2 years' accumulated market returns. Control variable set contains *Size* deciles, *B/M ratio* deciles, *Age*, average *Share turnover* of the past 12 months, log of (1+Number of *Analysts*), Deciles of the number of *Competing News*, *Friday* dummy, *IO(Institutional Ownership)*, market abnormal trading volume, and indicator variables for months. Panel A reports the results of market distraction effects while Panel B reports the estimated coefficients of attention-related control variables. Standard errors adjusted for heteroskedasticity and clustering of the announcement day are reported in parentheses. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Market Distraction Effects | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] | DVOL[0,1] |
| Market Shock | **-0.150*** ** | **-0.137*** ** | **-0.140*** ** | **-0.145*** ** | **-0.133*** ** | **-0.135*** ** |
| | (0.0266) | (0.0261) | (0.0262) | (0.0265) | (0.0260) | (0.0262) |
| Up Market | | **0.0999*** ** | | | **0.0965*** ** | |
| | | (0.0168) | | | (0.0168) | |
| Acc. Market Returns | | | **0.216*** ** | | | **0.213*** ** |
| | | | (0.0310) | | | (0.0309) |
| Indicator of Top Decile | | | | X | X | X |
| Controls | X | X | X | X | X | X |
| Constant | **1.020*** ** | **0.961*** ** | **1.002*** ** | **0.956*** ** | **0.900*** ** | **0.939*** ** |
| | (0.0682) | (0.0685) | (0.0678) | (0.0670) | (0.0674) | (0.0668) |
| Observation | 12,213 | 12,213 | 12,213 | 12,213 | 12,213 | 12,213 |
| $R^2$ | 0.093 | 0.096 | 0.098 | 0.107 | 0.110 | 0.111 |
| Panel B. Attention-related Control variables | | | | | | |
| Size | **-0.0457*** ** | **-0.0415*** ** | **-0.0415*** ** | **-0.0494*** ** | **-0.0454*** ** | **-0.0454*** ** |
| | (0.00729) | (0.00736) | (0.00733) | (0.00726) | (0.00734) | (0.00731) |
| B/M | -0.000375 | 0.00357 | 0.00457 | -0.000288 | 0.00353 | 0.00458 |
| | (0.00559) | (0.00557) | (0.00560) | (0.00554) | (0.00552) | (0.00554) |
| Turnover | 0.0251 | 0.0403 | 0.0447 | 0.0254 | 0.0402 | 0.0448 |
| | (0.0411) | (0.0414) | (0.0413) | (0.0397) | (0.0400) | (0.0400) |
| Age | **0.0302*** ** | **0.0288*** ** | **0.0284*** ** | **0.0365*** ** | **0.0351*** ** | **0.0348*** ** |
| | (0.0102) | (0.0102) | (0.0101) | (0.0101) | (0.0101) | (0.0101) |
| Analyst | 0.00701 | 0.00816 | 0.00866 | 0.00974 | 0.0108 | 0.0113 |
| | (0.0138) | (0.0137) | (0.0137) | (0.0136) | (0.0136) | (0.0135) |
| Competing News | **-0.0689*** ** | **-0.0679*** ** | **-0.0678*** ** | **-0.0724*** ** | **-0.0713*** ** | **-0.0713*** ** |
| | (0.00595) | (0.00587) | (0.00586) | (0.00591) | (0.00583) | (0.00582) |
| Friday | **-0.185*** ** | **-0.178*** ** | **-0.179*** ** | **-0.183*** ** | **-0.177*** ** | **-0.177*** ** |
| | (0.0323) | (0.0325) | (0.0323) | (0.0322) | (0.0325) | (0.0322) |
| IO | **0.275*** ** | **0.230*** ** | **0.227*** ** | **0.256*** ** | **0.212*** ** | **0.208*** ** |
| | (0.0325) | (0.0330) | (0.0328) | (0.0324) | (0.0329) | (0.0327) |

each stock is matched with 1 of 25 size-B/M portfolios at the end of June based on its market capitalization at the end of June and Book to Market ratio at the

end of prior year.

Secondly, daily abnormal return (ABR) for each stock is computed as the difference between stock's return and the matched portfolio's equal-weighted return.

$$ABR_t = R_{i,t} - PR_t \tag{2.10}$$

where $R_{i,t}$is the stock return and $PR_t$ is the matched portfolio return.

Thirdly, abnormal cumulative abnormal returns over different time horizons are obtained by adding up the daily abnormal returns.

$$CAR[2,61] = \sum_{i=t+2}^{t+61} ABR_i \tag{2.11}$$

If the market distraction hypothesis holds, we should expect that for those announcements made on high-market-news days, their cumulative abnormal returns after announcements are larger than announcements made on low-market-news days after controlling for their earnings surprises and firm characteristics, as investors gradually shift their attention back to firm-specific news after they resolve market-wide uncertainty. In this section, we perform regression analysis on the post-announcement cumulative abnormal returns while controlling for other possible sources of variation in investors' responsiveness. Specifically, we focus on the top decile group (FE10) and the bottom decile group (FE1) and regress the Cumulative Abnormal Returns of 60 trading days after announcements $CAR[2,61]$ on the $TopDecile$ dummy variable. Hirshleifer, Lim, and Teoh [2009] notice that the relation between announcement day abnormal returns and earnings surprise is highly nonlinear as small negative surprises usually have disproportionately big effects. Hence, we use the decile dummy of earnings surprise instead of the surprise itself following the literature. Moreover, the market shock dummy variable and control variables are all interacted with $TopDecile$. The reason why we choose 60 trading days to measure post-announcement drift is because Bernard and Thomas [1989] document that most of the drift after earnings announcements is significant over the 60 trading days window. The OLS specification is

as follows.

$$CAR[2,61] = \beta_0 + \beta_1 TopDecile + \beta_2 Marketshock + \beta_3(TopDecile \times Marketshock) + \sum_{i=1}^{n} c_i Control_i + \sum_{i=1}^{n} d_i(TopDecile \times Control_i) + \varepsilon \tag{2.12}$$

The coefficient $\beta_1$ measures the returns to good-news stocks relative to bad-news stock and the coefficient $\beta_3$ measures the effects of market shock on the sensitivity of investors' delayed reaction to different news. If investors are distracted by market shock on the announcement day, the coefficient of the interaction term between earnings surprise and Market news dummy, $\beta_3$, should be positive, as the market shock which causes initial under-reaction leads to a larger difference in post-announcement returns between good-news stocks and bad-news stocks.

Table 2.7 summarizes the estimation results. Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are reported in parentheses. Dependent variable $CAR[2,61]$ is shown under each column heading, and independent variables are listed in the first column of the table. The estimates of control variables' coefficients are reported in panel B of Table 2.7. In regression (1), we examine the market distraction effects only and in regression (2) we add control variables to the model. The estimated coefficients of the interaction term $TopDecile \times Marketshock$ are positive and significant at the 1% level for both specifications, which supports our inattention hypothesis: Investor reacting less to earnings news on high-market-news days cause stronger post-announcement drifts. Specifically, the post-announcement differential drift at normal times is 10.6% and it is increased by 47.6% for high-market-news days. (The sensitivity is $0.106 + 0.0505 \times 1 = 0.1565$ when the dummy variable $Marketshock = 1$ and 0.106 when $Marketshock = 0$.

Another important determinant of investors' attention we aim to test is *Market State*, which is examined in regression (3) without control variables and regression (4) with control variables. According to 'Ostrich Effect' by Karlsson, Loewenstein, and Seppi [2009], rising markets should attract more attention from investors than falling markets. The estimated coefficient of the 'Up Market' dummy is negative and highly significant, which is consistent with their 'Ostrich

Table 2.7: Determinants of Post-Earnings-Announcement Drift CAR[2,61]

CAR[2,61] is the cumulative abnormal returns of stocks over the post-earnings-announcement window (day 2 to day 61). Market Shock is an indicator variable, which is equal to 1 for high-market-news days and 0 otherwise. Up Market is an indicator variable for market state, which is equal to 1 for Up Market and 0 for Down Market. Acc. Market Returns is the past 2 years' accumulated market returns. Control variable set contains *Size* deciles, *B/M ratio* deciles, *Age*, average *Share turnover* of the past 12 months, log of (1+Number of *Analysts*), Deciles of the number of *Competing News*, *Friday* dummy, *IO(Institutional Ownership)* and indicator variables for months. All the control variables are interacted with TopDecile dummy. Panel A reports the results of market distraction effects while Panel B reports the estimated coefficients of attention-related control variables. Standard errors adjusted for heteroskedasticity and clustering of the announcement day are reported in parentheses. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Market Distraction Effects | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | CAR[2,61] | CAR[2,61] | CAR[2,61] | CAR[2,61] | CAR[2,61] | CAR[2,61] |
| *Top Decile* | **0.106*** ** | **0.217*** ** | **0.128*** ** | **0.231*** ** | **0.109*** ** | **0.219*** ** |
| | (0.00519) | (0.0459) | (0.00843) | (0.0462) | (0.00543) | (0.0457) |
| *Market Shock* | -0.00266 | -0.00339 | -0.00271 | -0.00443 | -0.00359 | -0.00472 |
| | (0.0132) | (0.0121) | (0.0133) | (0.0122) | (0.0131) | (0.0121) |
| *Top D X Market Shock* | **0.0505*** ** | **0.0496*** ** | **0.0459*** ** | **0.0461*** ** | **0.0479*** ** | **0.0475*** ** |
| | (0.0164) | (0.0159) | (0.0163) | (0.0157) | (0.0162) | (0.0156) |
| *Top D X Up Market* | | | **-0.0385*** ** | **-0.0273*** ** | | |
| | | | (0.00996) | (0.0102) | | |
| *Top D X Acc. Market Returns* | | | | | **-0.0608*** ** | **-0.0449** ** |
| | | | | | (0.0191) | (0.0195) |
| *Controls (Interacted)* | | X | | X | | X |
| *Constant* | **-0.0457*** ** | **-0.132*** ** | **-0.0455*** ** | **-0.127*** ** | **-0.0451*** ** | **-0.130*** ** |
| | (0.00406) | (0.0340) | (0.00687) | (0.0345) | (0.00436) | (0.0340) |
| *Observation* | 13,174 | 13,051 | 13,174 | 13,051 | 13,174 | 13,051 |
| $R^2$ | 0.042 | 0.055 | 0.044 | 0.057 | 0.045 | 0.058 |
| Panel B. Attention-related Control Variables | | | | | | |
| *Top D X Size* | | **-0.00927*** | | **-0.00969*** | | **-0.00932*** |
| | | (0.00545) | | (0.00549) | | (0.00551) |
| *Top D X B/M* | | 0.00235 | | 0.00143 | | 0.00158 |
| | | (0.00352) | | (0.00354) | | (0.00355) |
| *Top D X Turnover* | | -0.0272 | | -0.0326 | | -0.0321 |
| | | (0.0331) | | (0.0331) | | (0.0330) |
| *Top D X Age* | | -0.00234 | | -0.00162 | | -0.00173 |
| | | (0.00690) | | (0.00690) | | (0.00691) |
| *Top D X Analyst* | | -0.0132 | | -0.0134 | | -0.0132 |
| | | (0.0111) | | (0.0111) | | (0.0111) |
| *Top D X Competing News* | | -0.00287 | | -0.00301 | | -0.00307 |
| | | (0.00391) | | (0.00389) | | (0.00389) |
| *Top D X Friday* | | 0.0238 | | 0.0223 | | 0.0221 |
| | | (0.0213) | | (0.0210) | | (0.0209) |
| *Top D X IO* | | **-0.0704*** ** | | **-0.0586*** ** | | **-0.0612*** ** |
| | | (0.0214) | | (0.0219) | | (0.0222) |

Effect' hypothesis. The delayed response to earnings news is economically smaller (by 30%) in Up Market than in Down market. For robustness check, we also use the past 2 years' cumulative value-weighted market return to replace $UpMarket$ in regressions (5) and (6) and the conclusion still holds.

Panel B of the table presents the estimated coefficients of the control variables. Except for size and competing news, the results for the other factors all suggest that firms which are more salient to investors suffer less from investors' under-reaction and the delayed response to their earnings news is also smaller. More importantly, we can see that share turnover, age, analyst coverage, Friday dummy and institutional ownership all have opposite impacts on immediate reaction $DVOL[0,1]$ and post-announcement drift $CAR[2,61]$. The opposite signs of the control variables confirm the investor under-reaction hypothesis as a variable which affects the degree of under-reaction on announcement days should have opposite effects on the post-announcement drift.

### 2.5.3 Speed of Correction

If investors underreact to earnings news at announcement, they will adjust their initial assessments during post-announcement periods. This section aims to find out when investors shift their attention back to earnings news after market shock, and how long the market distraction effect lasts. For this purpose, we perform regression analysis of the post-announcement cumulative returns over different post-event horizons.

In Table 2.8, we examine various post-announcement windows, which are shown under the headings of the columns. Panel A suggests that investors shift their attention back to earnings news quickly after market shock, as the estimated coefficient of the term $TopD \times Marketshock$ for window [2,15] is already significant. This is consistent with the findings of Peng, Xiong, and Bollerslev [2007] from their high-frequency trading data. In contrast, Hirshleifer, Lim, and Teoh [2009] document that the distraction effects of competing earnings news on the post-announcement returns become significant only 45 days after announcements.

To see how long the market distraction effect persists, we also move the post-announcement window from [2,30] to [30, 60] and [60, 90] respectively. Results

Table 2.8: Speed of Correction

Different post-announcement windows are examined for investors' delayed response to earnings news. CAR[i,j] indicates the cumulative abnormal returns between day i and day j after the earnings announcement. Dependent variables are shown under the heading of each column. Market Shock is an indicator variable, which is equal to 1 for high-market-news days and 0 otherwise. Control variable set contains *Size* deciles, *B/M ratio* deciles, *Age*, average *Share turnover* of the past 12 months, log of (1+Number of *Analysts*), Deciles of the number of *Competing News*, *Friday* dummy, *IO(Institutional Ownership)* and indicator variables for months. All the control variables are interacted with the TopDecile dummy. Standard errors adjusted for heteroskedasticity and clustering of the announcement day are reported in parentheses. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Post-Earnings-Announcement Drift Over Different Horizons | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | CAR[2,15] | CAR[2,30] | CAR[2,45] | CAR[2,61] | CAR[2,90] |
| *Top Decile* | 0.0295 | **0.122*** ** | **0.181*** ** | **0.231*** ** | **0.214*** ** |
| | (0.0263) | (0.0339) | (0.0414) | (0.0462) | (0.0539) |
| *Market Shock* | **-0.0137** ** | -0.00682 | -0.00341 | -0.00443 | 0.00599 |
| | (0.00619) | (0.00843) | (0.0106) | (0.0122) | (0.0161) |
| *Top D X Market Shock* | **0.0255*** ** | **0.0266** ** | **0.0410*** ** | **0.0461*** ** | 0.0253 |
| | (0.00786) | (0.0111) | (0.0147) | (0.0157) | (0.0192) |
| *Controls (Interacted)* | X | X | X | X | X |
| *Constant* | -0.0170 | **-0.0909*** ** | **-0.114*** ** | **-0.127*** ** | **-0.0932** ** |
| | (0.0201) | (0.0260) | (0.0311) | (0.0345) | (0.0416) |
| *Observations* | 13,051 | 13,051 | 13,051 | 13,051 | 12,959 |
| $R^2$ | 0.030 | 0.047 | 0.051 | 0.057 | 0.036 |
| Panel B. Post-Earnings-Announcement Drift Over Different Event Windows | | | | | |
| | (1) | (2) | (3) | | |
| | CAR[2,30] | CAR[30,60] | CAR[60,90] | | |
| *Top Decile* | **0.122*** ** | **0.114*** ** | -0.0132 | | |
| | (0.0339) | (0.0312) | (0.0340) | | |
| *Market Shock* | -0.00682 | 0.00620 | 0.00524 | | |
| | (0.00843) | (0.00949) | (0.0124) | | |
| *Top D X Market Shock* | **0.0266** ** | 0.0167 | -0.0120 | | |
| | (0.0111) | (0.0121) | (0.0156) | | |
| *Controls (Interacted)* | X | X | X | | |
| *Constant* | **-0.0909*** ** | **-0.0436** * | 0.0398 | | |
| $R^2$ | (0.0260) | (0.0232) | (0.0253) | | |
| *Observations* | 13,051 | 13,051 | 12,959 | | |
| | 0.047 | 0.023 | 0.005 | | |

are reported in Panel B of Table 2.8. Column (1) in the table shows that the coefficient of the interaction term is significantly positive for the post-event window $[2, 30]$ (day 2 to day 30). However, this effect disappears for the period

between day 30 and day 60 (see column (2)). While the coefficient estimates for $TopDecile$ is still significantly positive, the coefficient of $TopD \times Marketshock$ becomes insignificant, which suggests that people still adjust their assessment during this post-event period $[30, 60]$. Nevertheless, the distraction of Market shock does not influence their adjustment anymore. Therefore, the part of under-reaction to earnings news due to market shock is corrected within 1 month after announcements for our sample period. Moreover, the underrection effect is not evident anymore for the post-event window $[60, 90]$ (See column (3)), as the coefficient estimate of $TopDecile$ is not significant either, which confirms Bernard and Thomas [1989]'s conclusion that most of the earnings news drift occurs in three calendar months (about 60 trading days) following announcements.

### 2.5.4 Total Reaction

Table 2.9 investigates the impacts of market shocks on investors' long-term response to earnings news. Specifically, we calculate the cumulative abnormal returns of stocks between day 0 and 60 (or 90) in order to see if the total reaction is affected by market distracting news and the market state. As shown in the table, when there is market distracting news on the earnings announcement day, investors' total reaction to earnings news is 28% larger compared with other trading days. (28% is obtained by dividing the coefficient of $TopDecile$ by the coefficient of the interaction term $TopD \times MarketShock$.) In addition, investors in Down Market react more strongly to earnings news in the long run than in Up Markets, as the coefficient for $TopD \times UpMarket$ is significantly negative. Interestingly, this result echoes Dellavigna and Pollet [2009]'s Friday effect. Dellavigna and Pollet [2009] find that the long-term response to Friday's earnings announcement is larger than to other earnings announcements. It seems that investors who are initially distracted away from earnings news will actually trade more on these news to correct their previous under-reaction, causing larger price reaction in the long run.

Table 2.9: Total Reaction to Earnings Announcements

Long-term response to earnings news is measured by the cumulative abnormal returns at announcement and after announcement. CAR[0,61] is the cumulative abnormal returns between day 0 and day 61. CAR[0,90] is the cumulative abnormal returns between day 0 and day 90. Market Shock is an indicator variable, which is equal to 1 for high-market-news days and 0 otherwise. Up Market is an indicator variable for market state, which is equal to 1 for Up Market and 0 for Down Market. Control variable set contains *Size* deciles, *B/M ratio* deciles, *Age*, average *Share turnover* of the past 12 months, log of (1+Number of *Analysts*), Deciles of the number of *Competing News*, *Friday* dummy, *IO(Institutional Ownership)* and indicator variables for months. All the control variables are interacted with Top Decile dummy. Standard errors adjusted for heteroskedasticity and clustering of the announcement day are reported in parentheses. Sample period is from January 2001 to December 2010. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | CAR[0,61] | CAR[0,61] | CAR[0,61] | CAR[0,90] | CAR[0,90] | CAR[0,90] |
| *Top Decile* | **0.222*** ** | **0.257*** ** | **0.366*** ** | **0.213*** ** | **0.244*** ** | **0.351*** ** |
| | (0.0054) | (0.0085) | (0.0475) | (0.0063) | (0.0095) | (0.0553) |
| *Market Shock* | -0.0192 | | -0.0175 | -0.0073 | | -0.0071 |
| | (0.0128) | | (0.0121) | (0.0159) | | (0.0153) |
| *Top D X Up Market* | **0.0621*** ** | | **0.0527*** ** | **0.0428** ** | | **0.0318*** |
| | (0.0167) | | (0.0161) | (0.0194) | | (0.0193) |
| *Market State* | | 0.0017 | -0.0036 | | -0.0080 | -0.0129 |
| | | (0.0078) | (0.0080) | | (0.0090) | (0.0095) |
| *Top D X Up Market* | | **-0.0534*** ** | **-0.0440*** ** | | **-0.0487*** ** | **-0.0385*** ** |
| | | (0.0103) | (0.0105) | | (0.0120) | (0.0124) |
| *Controls (interacted)* | | | X | | | X |
| *Constant* | **-0.104*** ** | **-0.107*** ** | **-0.178*** ** | **-0.0978*** ** | **-0.0944*** ** | **-0.146*** ** |
| | (0.0040) | (0.0064) | (0.0340) | (0.0046) | (0.0072) | (0.0411) |
| *Observation* | 13,174 | 13,174 | 13,051 | 13,079 | 13,079 | 12,959 |
| $R^2$ | 0.149 | 0.151 | 0.163 | 0.099 | 0.102 | 0.11 |

## 2.6 Trading Strategies and Market Distraction Effects

An alternative way of testing for investors' under-reaction and the magnitude of the market distraction effects is through the abnormal profits that can be generated from trading strategies that exploits investors' inattention. The conjecture is that if investors are distracted by market-level news, then the stronger return continuation after earnings announcements should bring about larger profits than other times.

### 2.6.1 Profitability of the 'PEAD' Portfolios

Following Jegardeesh and Titman [1993], we employ a rolling portfolio strategy which consists of long positions in good-news stocks and short positions in bad-news stocks to exploit the post-earnings announcement drift (PEAD). The sample period is from January 1986 to December 2010.[1] At the end of each month, earnings announcements which are released on that month are ranked into 5 quintiles based on their Forecast Error (earnings surprise) and then we buy stocks with the highest earnings surprise ($FE5$) and short-sell stocks with the lowest earnings surprise ($FE1$). This zero-cost portfolio is held for one month and rebalanced at the end of next month. The monthly portfolio returns are the equal-weighted average of individual stock's returns.

To assess the performance of this trading strategy, we regress portfolio's monthly returns on Fama-French risk factors and Carhart's Momentum factor [2], and the abnormal return should be captured by the constant term $\alpha$, which is the unexplainable part of the returns by risk factors. Newey-West standard errors with 12 lags are reported in parentheses. Panel B of Table 2.9 shows the average monthly return and the alpha (monthly abnormal return) of the trading strategy for the full sample. Consistent with existing papers (e.g. Jegardeesh and Titman [1993] and Chan, Jegadeesh, and Lakonishok [1996]), this 'PEAD' portfolio yields abnormally high returns which cannot be explained by traditional asset pricing models. As summarized in the table, the average monthly return of this portfolio is 1.73% and the abnormal return is 1.64%.

$$ERet = \alpha + \beta_1 \times Market + \beta_2 \times SMB + \beta_3 \times HML + \beta_4 \times Momentum + \varepsilon \quad (2.13)$$

In order to study the effects of market shocks, we use monthly volatility of VIX to measure the aggregate amount of market distracting news. We assume that volatile VIX indicates large amount of market news/shocks. If earnings

[1] The reason for choosing this sample period is because VIX data is available only starting from year 1986.

[2] Some stocks' return continuation might be caused by price momentum rather than earnings drift. To address this issue, we use Momentum factor to control for past winner and past loser's influence.

announcements are made on high-market-news months (characterized by highly volatile VIX), they should experience stronger post-announcement drift, which leads to higher abnormal returns of our 'PEAD' portfolios. Monthly volatilities of VIX are computed for the full sample period (1986-2010) and sorted into ten deciles. The months in the top decile are defined as high-market-news months. Summary statistics of the monthly volatility of VIX can be found in Panel A of Table 2.10. By comparing the abnormal returns from earnings announcements made on these high-market-news months with the rest of the sample period, we can see that larger abnormal profits can be generated following high-market-news months. As shown in panel B of Table 2.10, the average monthly return for the high-news months is 2.39%, which is almost 1.5 times as much as for the other months. After adjusted for risks, the zero-cost portfolios formed after high-market-news months also yield higher alpha than the other months. In addition, the comparison of Sharpe ratios also indicate that the impacts of the market distraction effect on our 'PEAD' portfolio is economically considerable.[1]

To further examine if the market distraction effect is statistically significant, we regress the portfolios' monthly returns on the common risk factors and the VIX Dummy which equals 1 for high-news months and 0 otherwise. To ensure the robustness of our regression results, we also replace the VIX Dummy with monthly volatility level of VIX. Results are shown under model specifications (1) and (2) in panel C of Table 2.10. Newey-West standard errors with 12 lags are reported in parentheses. The coefficient of VIX Dummy is positive and highly significant, implying that portfolios constructed at the end of high-market-news months generate superior abnormal returns. On average, high-market-new months generate around 1% higher abnormal return than the other months. Moreover, this result does not change qualitatively when the absolute level of volatility of VIX is used (see regression (2)).

$$ERet = \alpha + \beta_1 \times Market + \beta_2 \times SMB + \beta_3 \times HML + \beta_4 \times Momentum + \beta_5 \times VIXDummy + \varepsilon \tag{2.14}$$

[1]The annualized Sharpe ratio is the annualized portfolio return divided by the annualized volatility.

Table 2.10: Zero-cost Portfolios and Alphas

For each month from January 1986 to December 2010, we sort stocks with earnings announcements into five quintiles based on their earnings surprise (Forecast Error) and then construct a zero-cost portfolio by buying the stocks with the highest earnings surprise (FE5) and selling the stocks with the lowest earnings surprise (FE=1) for the purpose of exploiting the post-earnings-announcement drift. This portfolio is held for one month and rebalanced at the end of next month. The equal-weighted returns of the portfolio is calculated every month and regressed on the widely used Fama-French factors and Momentum factor to obtain the values of Alphas. The variable VIX Dummy is equal to 1 if the portfolio is formed at the end of the high-market-news month and 0 otherwise. Panel A of the table reports the summary statistics of the volatility of VIX. Panel B compares the performance of different samples. High-market-news refers to the months which experienced the highest (top 10%) volatility of VIX. Panel C summarizes the regression results of the portfolio's first month's returns and the second months' returns on the VIX Dummy (or the volatility of VIX) and risk factors. Newey-West standard errors with 12 lags are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| Panel A. Volatility of VIX | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | St.Dev | P10 | Median | P90 | No. obs |
| VIX VOL | 1.97 | 2.76 | 0.63 | 1.42 | 3.41 | 300 |

| Panel B. Four Factors Alphas(Monthly Returns) | | | | | | |
|---|---|---|---|---|---|---|
| | FE1(Bad news) Alpha | FE5(Good news) Alpha | FE5-FE1 Alpha | FE5-FE1 Sharpe Ratio | FE5-FE1 Monthly Return | No. obs |
| Full sample | **-0.66%*** ** | **0.98%*** ** | **1.64%*** ** | 1.67 | 1.73% | 299 |
| High-Market-News | **-1.39%*** | **0.78%** | **2.17%*** ** | 2.17 | 2.39% | 31 |
| Other months | **-0.60%*** ** | **0.85%*** ** | **1.45%*** ** | 1.59 | 1.65% | 268 |

| Panel C. Regression Analysis (Zero-cost Portfolios) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | *The First Holding Month* | | | | | | *The Second Holding Month* | |
| | (1) FE5-FE1 | (2) FE5-FE1 | (3) FE5-FE1 | (4) FE5-FE1 | (5) FE5-FE1 | (6) FE5-FE1 | (7) FE5-FE1 | (8) FE5-FE1 |
| Alpha | **0.0151*** ** | **0.0146*** ** | **0.0173*** ** | **0.0159*** ** | **0.0176*** ** | **0.0158*** ** | **0.0104*** ** | **0.0101*** ** |
| | (0.00197) | (0.00210) | (0.0036) | (0.0022) | (0.0038) | (0.0023) | (0.0019) | (0.0017) |
| VIX Dummy | **0.0106*** | | **0.0099*** | **0.0101*** | | | -0.0058 | |
| | (0.00595) | | (0.0058) | (0.0059) | | | (0.0056) | |
| VIX Volatility | | **0.0008*** ** | | | **0.0008*** ** | **0.0008*** ** | | -0.0002 |
| | | (0.0003) | | | (0.0003) | (0.0003) | | (0.0003) |
| Up Market Dummy | | | -0.0026 | | -0.0036 | | | |
| | | | (0.0043) | | (0.0044) | | | |
| Acc. Market Returns | | | | -0.0031 | | -0.0049 | | |
| | | | | (0.0059) | | (0.0054) | | |
| Market factor | **0.0871** ** | **0.0882** ** | **0.0880** ** | **0.0873** ** | **0.0896** ** | **0.0892** ** | **0.0887** ** | **0.0895** ** |
| | (0.0385) | (0.0400) | (0.0391) | (0.0386) | (0.0405) | (0.0398) | (0.0407) | (0.0415) |
| SIZE factor | **-0.124*** | **-0.126*** | **-0.128*** | **-0.129*** | **-0.132*** | **-0.134*** | **-0.288*** ** | **-0.285*** ** |
| | (0.0732) | (0.0736) | (0.0723) | (0.0701) | (0.0726) | (0.0705) | (0.0603) | (0.0607) |
| B/M | -0.0591 | -0.0711 | -0.0600 | -0.0596 | -0.0711 | -0.0704 | **-0.284*** ** | **-0.276*** ** |
| | (0.0706) | (0.0700) | (0.0706) | (0.0706) | (0.0700) | (0.0701) | (0.0981) | (0.0986) |
| Momentum | **0.159*** ** | **0.152*** ** | **0.160*** ** | **0.161*** ** | **0.155*** ** | **0.156*** ** | **0.134*** ** | **0.136*** ** |
| | (0.0485) | (0.0513) | (0.0486) | (0.0483) | (0.0507) | (0.0502) | (0.0416) | (0.0417) |
| No. obs | 299 | 299 | 299 | 299 | 299 | 299 | 298 | 298 |

In regressions (3) to (6), the Up Market dummy and the past 2 years' market cumulative returns are included into the regression models to see if market state also affects the profitability of our trading strategy. If investors' attention level is determined by market state, then post-announcement drift should be weaker

and abnormal returns should be smaller when earnings news are released in Up markets than in Down markets. Our finding is consistent with this 'Ostrich effect' hypothesis as the coefficients for Up Market dummy and the cumulative market returns are both negative.

As shown in the analysis on the speed of correction, the distraction effect of market shock is not significant anymore 1 month after the shock. We should therefore expect that the market distracting effect news has no impacts on the profitability of the long-short portfolio one month after the shock. To test this hypothesis, we extend the holding period of the long-short portfolios from 1 month to 2 months and examine the abnormal returns for the second holding month as well. Under model specification (7) and (8), the dependent variable is the portfolio returns of the second holding month while the independent variable remain the same. As can be seen in Table 2.10, the 'PEAD' portfolio still yields abnormal returns in the second month, which is manifested by the positive alpha, although its magnitude is diminished compared with the one of the first holding month. This result also echoes the findings in the literature that post-earnings-announcement drifts lasts up to 3 months. Nevertheless, the market distraction effect disappears as the coefficients of the VIX Dummy and the VIX Volatility are not significant anymore, which supports our previous conclusion that the initial under-reaction to earnings news due to market shocks can be corrected within 1 month after the announcements.

### 2.6.2 Robustness Check: Liquidity Risk

Since the PEAD portfolio needs to be frequently rebalanced, one must bear liquidity risk while engaging in trading this market anomaly. Sadka [2006] finds that market-wide liquidity fluctuation can account for between 40% and 80% of the cross-sectional variation of the momentum and PEAD portfolio returns. Pastor and Stambaugh [2003] also suggest that the innovations of their liquidity factor can explain half of the profits from a momentum portfolio. To see whether the abnormally high returns during periods of highly volatile VIX are caused by liquidity factors, we add the liquidity proxies proposed by Amihud [2002], Sadka [2006] and Pastor and Stambaugh [2003] to our previous regressions, respectively.

Table 2.11: Robustness Check: Liquidity Risk

The liquidity measures proposed by Amihud [2002], Sadka [2006] and Pastor and Stambaugh [2003] are added to the previous regressions to examine the impacts of liquidity risk on the rolling portfolio's returns. The sample period is from January 1986 to December 2010. The dependent variables are the zero-cost portfolio's monthly returns. VIX Volatility is the monthly volatility of index VIX. Amihud Level is the monthly level of illiquidity calculated based on Amihud [2002]. Amihud Innovation is the residuals of second-order autoregression of the Amihud Level. PS Level is the aggregate level of Pastor-Stambaugh market liquidity measure. PS Innovation is the monthly innovation in aggregate liquidity. Sadka FT is Sadka's Fixed-Transitory component of market liquidity. Sadka VP is Sadka's Variable-Permanent component of market liquidity. Newey-West standard errors with 12 lags are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

| | (1) FE5-FE1 | (2) FE5-FE1 | (3) FE5-FE1 | (4) FE5-FE1 | (5) FE5-FE1 | (6) FE5-FE1 |
|---|---|---|---|---|---|---|
| *Alpha* | **0.0105*** ** | **0.0146*** ** | **0.0146*** ** | **0.0143*** ** | **0.0147*** ** | **0.0151*** ** |
| | (0.00221) | (0.00201) | (0.00211) | (0.00245) | (0.00210) | (0.00223) |
| *VIX Volatility* | **0.000793*** ** | **0.000783** ** | **0.00107** ** | **0.000982** ** | **0.000748** ** | **0.000583** * |
| | (0.000285) | (0.000316) | (0.000497) | (0.000471) | (0.000342) | (0.000331) |
| *Amihud Level* | **0.000316*** ** | | | | | |
| | (7.10e-05) | | | | | |
| *Amihud Innovation* | | **0.000199** * | | | | |
| | | (0.000104) | | | | |
| *PS Level* | | | 0.0185 | | | |
| | | | (0.0365) | | | |
| *PS Innovation* | | | | 0.0136 | | |
| | | | | (0.0406) | | |
| *Sadka FT* | | | | | **-0.987** * | |
| | | | | | (0.448) | |
| *Sadka VP* | | | | | | -0.413 |
| | | | | | | (0.326) |
| *Fama French Factors* | YES | YES | YES | YES | YES | YES |
| *Momentum Factor* | YES | YES | YES | YES | YES | YES |
| *No. obs* | 299 | 299 | 299 | 299 | 299 | 299 |

[1] Estimation results are summarized in Table 2.11, in which the dependent vari-

[1]Following Amihud [2002], we calculate the individual stock's daily illiquidity as the ratio of its absolute return to the dollar trading volume and then average cross the trading days in that month to obtain the monthly illiquidity ratio. The monthly stock market illiquidity is the equal-weighted average of illiquidity ratios across stocks. In Sadka [2006], liquidity measure is defined as the price-impact caused by trades, and it consists of fixed and variable components. He uses intra-day trades data to estimate the price-impacts components of each firm every month, and market aggregate liquidity components are just the equal-weighted averages of the firms' estimate. The shocks extracted from each time series of market aggregate components are regarded as systematic liquidity factors. Pastor and Stambaugh [2003] use daily data of stock returns to measure the extent to which a given dollar trading volume causes stock's return

able is the monthly return of the 'PEAD' portfolio and the independent variables including the liquidity factors are displayed in the first column of the table.

In regressions (1) through (6), the Amihud's levels, Amihud's innovations, the Pastor-Stambough (PS hereafter) liquidity levels, PS innovations and Sadka's two liquidity components are examined respectively. Table 2.11 suggests that the market distraction effect is highly robust after we control for liquidity risk, as the coefficient of the volatility of VIX is significantly positive throughout the 6 model specifications. Moreover, out of the 6 liquidity measures, only Amihud's levels, innovations and Sadka's FT(Fixed-Transitory) component significantly influence the returns of our trading strategy. Specifically, positive FT liquidity shocks are negatively associated with portfolio returns. In other words, the more liquid the market is, the lower returns the PEAD portfolio can generate. This finding is consistent with the notion that investors must be compensated with high returns when they purchase illiquid assets. Since Amihud's measures capture the illiquidity of the market, the positive signs of the estimated coefficients also suggest the same.

## 2.7 Timing of Earnings Announcements

Our previous analyses suggest that investors tend to be distracted when there is market distracting news and thus react less to firms' earnings announcements than usual times. In this section, we investigate if managers take into the account the market distraction effects when they disclose firms' earnings information. Intuitively speaking, managers with good earnings news should have an incentive to avoid announcing news when investors are likely to be distracted. When it comes bad earnings news, there are two opposing factors which might affect managers' decision. On one hand, investors might react less to firm-level news on the announcement day when there is market distracting news and cause overpricing of the bad-news stocks in the short run. On the other hand, the total reaction to

reversal on the subsequent day. They compute the market liquidity level as the equal-weighted average of all the individual stocks' volume-related return reversal tendency on a monthly basis. Their idea is that in a market which is not perfectly liquid, order flows can move prices which are expected to partially reversed in the future. The monthly data on Pastor-Stambough 's and Sadka's liquidity factors are obtained from WRDS.

Table 2.12: Descriptive Statistics of 7 Macroeconomic Announcements

Panel A describes the 7 Macroeconomic Announcements which are examined in this paper. BLS: U.S. Bureau of Labor Statistics; BC: U.S. Bureau of the Census; BEA: U.S. Bureau of Economic Analysis. Panel B distinguishes the trading days with Macro-Announcements from the days without Macro-Announcements. Macro Announcements which were made on Saturdays or Sundays or when the stock market was closed are excluded from our sample.

| Panel A. Macro Announcements | | | | |
|---|---|---|---|---|
| Macro Indicator | Obs. | Frequency | Sample Period | Source |
| *CPI (Consumer Price Index)* | 120 | Monthly | 01/2010- 12/2010 | BLS |
| *PPI (Producer Price Index)* | 119 | Monthly | 01/2010- 12/2010 | BLS |
| *Unemployment* | 118 | Monthly | 01/2010- 12/2010 | BLS |
| *Housing Starts* | 120 | Monthly | 01/2010- 12/2010 | BC |
| *New Home Sales* | 119 | Monthly | 01/2010- 12/2010 | BC |
| *Trade Balance* | 119 | Monthly | 01/2010- 12/2010 | BEA |
| *GDP final* | 40 | Quarterly | 01/2010- 12/2010 | BEA |

| Panel B. Trading Days by Macro Announcement Status | | |
|---|---|---|
| | No. of Days | % of Days |
| Full sample | 2515 | |
| *With Announcements* | 678 | 26.96% |
| *Without Announcements* | 1837 | 73.04% |

bad news stocks tend to be higher than other times (as shown in Table 2.9).

Specifically, we investigate if managers try to avoid macro-economic announcements days when they have earnings news to release. The reason why we choose macro-economic announcements is because these announcements are believed to convey important information on economic fundamentals and are documented to have substantial impacts on the aggregate stock market. Moreover, their release dates are usually scheduled in advance. Therefore, firm managers should have enough time to respond and strategically change their news release dates. Among all the macro announcements, we focus on CPI, Housing, Newhome, PPI, Trade imbalance, Unemployment and GDP, because these indicators have been found to significantly influence the stock market and other financial markets. (See Flannery and Protopapadakis [2002] and Andersen, Bollerslev, Diebold, and Vega [2007].) Descriptive statistics of the 7 macro announcements are presented in Table 2.12.

Firstly, we calculate the total number of earnings news for days of the week and months of the year to see the distribution of earnings announcements in our

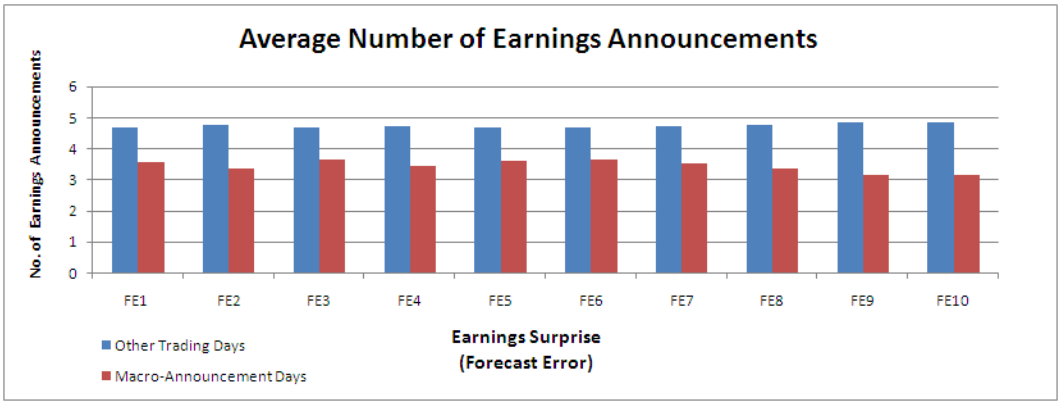



Figure 2.1: Average number of earnings announcements

sample period. As can be seen in panel A of Table 2.13, the release of earnings news exhibits strong seasonal patterns. The number of earnings announcements increases steadily from Monday to Thursday and drops sharply on Friday, which has the least earnings news release. Moreover, March, June, September and December tend to have much fewer earnings announcements than other months. This pattern holds across earnings news of different nature.

Secondly, taking into account the seasonal patterns of the earnings news release, we regress the number of the announcements for each trading day on the macroeconomic indicator variable, which is equal to 1 when there is at least one of the 7 macro announcements and 0 otherwise. Specifically, a Tobit regression model is employed to estimate the effects of the macro-announcements as the number of earnings announcements with a lower bound 0 do not follow a normal distribution and the traditional OLS estimators would be biased as well as inconsistent. Announcements made on holidays or weekends are excluded from the sample. Estimation results are reported in panel B of Table 2.13. After adjusting for the seasonality, we find that managers are less likely to release earnings news on days which have macroeconomic announcements as the coefficient of the Macro-dummy is significantly negative as shown in Table 2.13. Moreover, on a macro announcement days, the total number of earnings news is significantly reduced by more than 15% on average. (The average number of announcement is 46 across the sample and it is decreased by 7 on macro announcement days.)

This tendency holds across most types of news and is most pronounced for managers who have favorable news to release (FE8, FE9 and FE10). Figure 2.1 shows the average number of earnings announcements with and without macro-announcements, respectively. To see the effects of each type of macro announcement, we replace the Macro Dummy with 7 indicator variables for the macro announcements. panel C reveals that except for New Home Sales, all the other announcements are associated with fewer earnings news release, which suggests that macro announcements in general cause fewer earnings announcements.

Thirdly, to see if managers with good news/bad news to release have a stronger propensity to avoid the macro-announcement days compared with other managers, we calculate the fraction of earnings news (which is the number of each FE category announcements divided by the total number of announcements on that trading day), and regress the fractions of announcements on the independent variables of interest. A Tobit regression is conducted to estimate the coefficients of the macro dummies. Panel D and E of Table 2.13 confirm that managers with favorable earnings news to announce are more likely to shun macro-news compared to other managers. The proportion of the best earnings news (FE10) significantly decreases on macro announcement days as the coefficient of the Macro Dummy is significantly negative in regression (10) in panel D of the table. [1]

[1]We also analyse the effect of Macro announcement on the frequency of earnings news. Specifically, we calculate the ratio of the number of earnings announcement to the total number of announcements over the calendar quarter to control for the seasonal variance on the number of announcements. The main conclusions are qualitatively unchanged. Regression analysis on this ratio is included in Appendix A.

Table 2.13: Timing of Earnings Announcements

Panel A of this table shows the summary statistics of the number of earnings news and its distributions over days and months. FE is the earnings surprise decile. FE1 refers to stocks which have the lowest forecast errors. FE10 refers to stocks which have the highest forecast errors. Panel B presents test results of the effects of macroeconomic announcements on the number of earnings news release. The dependent variables are the number of earnings news, shown on each column heading. N is the total number of earnings announcements. NFE1 is the number of earnings news with lowest earnings surprise. NFE10 is the number of earnings news with highest earnings surprise. Macro Dummy is an indicator variable, which equals 1 when there is at least one of the 7 macro announcements, and 0 otherwise. Indicator variables for days and months are also included in the regressions. Announcements made on Saturdays or Sundays are excluded from the sample. In Panel C, we replace the Macro Dummy with 7 indicator variables for the macro announcements of interest. In Panel D and E, the dependent variable is the ratio between the number of each type of announcements and the total number of announcements on that trading day. For instance, PFE1 is the fraction of announcements with the lowest FE in the total number of announcements. A Tobit regression is employed to estimate the models and standard deviations are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A. Summary Statistics

| | Mean | St.Dev | Min | P10 | Median | P90 | Max |
|---|---|---|---|---|---|---|---|
| N (Full Sample) | 46 | 61 | 0 | 3 | 19 | 135 | 333 |

Distribution of Earnings Announcement: Day of the week

| | Mon | Tue | Wed | Thu | Fri | Sat | Sun | Total obs. |
|---|---|---|---|---|---|---|---|---|
| N (Full Sample) | 15021 | 27228 | 29661 | 37147 | 7447 | 90 | 98 | 116692 |
| FE1(bad news) | 1674 | 2438 | 2507 | 3446 | 963 | 6 | 7 | 11041 |
| FE2 | 1505 | 2527 | 2635 | 3496 | 879 | 6 | 7 | 11055 |
| FE3 | 1388 | 2566 | 2818 | 3499 | 777 | 2 | 9 | 11059 |
| FE4 | 1345 | 2687 | 2841 | 3597 | 576 | 5 | 8 | 11059 |
| FE5 | 1233 | 2784 | 2918 | 3540 | 569 | 3 | 6 | 11053 |
| FE6 | 1289 | 2685 | 3003 | 3546 | 529 | 6 | 6 | 11064 |
| FE7 | 1299 | 2674 | 2877 | 3640 | 567 | 3 | 6 | 11066 |
| FE8 | 1328 | 2495 | 2915 | 3675 | 629 | 4 | 6 | 11052 |
| FE9 | 1381 | 2622 | 2796 | 3629 | 625 | 8 | 1 | 11062 |
| FE10(Good news) | 1475 | 2427 | 2749 | 3705 | 715 | 7 | 3 | 11081 |

Distribution of Earnings Announcement: Month of the Year

| | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | NOV | DEC | Total obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Full Sample | 10732 | 12911 | 5494 | 16357 | 10778 | 1897 | 16572 | 10914 | 1835 | 16580 | 10689 | 1933 | 116692 |
| FE1(bad news) | 622 | 1263 | 842 | 1149 | 1385 | 215 | 1145 | 1414 | 240 | 1150 | 1399 | 217 | 11041 |
| FE2 | 913 | 1231 | 584 | 1454 | 1121 | 178 | 1479 | 1143 | 181 | 1479 | 1114 | 178 | 11055 |
| FE3 | 1213 | 1119 | 398 | 1690 | 898 | 167 | 1661 | 975 | 167 | 1724 | 882 | 165 | 11059 |
| FE4 | 1138 | 1169 | 425 | 1685 | 912 | 156 | 1768 | 880 | 156 | 1754 | 835 | 181 | 11059 |
| FE5 | 1251 | 1121 | 357 | 1824 | 790 | 140 | 1904 | 748 | 148 | 1812 | 793 | 165 | 11053 |
| FE6 | 1258 | 1122 | 350 | 1782 | 810 | 164 | 1813 | 819 | 173 | 1853 | 755 | 165 | 11064 |
| FE7 | 1173 | 1214 | 347 | 1686 | 899 | 171 | 1798 | 857 | 149 | 1769 | 846 | 157 | 11066 |
| FE8 | 1100 | 1241 | 387 | 1633 | 947 | 172 | 1695 | 942 | 166 | 1690 | 886 | 193 | 11052 |
| FE9 | 976 | 1299 | 455 | 1534 | 1019 | 203 | 1538 | 1086 | 179 | 1572 | 1029 | 172 | 11062 |
| FE10(Good news) | 728 | 1350 | 659 | 1358 | 1176 | 225 | 1358 | 1296 | 155 | 1308 | 1262 | 206 | 11081 |

Table 2.12 (Continued): Timing of Earnings Announcements

Panel A of this table shows the summary statistics of the number of earnings news and its distributions over days and months. FE is the earnings surprise decile. FE1 refers to stocks which have the lowest forecast errors. FE10 refers to stocks which have the highest forecast errors. Panel B presents test results of the effects of macroeconomic announcements on the number of earnings news release. The dependent variables are the number of earnings news, shown on each column heading. N is the total number of earnings announcements. NFE1 is the number of earnings news with lowest earnings surprise. NFE10 is the number of earnings news with highest earnings surprise. Macro Dummy is an indicator variable, which equals 1 when there is at least one of the 7 macro announcements, and 0 otherwise. Indicator variables for days and months are also included in the regressions. Announcements made on Saturdays or Sundays are excluded from the sample. In Panel C, we replace the Macro Dummy with 7 indicator variables for the macro announcements of interest. In Panel D and E, the dependent variable is the ratio between the number of each type of announcements and the total number of announcements on that trading day. For instance, PFE1 is the fraction of announcements with the lowest FE in the total number of announcements. A Tobit regression is employed to estimate the models and standard deviations are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel B. Regression Analysis on the Number of Earnings Announcements

| | (1) N | (2) NFE1 | (3) NFE2 | (4) NFE3 | (5) NFE4 | (6) NFE5 | (7) NFE6 | (8) NFE7 | (9) NFE8 | (10) NFE9 | (11) NFE10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Macro Dummy** | **-6.10**** | -0.45 | **-0.95***** | -0.47 | **-0.58*** | -0.31 | 0.08 | -0.32 | **-0.79**** | **-1.08***** | **-1.26***** |
| | (2.51) | (0.29) | (0.34) | (0.34) | (0.35) | (0.36) | (0.35) | (0.35) | (0.36) | (0.37) | (0.39) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 |

Panel C. Regression Analysis on the Number of Earnings Announcements

| | (1) N | (2) NFE1 | (3) NFE2 | (4) NFE3 | (5) NFE4 | (6) NFE5 | (7) NFE6 | (8) NFE7 | (9) NFE8 | (10) NFE9 | (11) NFE10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CPI | -7.46 | -0.60 | **-1.54**** | -0.22 | -0.73 | -0.65 | -0.21 | -1.04 | -1.04 | **-1.31*** | **-2.09***** |
| | (5.141) | (0.61) | (0.70) | (0.70) | (0.71) | (0.74) | (0.72) | (0.72) | (0.74) | (0.75) | (0.74) |
| Housing | -0.02 | -0.90 | 0.02 | 0.37 | 1.10 | **1.18*** | **1.69**** | **1.17*** | -0.20 | -0.48 | -0.97 |
| | (5.16) | (0.60) | (0.69) | (0.69) | (0.69) | (0.71) | (0.69) | (0.69) | (0.73) | (0.73) | (0.72) |
| Newhome | **11.79**** | 0.76 | 0.76 | **1.41**** | 0.34 | **2.06***** | **1.93***** | **2.57***** | **1.54**** | **1.64**** | 1.11 |
| | (4.99) | (0.58) | (0.67) | (0.67) | (0.70) | (0.70) | (0.69) | (0.67) | (0.71) | (0.71) | (0.70) |
| PPI | **-14.83***** | -0.89 | **-2.57***** | **-1.61**** | **-1.59**** | **-1.67**** | **-1.20*** | **-1.87***** | **-1.97***** | **-2.37***** | **-2.32***** |
| | (5.08) | (0.60) | (0.70) | (0.70) | -0.71 | (0.73) | (0.72) | (0.71) | (0.74) | (0.75) | (0.74) |
| Trade | **-13.59***** | -0.04 | -0.65 | **-1.75**** | **-2.08***** | **-1.87***** | **-1.46**** | **-1.27*** | **-2.33***** | **-2.18***** | **-1.88***** |
| | (4.99) | (0.59) | (0.67) | (0.68) | (0.70) | (0.72) | (0.70) | (0.69) | (0.73) | (0.73) | (0.72) |
| Unem | -3.90 | -0.42 | -0.40 | **-1.47*** | -0.48 | -0.73 | -0.53 | -0.70 | -0.70 | -0.02 | -0.34 |
| | (5.58) | (0.69) | (0.79) | (0.83) | (0.83) | (0.89) | (0.88) | (0.86) | (0.88) | (0.87) | (0.84) |
| GDP | -8.60 | -0.39 | -0.18 | -0.01 | 0.37 | -1.72 | -1.18 | **-2.37*** | -0.48 | -1.91 | **-2.15*** |
| | (8.55) | (1.04) | (1.17) | (1.19) | (1.20) | (1.35) | (1.30) | (1.33) | (1.28) | (1.34) | (1.30) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 |

Table 2.12 (Continued): Timing of Earnings Announcements

Panel A of this table shows the summary statistics of the number of earnings news and its distributions over days and months. FE is the earnings surprise decile. FE1 refers to stocks which have the lowest forecast errors. FE10 refers to stocks which have the highest forecast errors. Panel B presents test results of the effects of macroeconomic announcements on the number of earnings news release. The dependent variables are the number of earnings news, shown on each column heading. N is the total number of earnings announcements. NFE1 is the number of earnings news with lowest earnings surprise. NFE10 is the number of earnings news with highest earnings surprise. Macro Dummy is an indicator variable, which equals 1 when there is at least one of the 7 macro announcements, and 0 otherwise. Indicator variables for days and months are also included in the regressions. Announcements made on Saturdays or Sundays are excluded from the sample. In Panel C, we replace the Macro Dummy with 7 indicator variables for the macro announcements of interest. In Panel D and E, the dependent variable is the ratio between the number of each type of announcements and the total number of announcements on that trading day. For instance, PFE1 is the fraction of announcements with the lowest FE in the total number of announcements. A Tobit regression is employed to estimate the models and standard deviations are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel D. Regression Analysis on the Proportions of Different Earnings Announcements

| | (1) PFE1 | (2) PFE2 | (3) PFE3 | (4) PFE4 | (5) PFE5 | (6) PFE6 | (7) PFE7 | (8) PFE8 | (9) PFE9 | (10) PFE10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Macro Dummy** | **0.014*** | -0.007 | -0.005 | -0.001 | 0.004 | **0.018***** | 0.009 | -0.002 | -0.002 | **-0.012*** |
| | (0.008) | (0.007) | (0.007) | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 |

Panel E. Regression Analysis on the Proportions of Different Earnings Announcements

| | (1) PFE1 | (2) PFE2 | (3) PFE3 | (4) PFE4 | (5) PFE5 | (6) PFE6 | (7) PFE7 | (8) PFE8 | (9) PFE9 | (10) PFE10 |
|---|---|---|---|---|---|---|---|---|---|---|
| CPI | 0.028 | -0.019 | 0.007 | 0.001 | 0.002 | 0.019 | -0.005 | 0.009 | 0.006 | **-0.031**** |
| | (0.017) | (0.015) | (0.014) | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) | (0.015) |
| Housing | -0.025 | -0.004 | -0.003 | 0.018 | 0.013 | **0.037***** | **0.037***** | -0.006 | -0.001 | -0.011 |
| | (0.017) | (0.015) | (0.014) | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) | (0.015) |
| Newhome | 0.015 | -0.016 | -0.006 | **-0.046***** | 0.011 | 0.001 | **0.031***** | -0.001 | 0.007 | 0.007 |
| | (0.017) | (0.015) | (0.013) | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) | (0.014) |
| PPI | 0.021 | -0.016 | -0.001 | 0.005 | 0.018 | 0.013 | -0.015 | -5.76e-05 | -0.011 | **-0.025*** |
| | (0.017) | (0.015) | (0.014) | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) | (0.015) |
| Trade | **0.029*** | 0.016 | -0.003 | -0.020 | -0.004 | 0.017 | 0.009 | **-0.024**** | -0.021 | -0.002 |
| | (0.017) | (0.015) | (0.014) | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.013) | (0.014) |
| Unem | -0.018 | 0.018 | **-0.047***** | 0.018 | -0.012 | 0.010 | -0.008 | -0.015 | **0.030**** | 0.001 |
| | (0.020) | (0.017) | (0.017) | (0.017) | (0.015) | (0.014) | (0.015) | (0.014) | (0.015) | (0.017) |
| GDP | 0.044 | 0.032 | 0.007 | **0.070***** | -0.035 | -0.007 | -0.032 | 0.017 | -0.027 | **-0.070***** |
| | (0.029) | (0.025) | (0.024) | (0.025) | (0.022) | (0.021) | (0.022) | (0.021) | (0.023) | (0.025) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 | 2448 |

## 2.8 Conclusion

A bunch of papers have demonstrated that human's limited capacity in processing information or making investment decisions causes nontrivial market fric-

tions. It affects not only retail investors but also professional market makers. This paper is the first to link category-learning behavior with investors' underreaction to earnings news. Due to attention constraint, rational investors should optimally allocate more attention to market-wide information than to firm-level information. As a result, the well-documented phenomenon of underreaction to earnings announcements should be more pronounced when investors are distracted by market-level news. Consistent with this prediction, our univariate tests and multivariate regression analysis both suggest that investors are less responsive to earnings news when market shocks arrive at the same time as earnings announcements. This paper also confirms that mispricing caused by investors' category-learning propensity is of a temporary nature as the post-announcement cumulative abnormal returns are larger when investors are distracted initially. Moreover, the traditional 'PEAD' portfolio strategy is found to be more profitable when earnings announcements are made on turmoil times than other times. In addition, this paper provides empirical evidence for the 'Ostrich effect' hypothesis as our tests results show that Down market is associated with more sluggish responses to earnings news at announcement and larger abnormal returns afterwards.

Another interesting phenomenon we find here is that managers in reality are actually aware of the market distraction effects and they respond to it by moving their earnings releases away from macroeconomic announcements dates. This tendency is particularly evident for managers who have good news to disclose. Hence, this paper also contributes to the literature that managers strategically time their corporate events or announcements in order to maximize shareholders' or their own benefits. Our paper suggests that investors' category-learning preference not only guides investors' investment decision, but also exert influences on firms' managerial choice.

This paper also sheds light on the future empirical work on the consequences of investors' inattention in a wide variety of economic situations. For example, the category-learning behavior should be observed in other financial markets as well and our tests regarding the distraction effects of market-level news should be applicable to studying the releases of other firm-level information or corporate events.

# Chapter 3

# Securitization, Loan Quality and Regulation

**Summary**

This chapter presents a rational expectations general equilibrium model to study the economic consequences of securitization. We provide theoretical explanations of how securitization helps the economy obtain more capital, and why its advent inevitably causes deterioration in banks' asset quality. In addition, we evaluate the effects of proposed regulation which requires originating banks to retain a portion of the loans on their balance sheets. The outcome of the model shows the channels through which regulators can uplift banks' optimal lending standards and the market prices of securitized assets by imposing loan sale limits under different economic conditions. Consistent with prior literature, our model suggests that securitization alone does not necessarily lead to systematic failure of the banking sector.

## 3.1 Introduction

The past two decades witnessed the rapid growth of the secondary loan market, which was coupled with significant transformation within the banking system. In particular, the practice of 'Originate and Distribute' banking or disintermediation has profoundly changed the role of banks as intermediaries in providing capital

to the real economy. Instead of keeping their assets on the balance sheets, banks started selling securitized loans in the secondary market to outside investors, who could then directly lend money to the borrowers by investing in securities. According to Gande and Saunders [2012], the trading volume in the US secondary loan market soared from 8 billion dollars in 1991 to nearly 350 billion dollars in 2007. Undoubtedly, securitization has enabled banks to pump much more capital into the economy than before.

However, the 2007-2008 financial crisis revealed the other facet of securitization: the prosperity of the secondary loan market was accompanied by a plummet in loan quality. When the situation worsened in the summer of 2007 with the busting of the US housing bubble, the subprime mortgage crisis quickly evolved into a full-blown financial crisis, causing rippling effects throughout the economy. People were surprised to find that the initial loss in the mortgage market was still modest on scale while the whole financial system suffered a wealth evaporation tantamount to 8 trillion dollars. (Brunnermeier [2009], Mian and Sufi [2009], Keys, Mukherjee, Seru, and Vig [2010], and Demyanyk and Van Hemert [2011] provide thorough analyses on the immediate cause of the recent financial crisis.) Since then, the future of securitization has become an issue of contention among scholars and practitioners.

More and more people believe that securitization largely contributed to the deterioration of banks' asset quality, but what is the micro mechanism? What is the incentive for banks to issue bad-quality loans? What is the policymaker's optimal choice in regulating the market? In this paper, we seek to answer these questions in a unified framework. First of all, the primary benefit that securitization offers is that banks can redeploy their capital efficiently by selling the illiquid assets in pursuit of more profitable investment opportunities. We propose a parsimonious two-period model to show that with the aid of securitization, banks can achieve higher expected profits. We consider two long-term projects which arrive in the market at $t_0$ and $t_1$ respectively and both mature at time $T$. In the absence of secondary market, banks with limited capital can only invest in one of the projects, and are in a state of autarky. They would never fund negative NPV projects, and they could even forsake positive NPV projects today if they expect an even better project in the future. Now suppose they can securitize

$t_0$-initiated loans and sell them to outside investors at $t_1$. Banks are essentially given the opportunity to reallocate their capital. As a consequence, banks' selling behavior at $t_1$ should be driven by two motives: either the $t_0$-initiated loan is a lemon and overpriced by outsiders or the loan has positive NPV, but banks have encountered a better project and thus need to offload the existing one to finance the new one.

Outside investors are assumed to be rational in our model. They cannot observe the quality of the projects and thus anticipate that banks would sell both lemons and good-quality loans. By holding a pool of diversified securities, investors are able to obtain the expected value of the pool. In contrast with this assumption, the received wisdom was built upon investors' irrationality, blaming their inadequate appreciation of risks. For example, in the terms employed by Shin [2009] describing investors' irrationality, "there is a greater fool next in the chain. Final investor(e.g. pension fund) is the greatest fool." This paper, however, shows that the problem is actually rooted in the 'originate and distribute' banking itself, because uninformed investors can always break even in equilibrium of the model. We prove that the existence of the secondary market inevitably entails lemons as long as there is information asymmetry, even if loan buyers are perfectly rational.[1] In the unique pooling equilibrium, banks have low underwriting standards, under which they will issue loans for both positive NPV projects and negative NPV projects. In this paper, we do not consider the signaling effect of the fractions of loans retained in banks as in reality the fraction is difficult for investor to verify due to the complex structure of securitization. Keys, Mukherjee, Seru, and Vig [2010] also point out that "there is limited disclosure on who holds what in the originate-to-distribute chain". Without signalling, separating equilibrium cannot be sustained in our model. Suppose banks in equilibrium underwrite loans of positive NPV only. Anticipating this, outsiders will offer a good price for the securitized loans although they cannot observe the real returns

[1] We believe that the assumption of information asymmetry between banks and loan buyers is realistic. As well documented, banks not only possess hard information that investors cannot access, such as bank account records of borrowers, but also have localized soft information regarding the borrowers and their collateral (e.g. houses) (see Rajan, Seru, and Vig [2010], Gorton and Pennacchi [1995]). This informational friction cannot be completely eradicated, although it could be alleviated by requiring more information disclosure from banks' side or third-party rating.

of the assets. Expecting to pass any assets onto loan buyers in the secondary market, banks will in fact finance projects of any quality, even including the bad ones, which contradicts with the conjecture of separating equilibrium.

With the intention of elevating asset quality, both the EU commission and the US government are proposing that the originating banks should retain a portion of loans on their balance sheets. By doing so, banks would have a weaker incentive to finance negative-NPV projects as they would have to bear part of the loss. We evaluate this proposed regulation by analyzing the channels through which it influences banks' optimal lending decision, as well as outsiders' anticipation. The interaction between loan originators and loan buyers leads to a unique equilibrium, which consists of banks' optimal lending standard and a market clearing price. Let $\alpha$ refer to the maximum fraction of assets that banks are allowed to transfer to outside investors, it can be derived that both of the optimal underwriting criterion and equilibrium loan price are determined by $\alpha$. Our main findings are the followings: (i)Loan sales limits improves the equilibrium quality of loans. The outcome of equilibrium shows that banks' optimal lending standard is a decreasing function of $\alpha$. By requiring more loans to be retained, regulators can effectively increase the lowest return that banks would accept when funding projects. (ii) Tougher regulation on loan sales can also induce higher market prices. As will be shown in the model, investors form their expectation of loan values based on banks' lending choice. Since banks would adopt stricter criterion in choosing projects if they have to keep most of the loans on their books, outsiders in this case can rationally expect good-quality securities in the secondary market and are thus willing to pay a higher price. (iii) Regardless of the social costs of negative NPV projects and liquidity issues, our model demonstrates that banks' ax ante profit decreases with mandatory retention of loans.

The general equilibrium framework employed in this paper allows us to study the feedback effect between prices and banks' lending decision. Intuitively, we would expect banks' ex ante wealth to rise with a higher portion of loans allowed to be sold, simply because banks enjoy more flexibility in redeploying their resources. But this simple intuition is not necessarily true because the price of loans varies with the regulatory interventions as well. Our model shows that an increment in $\alpha$ causes two offsetting effects on banks' profit: (i) the option value

of securitization increases with $\alpha$. Intuitively speaking, the more illiquid assets banks can get rid of in the secondary market, the more efficient allocation of capital banks can achieve when encountering better projects; (ii) a high $\alpha$ incurs low-quality loans, which lowers the equilibrium price as market clearing price reflects loan purchasers' rational expectation of the project-based security value, and the amount of capital banks can obtain from the market diminishes as a consequence. We further show that this price effect in magnitude is only a fraction of the option value. We therefore conclude that the price effect is not enough to offset the benefits that securitization offers to the banks, and the banks' expected welfare is indeed enhanced with a looser loan sales constraint.

Moreover, we distinguish between normal times and booms to see how market participants respond under different economic prospects. We find that the equilibrium price and loan quality in the secondary loan market is subject to people's expectations about the future. In particular, the equilibrium loan price is procyclical. In times of strong economic growth, investors are willing to pay more for asset-backed securities as their conditional prediction on loan quality is adjusted upward due to increased average return of investments. During economic downturn, investors revise their forecasts accordingly, which drags down the price of securitized assets. Nevertheless, the change in equilibrium loan quality depends on loan sale limits imposed by regulators. When securitization is prohibited, banks will raise their lending standard at $t_0$ in economic expansion due to increased opportunity cost. In contrast, when banks are free to sell the entire loans to outside investors, banks' lending standard will drop significantly in economic expansion.

We also touch upon one of the liquidity issues in the extended model. A simplified maturity mismatch scenario is examined. Random deposit withdrawal can lead to liquidity shortfall of banks. With increasing probability of cash withdrawal in the middle of its operation, banks become more cautious towards lending and the underwriting standard is thus raised in the absence of securitization. Our model shows that securitization alleviates the maturity mismatch problem. As a result, banks' participation condition in the secondary loan market is considerably relaxed, depending on the magnitude of the random deposit withdrawal. In the meanwhile, expecting banks to give up good projects under liquidity shock,

outside investors are willing to offer a higher price for the securitized loans. Moreover, the equilibrium loan price is proved to be increasing with the probability of liquidity shock.

In line with a recent empirical study on securitization by Gorton and Metrick [2012], our model suggests that disintermediation/securitization alone should not lead to a systemic outage of the banking sector as long as banks make the 'optimal' lending decision to maximize their profits and investors rationally anticipate the pooling risks. Gorton and Metrick [2012] argue that the underlying reason for the recent financial market dislocation was the rife use of the securitized asset as collateral in raising short-term funding. Hördahl and King [2008] document that the leading US investment banks funded nearly half of their assets by using repo agreement. Since the ability of raising money from the repo market depends on the value of collateral, banks were effectively driven into insolvency when the secondary loan market experienced sharp devaluation, which caused liquidity dry-up in the repo market. The quality of securitized loans was in this manner playing a vital part when the short-term liquidity market and securitization market were deeply interrelated. Banks who failed to internalize the penalty costs associated with low-quality loans suffered from 'shadow banking' run.

In the literature, our work is closely related to Parlour and Plantin [2008], who are focused on the moral hazard problems associated with securitization in ex post monitoring, and Chemla and Hennessy [2013] who analyze the interplay of different market participants in the secondary loan market and provide policy implications on how to promote originator's monitoring effort.[1] Pennacchi [1988] and Gorton and Pennacchi [1995] also tackle similar moral hazard problems in the secondary loan market. In contrast, the present paper concentrates on the adverse selection problem of banks in *ex ante screening*. To the best of our knowledge, this is the first attempt that directly examines the adverse selection problem in the context of securitization. Hoerova, Holthausen, and Heider [2009] also study adverse selection in interbank borrowing during financial crisis. Yet their paper does not pertain to securitization/disintermediation and has no implications on

[1]Other papers studying the tradeoff between the benefit of liquid market and the cost of losing commitment to monitor include Aghion, Bolton, and Tirole [2004], and Faure-Grimaud and Gromb [2004].

loan quality or social welfare.

The rest of the paper is organized as follows. Section 2 reviews the most related papers in literature. Section 3 presents the essential pieces of the model, the resulting optimal actions of banks and outside investors, and how the general equilibrium is achieved. Section 4 analyses the implications of our model and the effects of the proposed regulation within different contexts. The benchmark framework is extended in section 5 wherein a simplified scenario of maturity mismatch is examined. Section 6 contains the main conclusions of the paper and suggests possible directions for future research.

## 3.2 Related Literature

### 3.2.1 Theories

Pennacchi [1988] is a pioneering work on the originate-to-distribute banking system. Specifically, they study the moral hazard problem inherent in securitization. Firstly, they show that competition for deposit financing and regulatory constraint in required capital make loan sales desirable for banks as banks can create value by providing screening and monitoring services, which helps reduce banks' cost of raising funds. They also demonstrate that weakened incentive to monitor loans of banks limits the extent of loan selling. To alleviate the moral hazard problem, they propose an incentive-efficient contract which gives the loan buyers recourse to claims on other banks' asset. This recourse would enable banks to sell the entire loan while retaining their incentive to monitor at the optimal level. Their model also explains why banks would purchase loans in the secondary market and why the loan sales volume had increased tremendously. They argue that banks which have greater advantage in cheap deposit financing but weaker lending opportunities would purchase loans in the secondary markets. Their model also predicts that a decline in deposit funding opportunities would cause an expansion of loan sales.

Gorton and Pennacchi [1995] also focus on the moral hazard problem associated with loan sales and propose a model of optimal contract between loan originators and loan buyers. Specifically, the moral hazard problem arises as

banks exert unobservable efforts to screen loan applicants and/or monitor borrowers after the loan is issued. To mitigate the problem, they assume that a bank can retain a portion of loans in its balance sheet and/or offer an implicit guarantee against borrower's default. They show that in the presence of these two contract provisions, banks' optimal effort level is no longer the most efficient one. Moreover, their model suggests that the portion of loans retained in the bank increases with loan sale premium and decrease with banks' internal capital cost and banks' probability of survival. To test the theoretical implications of the model, they analyse a bank's individual loan sales data and the empirical results support their propositions. They argue that loan sales is not simply a underwriting practice as banks still provide credit evaluation and monitoring services.

Holmstrom and Tirole [1997] present an equilibrium model of financial intermediation to study how the financial status of firms, intermediaries and investors impacts firms' investments, loanable funds, interest rates and intensity of monitoring. In their model, there are two moral hazard problems. Firstly, firm managers might shirk for their own private benefits, which decreases the probability of success of the project. Secondly, intermediaries' monitoring is costly. To solve these two problems, they use two incentive constraints such that managers will not shirk and intermediaries will monitor. In the absence of intermediation, firms with insufficient collateral will not be financed. In the presence of intermediation, monitoring serves as a partial substitute of collateral. Hence, firms with low net worth can be financed by a mixture of informed intermediary and uninformed investors. Their model suggests that in the event of capital squeeze, aggregate investment level will go down and capital-poor firms will be the first to lose financing. Moreover, they distinguish different sources of capital supply and document the impacts of changes in capital supply on investment, interest rate and solvency ratios of firms and intermediaries.

Parlour and Plantin [2008] develop a parsimonious model of endogenous liquidity to study when the secondary market is liquid and when it is socially desirable. They tackle both moral hazard problem and adverse selection problem in the model. Specifically, they build on Holmstrom and Tirole [1997]'s model of moral hazard and assume that through monitoring, banks can learn the final

payoff of the project perfectly and prevent firm managers' from shirking. In the meantime, monitoring is costly and banks might shirk when it expects that it can sell anything in the secondary loan market. In addition, the secondary loan market is liquid only when the adverse selection risk is low, i.e., only when the bank is willing to sell both good projects and bad projects when it has a preference shock. By maximizing firm managers' expected profits with all the agents' incentive compatibility constraints, the authors derive the optimal contracts offered by the firms in the absence of secondary loan market and the optimal contract in the presence of secondary loan market, respectively. Their model suggests that the liquidity of the secondary loan market depends on projects' probability of success and securitization is socially efficient only banks have high opportunity cost of capital, i.e., when the future investment opportunity is highly profitable or when bank's financial constraint is tight.

Shin [2009] starts with the analysis on intermediaries' balance sheets and show that the endogenous supply of credit depends on some key attributes of intermediaries' balance sheets. Specifically, he assumes that a bank aim to maintain its market equity at the value at risk level and he proves that a decrease in the default rate in the model would increase the equity value of the bank and the bank would thus seek to increase its notional debt and use the proceeds to finance more end-users investors. Moreover, due to the macroeconomic feedback effect, the interplay between expanded balance sheets and increased lending will be magnified, which can serve to explain the observed lending boom. The author argues that the origin of the subprime crisis lies in the incentive of banks' to fill the expanding balance sheets with new assets, and this is the reason why the banks would issue loans to subprime borrowers and keep bad loans on their own balance sheets instead of passing all the loans to other investors.

Hoerova, Holthausen, and Heider [2009] focus on the interbank market and examine how counterparty risk (the possibility that borrower becomes insolvent and cannot pay back the loan) impacts liquidity of the market and the interbank interest rate. Banks in their model encounter two types of shocks in the middle of their investment, namely liquidity shock and the shock to the riskiness of their long-term assets. They firstly analyse the model with no information friction, which means the riskiness of the long-term projects are public information,

and there are two separate markets (and different interest rates) for banks with liquidity shortage and safer assets and banks with liquidity shortage and riskier assets. When they take into account information asymmetry, multiple equilibria arise. Most importantly, their model shows that under certain conditions, adverse selection can cause dysfunction of the interbank market and even breakdown of the market in the extreme scenario.

Chemla and Hennessy [2013]'s work is closely related to ours. There are four types of agents in their model, namely loan originators, uninformed rational investors, speculators and market makers. Using backward induction, they solve in order the optimal portfolio choices of uninformed investors, market equilibrium prices in pooling equilibrium and separating equilibrium and loan originators' optimal effort levels under different market conditions (opacity or transparency). Their model suggests originators' optimal effort level is lower than first-best in all equilibria due to information asymmetry and they would choose low/zero retentions in equilibrium if they are faced with severe financial constraint and/or loan prices are highly informative. In addition, they prove that mandatory retentions of loans in originators enhances social welfare as it can increase effort incentives efficiently and effort can be also promoted by requiring junior retentions, tranching, investors sophistication and informative prices. One of the major differences between their models and ours is that they assume that traders are capable of generating information on asset quality and prices in the secondary market can be informative while we assume that investors do not receive any signal regarding asset quality.

### 3.2.2 Empirical Studies

There is an extensive literature on the economic consequences of securitization. For example, in the context of the credit expansion in the US, Mian and Sufi [2009] examine three potential explanations respectively, namely income-based hypothesis, credit-supply-based hypothesis and house price expectation-based hypothesis, in order to find out the true driving force behind the rise in mortgage credit before the 2007 financial crisis. They utilize a unique subprime ZIP code data in order to study the geographical variation in subprime mortgage growth. In particular,

they associate the ZIP codes with mortgage default rates and the main findings are the following: (1) subprime neighborhoods experience weaker income growth while stronger mortgage credit growth compared with prime neighborhoods during their sample period. (2) subprime-prime interest rate spread dropped significantly between the crisis despite the increased riskiness of subprime mortgages. (3) Credit growth in the US was accompanied by the expansion of subprime mortgage securitization and the increase in rate of securitization is much higher in subprime ZIP codes compared to prime ZIP codes and the increase in mortgage defaults are sharply amplified in subprime ZIP codes. (4) Similar results are also obtained in those elastic-house-supply areas where house price growth is flat. These empirical facts all together supports the hypothesis that the explosive growth of subprime mortgages was caused by the excessive supply of credits by lenders.

Keys, Mukherjee, Seru, and Vig [2010] concentrate on the impacts of securitization on the incentive of financial intermediaries to conduct diligent screening. They empirically examine the relationship between securitization and screening standards of subprime mortgage loans. In practice, screening loan applicants involves collecting both 'hard' information (such as credit scores) and 'soft' information (such as future income stability). Since credit score is easy to obtain, lenders do not need to exert much effort in collecting hard information. Since investors in the secondary loan market purchase securities only based on hard information, securitization might causes weaker incentive of lenders to collect soft information. In particular, the authors use FICO scores as a measure of 'hard' information and point out that a FICO score of 620 is a threshold, above which loans are much easier to be securitized. Their empirically document a discontinuity in the number of securitized loans around the credit threshold- loans above the credit threshold are securitized twice as many as those below the threshold. Strikingly, the default rate of those 'better quality' loans is 25% higher than that of 'lower quality' loans. Moreover, they compare different portfolios with virtually identical risk profiles and find that the ease of securitization significantly attenuates lenders' screening efforts. Their results suggest that securitization might have caused a declined screening standards.

Gorton and Metrick [2012] study the impacts of securitization on economy from another perspective. They describe the 2007-2008 financial crisis as a run on the repo market. They argue that different from traditional banking, securitized banking relied on repo agreements as the main source of funding and they define the combination of securitization and repo finance as 'securitized banking'. They analyze a novel data on the credit spreads of securitized bonds to show the contagion effects of subprime-housing related asset on other assets which have no connection to housing through the short-term financing channel. Their empirical findings suggest that the weakening of subprime does not necessarily cause the systematic problem among banks. It is the increased repo haircuts and increased amount of required collateral that drove the US banking system insolvent.

Besides, Demyanyk and Van Hemert [2011] and Acharya, Schnabl, and Suarez [2013] also empirically examine different aspects of securitization. Demyanyk and Van Hemert [2011] document a monotonic decline in loan quality between year 2001 and year 2007 when the subprime mortgage market grew dramatically. Moreover, they find that the subprime mortgage rate spread decreased steadily during their sample period despite the deteriorating mortgage quality. They argue that it is the unsustainable growth of securitization caused to the collapse of the market. Acharya, Schnabl, and Suarez [2013] present analysis on asset-backed commercial paper (ABCP) conduits to show that securitization in reality failed to transfer risk from the banking sector to outside investors and they argue that by devising various securitization methods, banks largely reduced the require regulatory capital while retaining the risks on their balance sheet.

## 3.3 The Model

### 3.3.1 Setup

In the benchmark model, there are only three dates - $t_0$, $t_1$ and $T$, and two types of risk-neutral agents- banks, and outside investors. The net risk-free interest rate is 0 and the subjective time discount factor is 1. The key ingredients of the model are stated as follows.

**Banks**. There is a continuum of identical banks with measure 1, each of

which has access to its own customer base, and has only one unit of capital (i.e. cash) at $t_0$. No other financial resources are available. For each bank, there are two risky long-term projects with constant returns to scale emerging at time $t_0$ and $t_1$ respectively. Projects are scalable and identical ex ante and will both pay off at time T.[1]

**Projects**. Issuing loans on the projects will bring the bank either return $R$ or 0 due to limited liability at time $T$, where $R > 1$. Let us denote the probability of realizing $R$ by $\widetilde{\theta}_i$ for the project arriving at $t_i$, where $i = 0, 1$. The term $1 - \widetilde{\theta}_i$ thus measures the default rate. $\widetilde{\theta}_i$ is random ex ante for both banks and investors, and is drawn from the same distribution over the support $[0, 1]$ with positive density everywhere. The uncertainty of $\widetilde{\theta}_i$ is resolved at $T$. Accordingly, the expected return of loans can be expressed by $\widetilde{R}_i \equiv R\widetilde{\theta}_i$, where $\widetilde{\theta}_i$ is assumed to be independent across time and across banks.

**Information Asymmetry**. A bank, through its screening technology and relationship with its customers, can perfectly observe the quality of the projects (i.e. the realization of $\widetilde{\theta}_i$, $i = 0, 1$). That is, the bank is fully aware of the true value of $\widetilde{R}_i$ once the project has come up at $t_i$ , while an outsider (including potential loan buyers) doesn't know the realizations of $\widetilde{R}_0$ and $\widetilde{R}_1$ but only their distributions. We use $R_i$ to denote the true value of $\widetilde{R}_i$, $i$ = 0,1.

**Bank's Underwriting Decision**. At time $t_0$, the bank has only one unit of initial capital, and need to choose between originating a loan on the $t_0$ project and retaining the money. At time $t_1$, the bank is faced with five options based on its previous action: (1) hold the $t_0$-initiated loan until its maturity; (2) sell the $t_0$-initiated loan in the secondary loan market and keep the proceeds; (3) sell the $t_0$-initiated loan and invest in the $t_1$ project; (4) continue carrying forward its initial capital if it didn't originate the loan for the $t_0$ project; (5) invest the initial capital in $t_1$ project if it didn't originate the loan for the $t_0$ project. Note that banks in our model cannot sell (collateralize) the $t_1$- loan *opportunities*. In other words, banks have to initiate loans before distributing them.

[1]This assumption is for simplicity purpose. Under the alternative assumption that the second loan matures later than the first loan, the model outcomes and main conclusion of the paper do not change.

**Rational Investors**. Outside investors in our model make rational decisions. They are aware of the information asymmetry and assess the values of the loans conditioned on their information set as well as banks' underwriting decisions. We posit that the secondary loan market is competitive and buyers are on the long side of the market. Loan buyers should therefore break even in market clearing, and the market clearing price of $t_0$-initiated loans, denoted by $P$, should be equal to investors' expected value of loans.

**Regulation**. A common regulation practice for governments is to impose the maximum $\alpha$ portion of loans which loan originator can sell in the secondary market. By holding at least $1 - \alpha$ portion of the stakes in the borrowers, banks will have a stronger incentive to finance high-quality projects. The maximum $\alpha$ set by authorities therefore indicates how much control the regulator exerts over the market. When $\alpha = 1$, there is essentially no regulation, and banks can utilize the secondary market to the largest extent; when $\alpha = 0$, loan sales in the secondary market are banned.

Figure 3.1 summarizes the sequence of events.

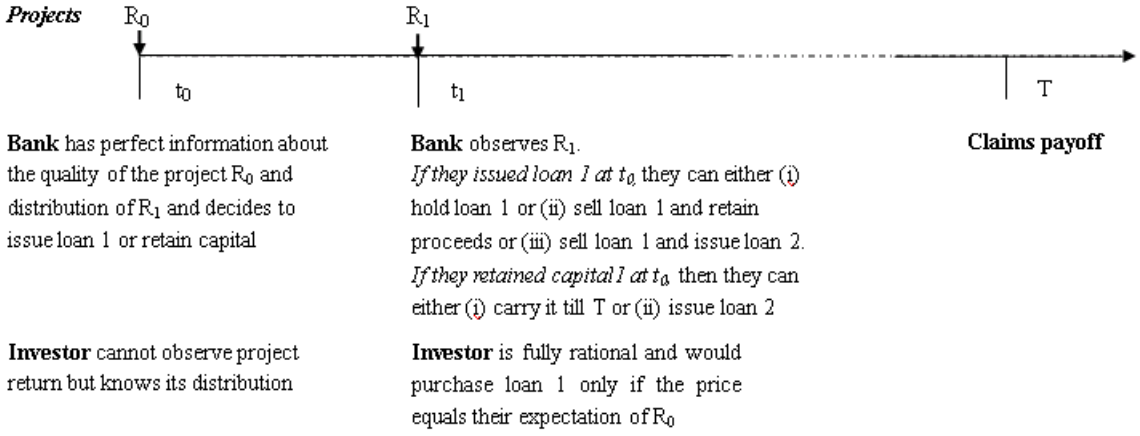



Figure 3.1: Timeline of events

Another issue we would like to clarify here is that this paper does not consider a signaling effect of the fraction of loans banks retain. Intuitively, the more

loans a bank keeps on its book, the higher the loan quality the outside investor would expect. However, the prerequisite is that buyers are perfectly informed of the fraction of loans retained by each bank, which in reality is difficult to access for outsiders. Firstly, unlike syndicate lending in primary markets, loan sales in secondary markets often involve a chain of resales. The multiple layers of turnover limits investors' ability to identify the sources of the loans, not to mention the exact portion that each originator reserves. The complexity inherent in securitization is in fact one of the reasons why government intervention is needed to alleviate information asymmetry.[1] Secondly, securitization is characterized by pooling various assets and passing them as a pack onto general investors. As a result, a single buyer in the secondary market usually possesses various securitized loans issued by different banks. Due to the benefits of diversification, investors lack incentive to spend resources in finding out what proportion of loans each originator retains. In reality, the signaling effect did not seem to be significant in the securitization market, otherwise, we would not have observed the meteoric declines in banks' underwriting standards before the financial crisis.

### 3.3.2 Characterization of the General Equilibrium

In this section, we analyze the optimal underwriting standards of banks, $R^*$, which is the minimum expected return of projects that banks will accept at $t_0$, as well as the market clearing price $P$ in the secondary loan market. As will be elaborated later, banks' optimal decision rule is that they strictly prefer to loan out the initial capital at $t_0$ if $R_0 > R^*$, reject the project if $R_0 < R^*$, and are indifferent when $R_0 = R^*$, where the threshold $R^* \geq 0$.[2]

**Definition 1** *A pair of* $(P, R^*)$ *constitutes an equilibrium, if (I): given price* $P$*, banks' optimal decision rule is characterized by* $R^*$*; and (II): given the decision rule* $R^*$*, the price* $P$ *clears the secondary market.*

[1] Keys, Mukherjee, Seru, and Vig [2010] also point out that there is very limited disclosure regarding who holds what in the 'originate-to-distribute' chain.

[2] When banks are indifferent, their choice does not affect $P$ because the probability of $\widetilde{R}_0 = R^*$ is 0.

The two conditions above will be examined respectively, and we will show that the interplay between the two agents results in the equilibrium of the model.

#### 3.3.2.1 Determination of banks' optimal underwriting standards given loan price

Given the secondary loan price $P$, banks' optimal underwriting standards at $t_0$ can be worked out through backward induction. At $t_1$, there are two possible scenarios based on bank's previous choice:

i. If it rejected the project at $t_0$, the value of the initial capital at $t_1$ will be $V_C \equiv \max(1, R_1)$, as the cash can either be carried forward to $T$ with gross return of 1, or be invested in the $t_1$-arriving project with expected return $R_1$;

ii. If the bank originated the loan at $t_0$, it will have to hold at least $1-\alpha$ fraction of the asset until maturity due to regulatory requirement, which yields $(1-\alpha)R_0$. The remaining proportion $\alpha$, which is allowed to be sold, can be managed in two ways: it can be either held until time $T$, with expected return $R_0$ or sold at price $P$ with the final value of $P\max(1, R_1)$.[1] The disposable part of the loan is thus worth $\max(R_0, P\max(1, R_1)) = \max(R_0, P, PR_1)$ per unit, the intuition being that banks are willing to sell the loans only when the price exceeds the loans' expected value *or* there is a more profitable investment opportunity available.[2] As the primary channel of redeploying capital, the securitization market essentially offers the bank a call option on future projects, which can be measured by the difference term $\max(R_0, P, PR_1) - R_0 \geq 0$. The properties of this underlying option will be explored in more detail later. To sum up, the value of $t_0$-originated loan at $t_1$, consisting of the retained part and sellable part, amounts to $V_L \equiv \alpha\max(R_0, P, PR_1) + (1-\alpha)R_0$.

[1] Their decision depends on the outside investment opportunities

[2] It is easy to prove that the optimal fraction of loans banks would sell in the market is the upper bound $\alpha$ imposed by government. In a nutshell, when banks can benefit from securitizing their loans, they should exploit it up to the maximum. Detailed proof is included in the Appendix.

Let us return to $t_0$, when $R_0$ is the bank's private information, and $R_1$ is uncertain. Since agents do not discount future cashflows in our model, the value of carrying cash forward is simply the expected value of $V_C$ conditioned on $\widetilde{R}_1$, which can be written as $E_{\widetilde{R}_1}(V_C) = E_{\widetilde{R}_1} \max(1, \widetilde{R}_1) \equiv C$. [1] Similarly, the value of investment on loan should be $E_{\widetilde{R}_1}(V_L) = \alpha E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) + (1-\alpha)R_0$.

We now introduce this function $f(R_0, P, \alpha) \equiv \alpha E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) + (1-\alpha)R_0$. The value of originating the loan at $t_0$ is determined by three variables: project quality, anticipated price in the secondary market, and the portion of loans that banks can sell to the general investors. It is easy to verify that $\frac{\partial f}{\partial R_0} > 0$, $\frac{\partial f}{\partial P} > 0$, and $\frac{\partial f}{\partial \alpha} > 0$, implying that in the face of high loan price /good project quality /loose regulation, banks are more likely to initiate loans at $t_0$.

The following condition holds when banks are indifferent between holding cash and issuing a loan:

$$\alpha E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) + (1-\alpha)R_0 = E_{\widetilde{R}_1} \max(1, \widetilde{R}_1) \tag{3.1}$$

$$\alpha \underbrace{[E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) - R_0]}_{\text{Expected option value}} + R_0 = \underbrace{E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)}_{\text{C: Opportunity cost}} \tag{3.2}$$

As shown in Equation 3.2, the right hand side of the equation represents the opportunity cost of issuing loans. Let $C$ refer to the opportunity costs. The left hand side of the equation is the benefits of issuing a loan at $t_0$. The foregoing analysis of function $f$ suggests that equation (1) has a unique solution with respect to $R_0$, as the left hand side of the equation is strictly increasing in $R_0$. We denote the solution by $R_0(P, \alpha)$. Given the values of $P$ and $\alpha$, we can work out the threshold project return $R_0(P, \alpha)$, at which banks are indifferent. Accordingly, the following decision rule directs banks' underwriting behavior: they strictly prefer to invest all their money in a loan if and only if the expected return from financing the project surpasses the threshold, namely $R_0 > R_0(P, \alpha)$, otherwise, banks will reserve its capital.

[1] Here constant C is fixed when the distribution of $\widetilde{R}$ is given.

The threshold return $R_0(P, \alpha)$ is plotted in Figure 3.2 as a function of $P$ and $\alpha$.[1] There are two special cases we would like to emphasize first:

i. Strict regulation and (or) undesirable market prices prohibit banks from securitizing their illiquid assets. When $\alpha = 0$, no selling is allowed in the secondary market. The lowest expected return of project that banks will accept under this circumstance at $t_0$ is always equal to $C$, which is the value of holding cash till $t_1$. In other words, banks are willing to issue the loan while giving up the investment opportunity for the next period only if the project quality at $t_0$ is high enough (higher than the opportunity cost). The highest underwriting standard also arises when the anticipated market price $P < 1$, regardless of $\alpha$. The rationale is that when $P < 1$, retaining initial capital till $t_1$ is always preferred over selling loans at $t_1$ as $\max(1, \widetilde{R}_1) \geq \max(1, P\widetilde{R}_1)$. Hence, the only reason for banks to originate loans at $t_0$ without securitization is that the current project is expected to be better than the future investment opportunities, i.e., $R_0 > E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)$. For the above two cases, banks would adopt the toughest lending standard $C$.

ii. When $\alpha = 1$, banks can transfer all their assets to loan purchasers. The vertical line in the graph shows that in the absence of regulation, banks are willing to undertake any project as long as they can sell it later at a price which is higher than 1.[2]

Apart from the extreme scenarios, the most prominent feature displayed in the graph is that for a given market price, banks' optimal underwriting standard decreases with respect to the portion of assets they can offload in the secondary market. Likewise, for a fixed value of $\alpha$, the higher the market price is, the lower expected return banks would require to originate a loan. Mathematically, it can be derived that $\frac{\partial R_0}{\partial P} = \frac{-f_P}{f_{R_0}} \leq 0$ and $\frac{\partial R_0}{\partial \alpha} = \frac{-f_\alpha}{f_{R_0}} \leq 0$.[3]

[1] Since the upper bound of the distribution of $\widetilde{R}_0$ is $R$, the domain of $P$ is set to be $[0, R]$ as the price shouldn't be higher than the maximum return.

[2] As analyzed before, when $P > 1$, banks would apply the highest lending criterion, even if there is no regulation.

[3] When $P > 1$, the strict inequalities hold: $f_P > 0$ and $f_\alpha > 0$. Hence, $\frac{\partial R_0}{\partial P} < 0$ and $\frac{\partial R_0}{\partial \alpha} < 0$ when $P > 1$.

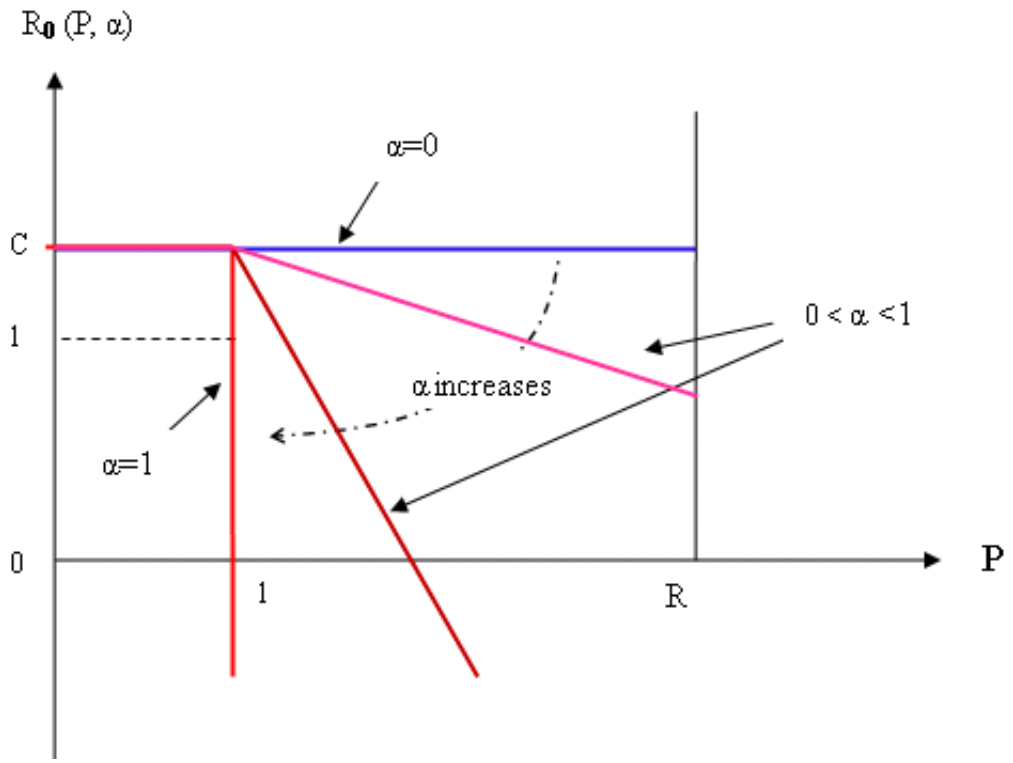



Figure 3.2: Threshold return $R_0(P, \alpha)$

As shown in Figure 3.2, $R_0(P, \alpha)$ can be negative, meaning projects with any quality will be undertaken. Considering that the distribution of $\widetilde{R}_0$ has no negative support, banks' optimal lending standard $R^*$ should be written as

$$R^* = \max(R_0(P, \alpha), 0) \tag{3.3}$$

Figure 3.3 summarizes banks' optimal lending choice at time $t_0$ in response to different levels of market price and regulation.

**Corollary 1** $\frac{\partial R^*}{\partial P} \leq 0$ *and* $\frac{\partial R^*}{\partial \alpha} \leq 0$.

Banks' lending choice at the initial stage depends on the price they anticipate in the aftermarket, and the limit of loan sales set by authorities. Not surprisingly,

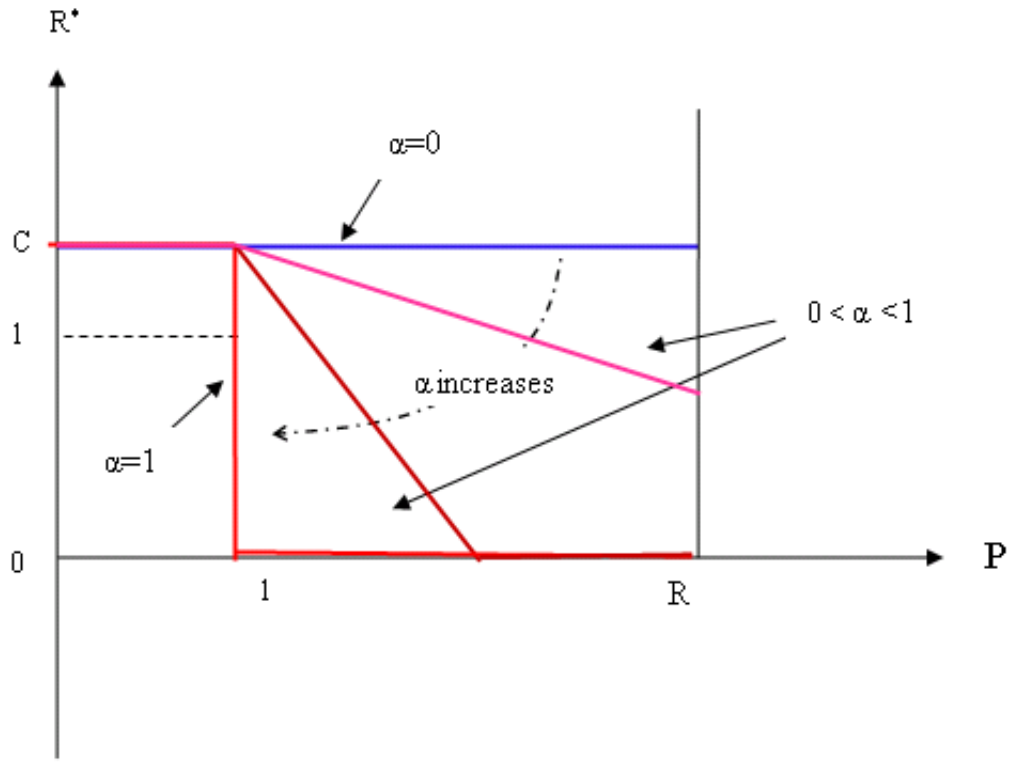



Figure 3.3: Bank's optimal lending standard $R^*$

their credit standard declines with increasing market price and $\alpha$. This result is consistent with the empirical facts of the securitization market. In the years that preceded the financial crisis, securitized loans experienced increasing default rates. In the meantime, Bord and Santos [2012] document the trend of declining proportion of term loans that were retained in the banking sector for the same period.

#### 3.3.2.2 Determination of market clearing price given banks' underwriting decision

As analyzed before, banks' selling behavior at $t_1$ should be driven by two motives: either the $t_0$-initiated loan is a lemon and overpriced by outsiders or the loan has a positive NPV, but banks have encountered a better project and thus need to

offload the existing one to finance the new one. Due to the lack of transparency in the secondary loan market, investors do not observe the qualities of the securitized assets and they cannot distinguish between the two motives of banks' selling behavior. As a consequence, loan buyers bet on average and pay a single average price. In our model, their rational expectation is formed purely based on all the information available to them.

First of all, the decision rule of banks at $t_0$ suggests that the expected return of the loan on sale should not be lower than banks' underwriting standard, which is $R_0 \geq R^*$. Otherwise, banks would not have originated it in the first place. Second of all, banks are willing to offload the $t_0$-innitiated loan either when the market price of the loan is high enough or when they face better investment opportunities, which implies that $P\max(1, R_1) \geq R_0$. We posit that investors are on the long side of the market, i.e., they only break even when market is clear. Therefore, the equilibrium price of loan on sale should satisfy investors' conditional expectation of its true value.

$$P = E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0 | P\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*) \tag{3.4}$$

To see how investors' expectation varies, we define a function $h(P, R^*) \equiv E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0 | P\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*)$, whose domains are $P \in [\frac{R^*}{R}, R]$ and $R^* \in [0, R]$.[1] As depicted by Figure 3.4, the main feature of the graph is that $h(\cdot, R^*)$ is increasing in $P$ for any given $R^*$ and then the curves move downwards with descending $R^*$.[2] Intuitively, low lending standards in the first period would certainly drive down investors' expectations. However, when the underwriting standard is given, a higher market price is suggestive of better quality assets as investors would not sell them otherwise.

It can be proved that for any given value of $R^* \in [0, R]$, a solution for P in Equation 3.4 exists.[3] Moreover, we define function $g(R^*)$ as the solution to

[1] Proof: $P\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*$, which suggests $P \geq \frac{R^*}{\max(1,\widetilde{R}_1)} \geq \frac{R^*}{R}$. In addition, since $P \leq R$ is given, the range of $P$ should be $[\frac{R^*}{R}, R]$.

[2] It is trivial to verify that $\frac{\partial h}{\partial P} \geq 0$ and $\frac{\partial h}{\partial R^*} > 0$.

[3] See Appendix B for proofs.

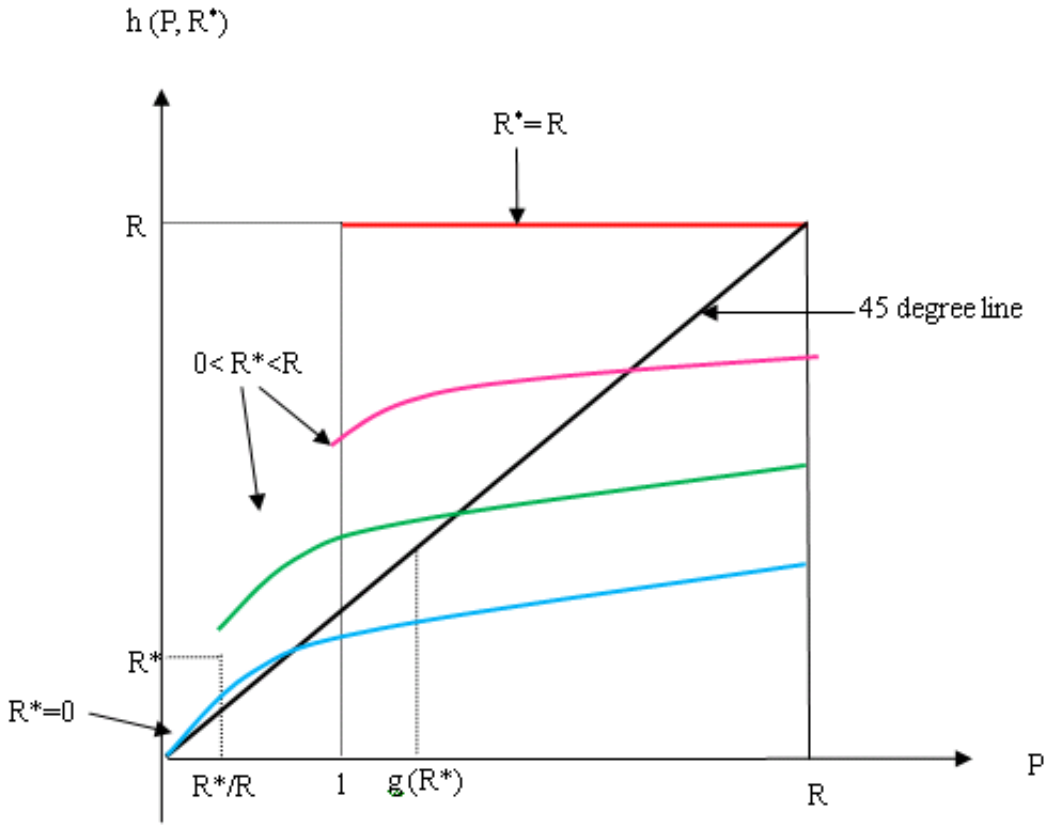



Figure 3.4: Investors' expected loan return $h(P, R^*)$

Equation 3.4 so that we can study how the optimal lending choice of banks at the first period affects the secondary market price.[1] Hence, $g(R^*)$ is an implicit function defined by $h(P, R^*) = P$ with $g(R) = R$.

**Lemma 1** *$P = g(R^*)$ strictly increases with $R^*$.*

**Proof** If $R^* > R^{*\prime}$, then $h(g(R^{*\prime}), R^*) > h(g(R^{*\prime}), R^{*\prime}) = g(R^{*\prime})$. This together with $h(\cdot, R^*)$ is an increasing function and $h(R, R^*) < R$ implies that $h(P, R^*) = P$ has a solution within $(g(R^{*\prime}), R)$. Then $g(R^*)$ is within this interval, as it is the biggest root of $h(P, R^*) = P$. Therefore, $g(R^*) > g(R^{*\prime})$. □

[1] In the case of $h(P, R^*) = P$ having multiple solutions, $g(R^*)$ equals the biggest root.

Intuitively speaking, rational investors form model-consistent expectations, which means their predictions are always valid on average. As a result, market equilibrium price should reflect the level of expected loan qualities, which should be increasing with banks' underwriting standards. In addition, Equation 3.4 suggests that $g(R^*) \geq R^*$, meaning that the market price of securitized assets is never lower than the threshold return banks accept at time $t_0$.

For $P \in [g(0), R]$, the inverse function of $g(R^*)$ exists, which is given by $R^* = k(P)$. By definition, $k(P)$ is continuous and increasing over $P \in [g(0), R]$, with $k(R) = R$ and $k(P) \leq P$.[1] Figure 3.5 illustrates this function.

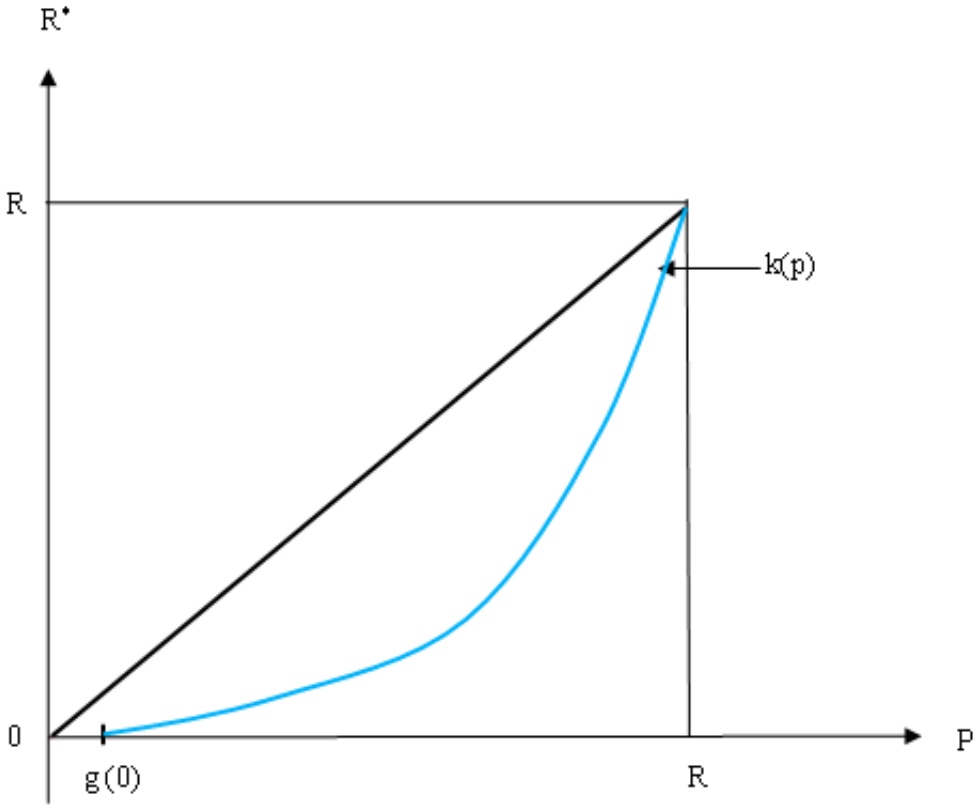



Figure 3.5: The inverse function $k(p)$

[1] Because $g(R) = R$ and $g(R^*) \geq R^*$.

**Remark 1** *The value of $g(0)$ depends on the upper bound, $R$, of the random return $\widetilde{R}_i$.*

*The value of $g(0)$ deserves special attention as it measures the lowest price investors would offer when they know that banks would underwrite loans for any project at $t_0$ (i.e., $R^* = 0$). Let us consider the case when $\widetilde{R}_i$ is uniformly distributed over $[0, R]$. According to its definition, $h(P, 0)$ is investors' expected value of the loans given that banks' lending standard $R^*$ is 0 and the market price is $P$. It can be derived that:*

$$h(P,0) = E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0 | P\max(1,\widetilde{R}_1) \geq \widetilde{R}_0) = \left\{ \begin{array}{cc} P\frac{R^3+2}{3R^2+3} & if \quad P \leq 1 \\ \frac{3PR^3-2R^3+2P^3}{6PR^2-3R^2+3P^2} & 1 \leq P \leq R \end{array} \right\}.$$

*Obviously, $P = 0$ solves $h(P, 0) = P$. But if $\frac{R^3+2}{3R^2+3} > 1$, we have $h(P, 0) > P$ when $P \leq 1$, and thus there exists at least another solution $\widehat{P} > 1$. By definition, $g(0) = \widehat{P} > 1$. The value of $g(0)$ is therefore determined by $R$, the upper bar of project return. Recall that the necessary participation condition of banks is that $P > 1$ . $g(0) = 1$ is critical in that banks would not participate in the market if the expected secondary market is lower than 1. On the other hand, in the face of lowest lending standard, investors could only pay a price lower than 1 if $R$ is too small such that $g(0) < 1$ , which precludes the possibility of equilibrium with $R^* = 0$. In other words, when $g(0) < 1$, banks will never initiate loans with 0 expected return. We will discuss this point in depth later.*

### 3.3.3 The Equilibrium

The equilibrium of the model is determined through the interaction between banks and loan purchasers. As shown before, they gauge how the other party would respond, and base their optimal actions on that. Equilibrium is thus a stable situation where all competing influences are balanced. In our model, two agents' participation conditions should be both satisfied to obtain equilibrium, i.e., the following equations must hold simultaneously:

$$\begin{cases} R^* & = \max(R_0(P,\alpha), 0) \\ P & = E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0 | P\max(1,\widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*) \end{cases} \tag{3.5}$$

For any $\alpha \in [0,1]$ there is a unique equilibrium, denoted by $P(\alpha)$ and $R^*(\alpha)$ , which solves the above equation system.

As discussed earlier, $g(0)$ varies, relying on the value of $R$. We therefore distinguish between the cases when $g(0) \leq 1$ and when $g(0) > 1$. Figure 3.6.1 and 3.6.2 demonstrate the equilibria - the intersection points of the curves represent sets of equilibrium price and lending standard for different levels of $\alpha$. It is interesting to see that when $g(0) < 1$, the underwriting standard of banks $R^*$ is always positive (as shown in figure 3.6.1) - banks are selective when funding projects; When $g(0) > 1$ in contrast, $R^*(\alpha)$ reaches the lower bound for $\alpha$ close to 1 - banks would take on any project disregarding its quality. The second case is certainly worth further analysis. In our model, investors are rational, but they are willing to offer a good price despite banks' low lending standard as long as the possible maximum return of loans is high enough. Intuitively speaking, to overcome the information asymmetry, risk neutral loan buyers usually hold a portion of a diversified asset pool, and hence they only care about the average return of the securitized loans. Since the average return should increase with the upper bound of the distribution, investors would accordingly adjust their expectation upwards as well. Moreover, an important motive for banks to sell securitized assets is to reallocate money to a better project at $t_1$. In the case of a high $R$, banks are more likely to give up good-quality $t_0$-initiated assets for an even greater return from the $t_1$ project. By comparing the curves of function $k(P)$ in Figures 3.6.1 and 3.6.2, we can see that greater $R$ boosts the price investors would offer given the same underwriting standard. [1]

Both of the graphs indicate the critical role of $\alpha$ in determining the equilibrium price and lending standards: as the limit of loan sales $\alpha$ decreases, the intersection point moves towards northeast, indicating higher price and stricter underwriting criterion. Authorities can thereby regulate the market through this channel by setting the optimal $\alpha$ to attain the desirable level of price and $R^*$. We will examine the mechanism in the next section.

[1] $R^H$ in Figure 3.6.2 represents a higher upper bound of $\widetilde{R}_i$. In addition, increased $R$ causes a higher opportunity costs of issuing loans, which is captured by the difference between $C_1$ and $C_2$.

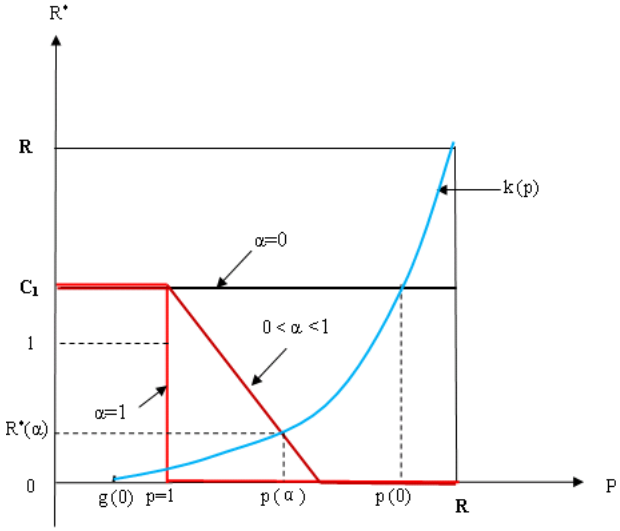



Figure 3.6.1. Equilibrium with g (0) <1

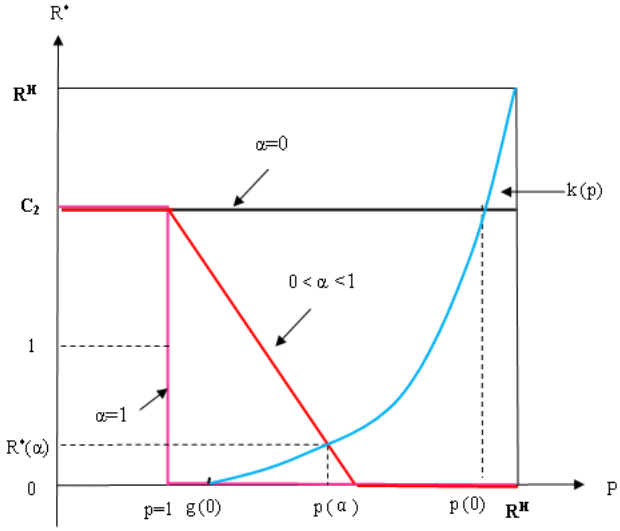



Figure 3.6.2. Equilibrium with g (0) >1

Figure 3.6: Equilibria with different $g(0)$

## 3.4 Implications of the model

### 3.4.1 Deterioration of loan quality in a free market

Low-quality mortgage has been accused of triggering the recent financial crisis. In this subsection, we will examine how the advent of securitization alters the banks' credit standard $R^*$.

According to its definition, $R^*(\alpha)$ is the equilibrium lending standard under the regulation that at most $\alpha$ portion of loans can be sold to investors. In the extreme scenario of $\alpha = 1$, no regulation is imposed on the secondary markets and banks are free to offload any portion of their illiquid assets. Our model shows that in the absence of regulation, disintermediation alone will necessarily lead to deterioration of loan quality.

**Proposition 1** *When the secondary loan market is unregulated, banks originate loans for negative-NPV projects, that is,* $R^*(\alpha = 1) < 1$.[1]

[1]

Proposition 1 is one of the key results of this paper. Projects with expected return $R < 1$ are regarded to have negative NPV and should never be implemented in an ideal world.[1] However, banks with access to the free secondary loan market would underwrite bad projects as well, leading to deterioration in the average loan quality. The fundamental reason lies in risk pooling caused by information asymmetry. Lacking private information on the projects, investors cannot distinguish two motives of banks' selling behavior: either loans are lemon or banks have encountered better investment opportunities. As a consequence, loan buyers bet on average and pay a single average price. By holding a diversified portfolio of loans, they can realize the expectation value. For this reason, even though investors rationally anticipate that there are lemons trading in the market, they are willing to participate in the secondary market. In the meanwhile, banks expect that they can sell bad loans in the secondary market, which in effect gives them an incentive to initiate bad loans at $t_0$.

**Remark 2** *The lowest lending standard can arise in an unregulated market. As shown in Figure 3.6.2, with $g(0) > 1$, underwriting criterion $R^*(\alpha = 1) = 0$, under which a project with any quality will be accepted at $t_0$.*

*Let us continue with the previous example with random return $\widetilde{R}_i \sim unif\ [0, R]$. If the upper bound $R$ is sufficiently high such that $\frac{R^3+2}{3R^2+3} > 1$, we shall see $g(0) > 1$. In this case, it can be verified that $R^* = 0$. In contrast, if $R < \overline{R}$, where $\overline{R}$ is the biggest root of $R^3 - 3R^2 - 1 = 0$, then we can prove $R^* = \frac{R-\sqrt{R^2+\frac{R}{3}(R^3-3R^2-1)}}{R} > 0$.*

*To assess the loan quality in the secondary market, recall that investors' rational expectation is $\widetilde{R}_0 \in \{\widetilde{R}_0 | P \max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*\}$, which is fulfilled in equilibrium. Figure 3.7.1 and Figure 3.7.2 illustrate banks' selling decision at time $t_1$ in the absence of regulation ($\alpha = 1$). The shaded areas in the graphs*

**Proof** Proof by contradiction: Suppose $R^*(\alpha = 1) \geq 1$. From investors' participation condition, i.e., equation(3), we obtain that $P > 1$. But if $P > 1$, then $R^*$ must be 0 according to figure 2, which contradicts with the initial assumption that $R^*(\alpha = 1) \geq 1$. Therefore, $R^* < 1$ if $\alpha = 1$. □

[1] Without securitization, equation (4) shows that banks will choose the highest lending standard $C = E_{\widetilde{R}_1} \max(1, \widetilde{R}_1) > 1$. Negative-NPV projects will never be financed.

*represent the set of loans (with expected return $R_0$) to be sold in the secondary market. In particular, Figure 3.7.2 is the case when upper bound $R > \overline{R}$. The equilibrium price in this case is $P > 1$ and the lending standard is $R^* = 0$. Figure 3.7.1 is for $R \leq \overline{R}$, when we have $P = 1$ and $R^* = \frac{R - \sqrt{R^2 + \frac{R}{3}(R^3 - 3R^2 - 1)}}{R} > 0$. From the graph, we can identify two motives of selling loans: either the securitized asset is overpriced ( $\widetilde{R}_0 < P$) or a better project has come out at $t_1$ ($\widetilde{R}_1 > \frac{\widetilde{R}_0}{P}$). These two figures essentially display the distribution of expected returns of loans in the secondary market. It is worth mentioning that when $R$ is big enough (in Figure 3.7.2), the worst loans (with $R_0 = 0$) could be on sale in the market.*

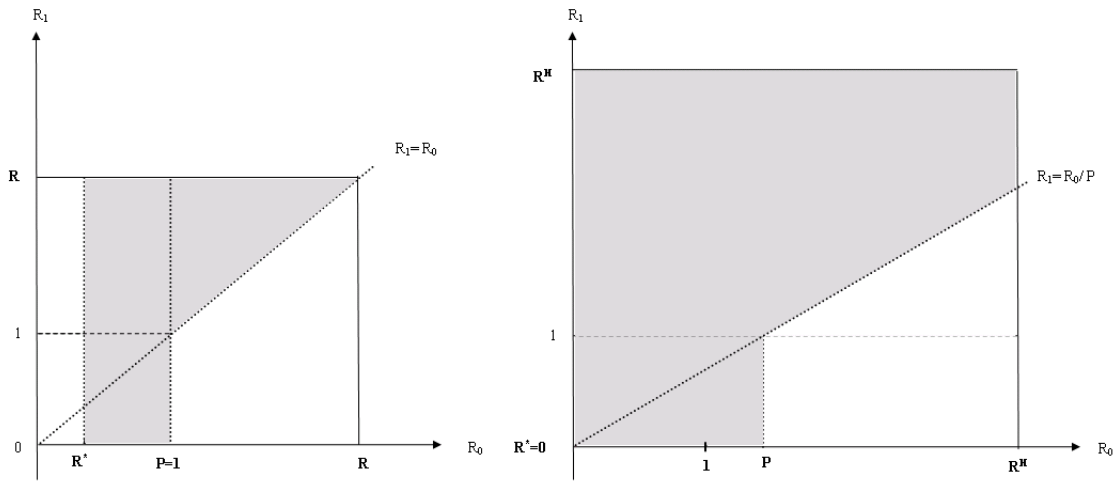



Figure 3.7.1. Bank's selling decision at $t_1$ with g(0)<1 in unregulated market

Figure 3.7.2. Bank's selling decision at $t_1$ with g(0)>1 in unregulated market

Figure 3.7: Banks' selling decision at time $t_1$

Moreover, lower lending standard suggests that more investments will be carried out, which is consistent with the fact that the opening of the secondary loan market led to massive capital inflows. In addition, the empirical study by Gande and Saunders [2012] shows that loan sales alleviate firms' financial constraint, and firms tend to spend more in investments during the post-loan sale period.

### 3.4.2 The effect of business cycle on securitization market

Investment opportunities in our simplified economy are characterized by their random returns $\widetilde{R}_i$ with domain $[0, R]$. For the given uniform distribution, the average return of the projects is increasing in the upper boundary $R$. For this reason, the level of $R$ can be used as an indicator of the economic condition. Economic expansion and recession are represented by great $R$ and small $R$ respectively. Our model reveals how fluctuating levels of economic growth exert impacts on the securitization market with unchanged regulatory environment (fixed $\alpha$).

i. **Equilibrium Loan Price:** Recall banks' participation condition (Equation (3.2)), when the upper bound of $\widetilde{R}_i$ rises to $R^H$, banks will adopt a stricter lending standard given the same market price and $\alpha$, as the opportunity cost of issuing loans is increased. The arrow in Figure 3.8.1 captures this trend.[1] On the other hand, with greater average return (higher $R$), rational investors are willing to pay a higher price given the same lending standard of banks, which is depicted by the arrow in Figure 3.8.2. Intuitively speaking, investors rationally anticipate that banks are more likely to give up good quality loans for better opportunities during an economic boom.[2] As described in Figure 3.8.3, given the same regulation constraint, the equilibrium price of securitized loans is higher during an boom than in a recession. To conclude, the equilibrium price of securitized loans is closely related to the aggregate

[1]

**Proof** We prove that banks' lending standard is increasing in the opportunity cost $C$, namely, $\frac{\partial R_0}{\partial C} \geq 0$. When $P < 1$, $R_0 = C$, which means $\frac{\partial R_0}{\partial C} > 0$; When $\frac{1}{\alpha} < P < R$, $R_0 = 0$, which suggests $\frac{\partial R_0}{\partial C} = 0$.

Banks' participation condition can be rewritten as $\alpha[E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) - R_0] + R_0 = C$, based on which we obtain that $\alpha[\max(R_0, PC) - R_0] + R_0 = C$, which gives $\max[0, \alpha(PC - R_0)] = C - R_0$. If $\alpha(PC - R_0) \geq 0$, then $\alpha(PC - R_0) = C - R_0$, based on which $R_0 = \frac{1-\alpha P}{1-\alpha} C$ can be obtained. When $1 < P < \frac{1}{\alpha}$, $\frac{\partial R_0}{\partial C} = \frac{1-\alpha P}{1-\alpha} > 0$. Therefore, for $P \in [0, R]$, $\frac{\partial R_0}{\partial C} \geq 0$. Moreover, for a given distribution of $\widetilde{R}_i$, $\frac{\partial C}{\partial R} > 0$. Hence, $\frac{\partial R_0}{\partial R} \geq 0$, namely, banks' optimal lending standard should increase with the upper bound $R$.

□

[2]We prove that the curve of $k(P)$ shifts to the right as $R$ increases. See Appendix for details.

economic performance, and thus should evolve in accordance with business cycles.

ii. **Equilibrium Lending Standard:** Figure 3.8.3 also indicates two channels through which economic prospect affects banks' lending standard in equilibrium. First of all, faced with high opportunity cost in times of strong economic growth, banks are reluctant to fund low quality projects as they have a better chance to encounter good ones tomorrow than in a recession, which uplifts their underwriting criterion. On the other hand, however, outside investors are more tolerant towards a low lending standard when they foresee that investment projects are on average highly profitable and would like to pay a higher price given the same underwriting standard. We use two arrows in Figure 3.8.3 to identify the two competing forces. The net effect on $R^*$ largely depends on the limit of loan sales $\alpha$. When $\alpha = 1$, banks can transfer all the loans to outside investors and the lending standard $R^*$ will drop as a consequence as banks do not bear the costs of lemon. When $\alpha = 0$, banks will increase $R^*$ to $C_H$. When $0 < \alpha < 1$, the lending standard in equilibrium will increase with the upper bound $R$ if $\alpha$ is close to 0 and decrease with $R$ when $\alpha$ is close to 1.

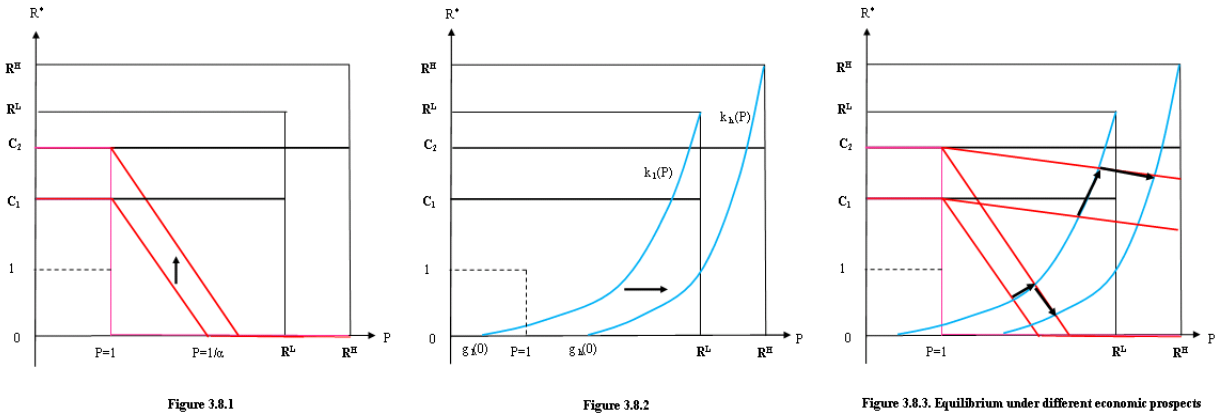



Figure 3.8: Equilibria under different economic prospects

### 3.4.3 The effect of regulation on bank's lending standard

In our model, the equilibrium loan price $P(\alpha)$ and lending standard $R^*(\alpha)$ are expressed as functions of $\alpha$. By steering the limit of loan sales, regulators can promote their objectives on asset prices and loan qualities. Firstly, market pricing information is generally regarded as an indicator of the financial health of the banking system. When regulators tighten their control over loan sales, the market price of loans should move up as a result.

In our framework, the partial derivative function of $P$ with regard to $\alpha$ can be shown as follows:[1]

$$P'(\alpha) = \left\{ \begin{array}{cc} \frac{-f_\alpha}{f_P + f_k k'} & \text{if} \quad R^* > 0 \\ 0 & \quad R^* = 0 \end{array} \right\} \tag{3.6}$$

Since $P'(\alpha) \leq 0$, regulators can enhance the market price by lowering the upper bar of loan sales. We depict this pattern in Figure 3.9.1 and 3.9.2 by showing the relationship between the equilibrium loan price $P$ and $1-\alpha$. When $g(0) \leq 1$, $P$ is strictly increasing with respect to $1-\alpha$ while in the case of $g(0) > 1$, $P$ is a constant equalling $g(0)$ when $1-\alpha$ is close to 0 and then increases with $1-\alpha$. These two scenarios correspond to different upper bounds of expected asset return. In general, the greater portion of loans that is retained within the banks, the higher loan price should be observed in the securitization market.

Compared to loan prices, regulators are usually more concerned with loan quality, as negative NPV projects usually bring about detrimental social costs. The equilibrium lending standard in our model is also a function of $\alpha$, namely,

[1] **Proof** when $R^* > 0$, $P(\alpha)$ is implicitly defined by $f(k(P), P, \alpha) = E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)$. Hence, $P'(\alpha) = \frac{-f_\alpha}{f_P + f_k k'}$; When $R^* = 0$, $P$ is a constant $g(0)$. $P'(\alpha)$ is thus equal to 0. □

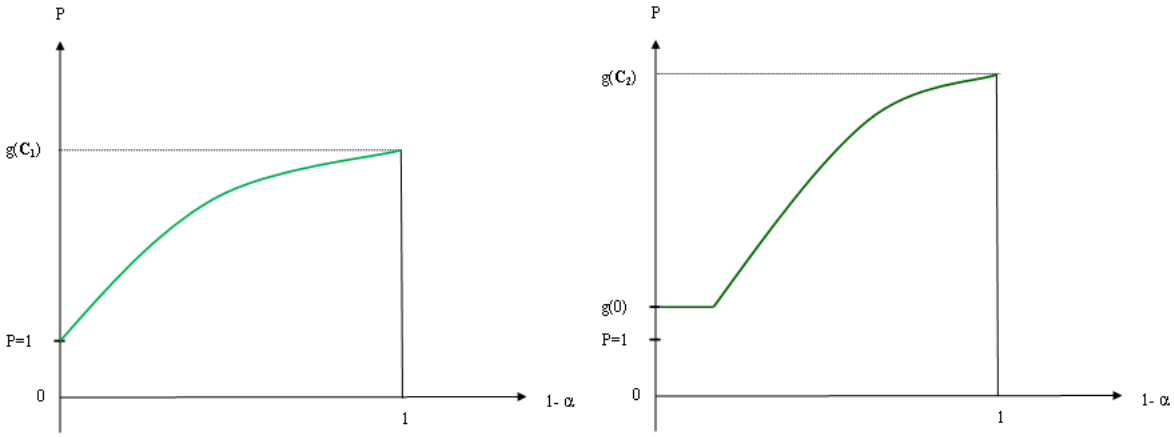



Figure3. 9.1. Equilibrium price and the retained portion of loans (with g(0)<1)

Figure 3.9.2. Equilibrium price and the retained portion of loans (with g(0)>1)

Figure 3.9: Equilibrium price and the retained portion of loans

$R^*(\alpha)$. Moreover, banks tend to lower their lending criteria when they are subject to looser loan sale constraint.

**Proposition 2** *The equilibrium lending standard satisfies* $\frac{dR^*(\alpha)}{d\alpha} \leq 0$ *and the strict inequality holds when* $R^* > 0$. *That is, a larger retained portion* $(1-\alpha)$ *leads to better quality of the securitized loans.*[1]

Proposition 2 indicates that by raising the required portion of loans retained within banks, regulators can effectively improve loan quality. Figure 3.10 illustrates the underlying mechanisms. As $1-\alpha$ increases, there are two conduits for regulation to influence lending standard $R^*$. First is through the direct cost effect. With a bigger portion of loans remaining on the books, banks bear more risks of the assets. Thus they have less incentive to initiate bad-quality loans,

1

**Proof** $R^*(\alpha)$ can be written as $k(P(\alpha))$. Therefore, $R^{*\prime}(\alpha) = k^{'}(P)P^{'}(\alpha) \leq 0$, as $k^{'}(P) > 0$ and $P'(\alpha) \leq 0$ by equation(4). Also, $R^{*\prime}(\alpha) < 0$ when $R^* > 0$, because $P'(\alpha) < 0$ when $R^* > 0$.□

which is shown by $\frac{\partial R_0(P,\alpha)}{\partial \alpha} < 0$. On the other hand, however, our general equilibrium framework reveals the second (indirect) effect caused by regulation. An expansion in $1-\alpha$ also increases the anticipated market price $P$, which would in turn encourage banks to originate more loans, including the bad ones. Based on the model, we can derive that, $\frac{\partial R_0(P,\alpha)}{\partial P} \cdot \frac{\partial P(\alpha)}{\partial \alpha} > 0$. The consequence of these two opposite effects is not straightforward. From the model, we can find that the total effect remains positive. On balance, lending standard increases with $1-\alpha$. As shown in Figure 3.10, the vertical arrow captures the direct effect while the other arrow traces the indirect effect.

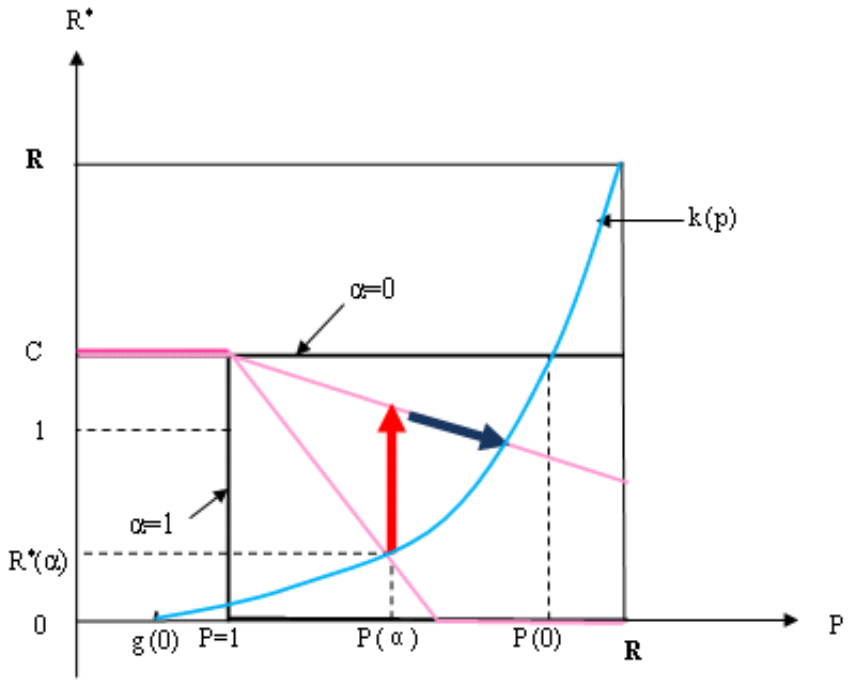



Figure 3.10: The opposing effects of regulation on equilibrium lending standard

It should be emphasized that tough regulation is not always desirable. For instance, when $\alpha = 0$, banks are forbidden to transfer any illiquid assets to outside investors. Without the benefits from recycling their funds in the secondary loan market, banks are prone to adopt high criteria in choosing projects. As can be seen in Figure 3.2, we obtained $R^* = C > 1$ when $\alpha = 0$. In other words, in

the absence of the secondary loan market, the underwriting standard is so high such that banks would even forsake some positive NPV projects if $1 < R_0 < R^*$. From a regulator's perspective, there exists an 'optimal' point of $\alpha$ such that $R^*(\alpha^*) = 1$. However, it is hard to conclude that $R^*(\alpha^*) = 1$ is always the best solution as it might not lead to the best allocation of social resources.[1] The banks' profit maximization problem follows in the next subsection.

### 3.4.4 'Optimal' $\alpha$ - Banks' profit maximization problem

In our model, loan buyers' expected profit should be nil as they break even on average no matter what limit of loan sale is imposed. For this reason, we focus on the other agent(banks) of the model and analyze how the regulators' decision affect their profits, leaving other matters (e.g. social costs, liquidity issues) aside for the moment.

At $t_0$, banks could obtain $E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)$ from holding cash *or* $f(R_0, P, \alpha) = \alpha E_{\widetilde{R}_1} \max(R_0, P \max(1, \widetilde{R}_1)) + (1-\alpha)R_0$ from initiating the loan with expected return $R_0$. In equilibrium, they should be able to achieve the maximum of the two.[2] The ex ante profit of banks is thus expressed by $W(\alpha) = E_{\widetilde{R}_0}(\max[f(\widetilde{R}_0, P, \alpha), E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)])$.

**Proposition 3** *The ex ante profit of banks satisfies* $\frac{dW(\alpha)}{d\alpha} > 0$. *Banks' expected profit increases when a smaller fraction of loans is required to be retained within the banks.*

**Proof** To prove $\frac{dW(\alpha)}{d\alpha} > 0$, it suffices to show that $\frac{df(R_0, P(\alpha), \alpha)}{d\alpha} > 0$ for any $R_0$.

[1] For example, suppose project returns $R_0 = 0.9$, and $R_1 = 2$. Given $R^*(\alpha^*) = 1$, banks would have to reject the $t_0$ project and then invest its one unit of capital in the $t_1$ project. In contrast, under lax regulation such that the $R^*(\alpha) = 0.9$, banks would fund the $t_0$ project and then sell it at price $P > 1$ in the secondary market. Now banks have obtained $\alpha P$ and would invest it in the $t_1$ project. If $\alpha P > 1$, more money is invested in the $t_2$ project than in the previous case. If we assess social welfare solely based on gross profits, the second case might be more desirable if the benefit from the $t_1$ project exceeds the loss associated with the $t_0$ project.

[2] If $R_0 < R^*$, banks will carry capital till time $t_1$; If $R_0 > R^*$, banks will originate loans and obtain $\alpha E_{\widetilde{R}_1} \max(R_0, P \max(1, \widetilde{R}_1)) + (1-\alpha)R_0$; If $R_0 = R^*$, banks are indifferent because those two options would lead to the same result.

Since $\frac{df(R_0,P(\alpha),\alpha)}{d\alpha} = f_\alpha + f_P P'(\alpha)$, where$f_\alpha = E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) - R_0 > 0$, $f_p \geq 0$ and $P'(\alpha) \geq \frac{-f_\alpha}{f_P + f_k k'}$, we obtain that $\frac{df(R_0,P(\alpha),\alpha)}{d\alpha} \geq f_\alpha - f_P \frac{f_\alpha}{f_P + f_k k'} = \frac{f_k k'}{f_P + f_k k'} f_\alpha > 0.$, which completes our proof. □

It is interesting to see that an increment in $\alpha$ causes two offsetting effects on banks' profit. The partial derivative function $\frac{df(R_0,P(\alpha),\alpha)}{d\alpha}$ specifies the two channels: (i) $f_\alpha$ effectively measures the option value of securitization, which is always positive. Intuitively speaking, the more illiquid assets banks can get rid of in the secondary market, the more efficient allocation of capital banks can achieve when encountering better projects; (ii) Price effect is reflected by the second term of the expression $f_P P'(\alpha)$. As we analysed before, high $\alpha$ incurs low-quality loans, which lowers the equilibrium price, and the amount of capital banks can obtain from the market diminishes as a consequence. Yet the price effect in magnitude is only a fraction of the option value, so the overall impact stays positive. With the purpose of maximizing banks' profits, regulators should not impose any constraint in loan sales. The underlying reason is that the securitization market offers banks an opportunity (an option) to reorganize social resources in a more efficient way and banks can make most of it when $\alpha$ is equal to 1.[1]

This paper explicitly models the benefits of securitization by incorporating a call option on future investment opportunities.

$$\alpha \underbrace{[E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) - R_0]}_{\text{Expected option value}} + R_0 = C$$

$E_{\widetilde{R}_1} \max(R_0, P, P\widetilde{R}_1) - R_0$ measures the option value of securitization. Recall that the equilibrium price of loans are established such that the price represents the expected value of $R_0$.[2] Hence, $E_{\widetilde{R}_1}[P] = R_0$ in equilibrium. In other words, banks cannot profit from mispricing on average. Given a fair market price $P$, the payoff of the option hinges on the realization of $\widetilde{R}_1$. The underlying option

[1]Without securitization, banks' ex ante profit is given by $W(\alpha) = E_{\widetilde{R}_0}[\max(\widetilde{R}_0, E_{\widetilde{R}_1} \max(1, \widetilde{R}_1))]$. With the aid of securitization, banks' expected profit is increased to $W(\alpha) = E_{\widetilde{R}_0}[\max(\alpha(E_{\widetilde{R}_0,\widetilde{R}_1} \max(\widetilde{R}_0, P \max(1, \widetilde{R}_1)) - \widetilde{R}_0) + \widetilde{R}_0), E_{\widetilde{R}_1} \max(1, \widetilde{R}_1))]$. When $\alpha$ is set to be 1, the expected profit reaches its maximum.

[2]See Equation 3.4 for investors' participation condition.

can thus be viewed as a standard call option on $\widetilde{R}_1$, the return of future projects, with strike price $\frac{R_0}{P}$. The value of an option is a monotonic increasing function of the volatility of the underlying asset. Given a certain distribution of $\widetilde{R}_i$, greater volatility of $\widetilde{R}_i$ suggests higher option value. For this reason, securitization should be more valuable to banks when the investments are riskier.

## 3.5 The Extended Model with Maturity Mismatch

As well documented, maturity mismatch makes the modern banking system vulnerable to liquidity shocks. In the benchmark model, we did not address liquidity issues. Gorton and Metrick [2012] points out that 'Securitized banking is the business of packaging and reselling loans, with repo agreements as the main source of funds.' and the 2007-2008 crisis was essentially a repo market run. In support of their findings, our model implies that securitization alone would not lead to the systemic failure of the banking sector. In addition, as asserted in Acharya and Naqvi [2012], banks bear liquidity risk as they are subject to random deposit withdrawals. In the event of liquidity shortfalls, banks will suffer from fire sales or resort to external financing at high costs.

In this section, a simplified case of liquidity shock is analyzed. We assume that banks' initial capital consists of equity capital and deposits. Depositors can withdraw cash $L(< 1)$ from the bank at either time $t_1$ or $T$ with probability $\lambda$ and $1 - \lambda$ respectively (see the timeline of cash withdrawal in Figure 3.11). Failing to pay back depositors will cause liquidation of the bank and the cashflow to the shareholders of the bank will be 0 due to limited liability.

We examine the effects of liquidity shock in two scenarios, one with $\alpha = 0$ and one with $\alpha = 1$. When $\alpha = 0$, selling loans in the secondary market is banned. From Figure 3.12, we can see that the lending standard now is uplifted to $C_s = C\frac{1-\lambda L}{1-\lambda}$, where $C = E_{\widetilde{R}_1} \max(1, \widetilde{R}_1)$, due to potential liquidity shock. Banks will take on the risk of falling short of liquidity only when the project is highly profitable. When $\alpha = 1$, banks call sell as much loans as they want. As

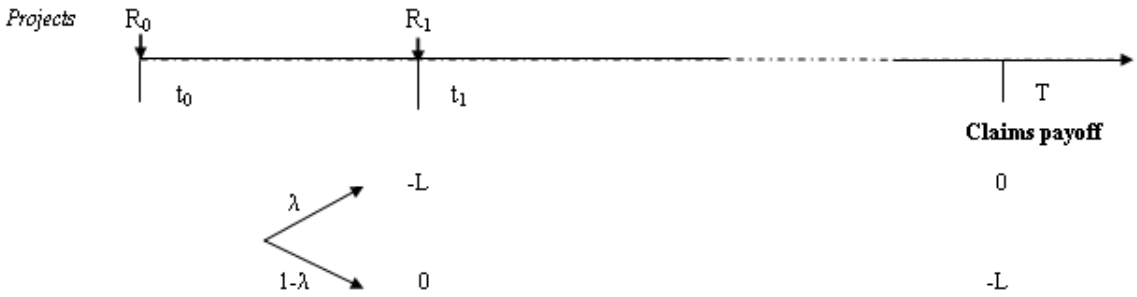



Figure 3.11: Time line with liquidity shock

shown in the previous section, banks will not participate in the secondary market if the anticipated loan price is lower than 1. Interestingly, banks' participation condition is relaxed in the presence of uncertain deposit withdrawal. The lowest price banks would accept now is $P = L$ because securitization adds value to the bank in that it resolves maturity mismatch as long as $P \geq L$.

At the same time, rational investors expect banks to sell the loan when there is liquidity shock $L$ at $t_1$ or $P \max(1, R_1) \geq R_0$ when there is no liquidity shock. Therefore, investors' expectation of the loan quality should be $h(P, R^*, \lambda) \equiv (1 - \lambda)E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0|P \max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*) + \lambda E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0|\widetilde{R}_0 \geq R^*)$, which increases with probability $\lambda$. Moreover, the equilibrium price $P$ should satisfy investors' conditional expectation:

$$P = (1 - \lambda)E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0|P \max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*) + \lambda E_{\widetilde{R}_0,\widetilde{R}_1}(\widetilde{R}_0|\widetilde{R}_0 \geq R^*) \quad (3.7)$$

In the presence of potential liquidity shock, the solution to Equation 3.7 now depends on both $R^*$ and $\lambda$. Denote the solution $P = g(R^*, \lambda)$. It is easy to prove that $g(R^*, 0) < g(R^*, \lambda)$ for any $\lambda > 0$. Therefore, $k(P)$, the inverse function of $g(R^*)$, should move to the right when $\lambda > 0$, as depicted in Figure 3.12. Intuitively speaking, since banks might sell off good projects when it experiences random cash withdrawal, rational investors would expect loans of higher quality to be traded in the secondary market. The equilibrium results are shown in Figure 3.12.

The equilibrium lending standard is decreasing with $\lambda$, the probability of liquidity shock at $t_1$ and when $\lambda$ is high enough, the equilibrium price of securitized loans will go up as a result.[1]

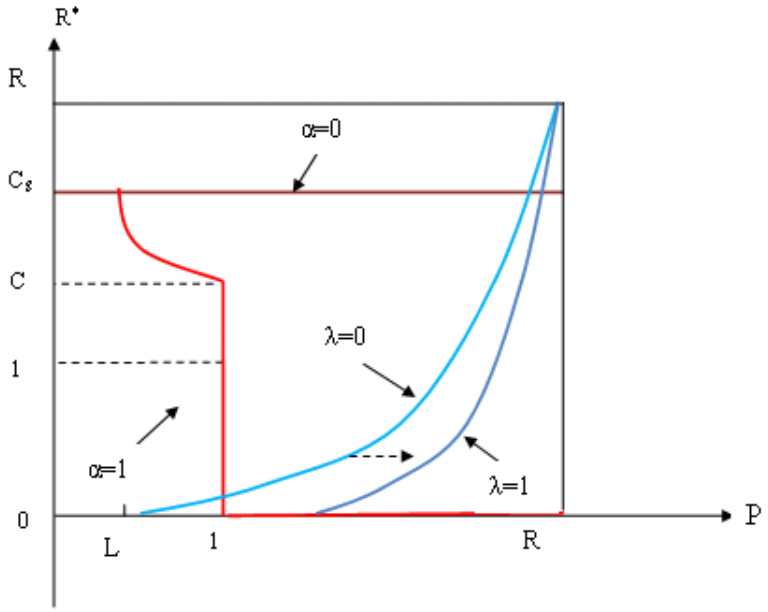



Figure 3.12: Equilibrium with maturity mismatch

## 3.6 Concluding Remarks

This paper presents a model of pure adverse selection in the context of securitization. We employ a rational expectations framework to examine the roles of banks, outside investors and regulators, and their interactions in the secondary loan market. Our work contributes to the literature in three ways. Firstly, it provides a theoretical explanation of why unregulated securitization necessarily causes deterioration in loan quality even when investors are rational. Secondly, it shows that securitization is value-enhancing by using an underlying call option, which increases banks' expected wealth. Thirdly, it suggests that by imposing

[1]See Appendix B for proofs of Figure 3.12

loan sales limits, governments can effectively alter banks' credit standard, and the equilibrium price of securitized assets. Our parsimonious model also reveals the channels through which regulation takes effects.

To better understand the impacts of securitization, two other important elements outside the model should be considered. Moral hazard is the first issue, and it is related to banks' ex post effort in monitoring loans. Parlour and Plantin [2008] offer a comprehensive analysis on this topic. Besides that, our model can be extended by considering outside financing of banks from short-term money market. As documented by Gorton and Metrick [2012], securitized assets are often used by loan issuers as collateral to raise money in repo markets, which they consider as an indispensable component of the securitized-banking system. The rife use of loans as collateral causes more concern on the its quality, as the banks' ability of obtaining short-term financing is tied to the market value of its collateral. Hence, it would be interesting to see how rational agents in our model would react when the liquidity market and the secondary loan market are interconnected.

# Chapter 4

# Risk-taking Choice in Hedge Fund Tournaments

**Summary**

We propose a parsimonious model to investigate how a hedge fund manager's risk shifting decision is affected by the manager's tournament concern, incentive contract and liquidation threat. With a one-year horizon and a pre-determined concave fund flow function, a hedge fund manager's risk-taking varies dramatically with his interim absolute performance, performance relative to the industry and the industry's interim portfolio strategy. We document that when competing for more funds, managers would adopt two distinctive risk shifting strategies, 'contrarian' and 'mimicking', depending on their relative performance. The combined effects of the High-Water-Mark (HWM) and tournaments show that the extreme risk-taking propensity induced by HWM can be largely mitigated by the manager's fund flow concern, while the manager's mimicking behavior can be suppressed by the managers' desire to secure a performance fee when the fund's value is above HWM. When the fund's interim performance approaches a pre-specified liquidation bound, the manager with a strong tournament incentive will try to maximize his tracking error variance by choosing the contrarian portfolio strategy to the industry to avoid potential fund outflows rather than playing safe; if given an outside opportunity, managers with a poor relative performance will even voluntarily shut down the funds, especially when the industry as a whole

has large risk exposures.

## 4.1 Introduction

The past two decades have witnessed the explosive growth of hedge funds. The number of hedge funds increased rapidly from only 610 to more than 3600 during the 1990s. As of June 2009, there were more than 8900 hedge funds operating worldwide and managing assets worth 1.43 trillion dollars according to Hedge Fund Research.[1] Fierce competition in the industry induces fund managers to take into account not only their absolute performance but also their relative standing in the industry when they make investment decisions. Brown, Goetzmann, and Park [2001] document that hedge funds with poor performance relative to the industry have a dramatically higher probability of termination. Moreover, investors chase performance. Hedge funds usually allow their investors to withdraw money at certain points of the investment period. Therefore, investors have the opportunity to reallocate their money and shift their investments to better-performing funds. Since the management fee is tied to the size of assets under management (AUM), hedge fund managers have a strong incentive to outperform their peers in order to attract more money. In practice, various hedge fund indices have been created for both managers' and investors' reference.

Although extensive research has been conducted on tournament behavior in the mutual fund industry, the existing models on mutual funds cannot be directly applied to hedge funds as there are some remarkable distinctions between these two types of public investment tools. Firstly, in comparison with mutual funds, hedge funds have a more complex compensation structure featuring a High Water Mark(HWM) provision, which entails different risk taking incentives from that of mutual funds. Secondly, hedge funds have been empirically documented to have a convex fundflow-performance relationship while this relationship has been found to be concave for mutual funds. The different shape of the fund flow function might lead to different risk shifting behavior. Thirdly, hedge funds generally have a higher attrition rate compared to mutual funds.(See Getmansky [2012].) In most mutual fund models, the possibility of funds' shutdown is neglected.

[1]The total assets under management(AUM) went up to 2.04 trillion in early 2012.

When it comes to hedge funds, however, we believe that fund termination also plays a non-trivial role in managers' risk taking decisions. Brown, Goetzmann, and Park [2001] empirically examine the termination of hedge funds and point out that once a manager exits the market, his chance of reappearing in the hedge fund industry is very small, which emphasizes the importance of the liquidation threat in manager's risk choice. The existing papers on hedge fund managerial risk choice are concentrated on the incentive contracts and on the role of HWM. Our paper is the first theoretical analysis of the incentive effects of hedge fund tournaments.

We develop a parsimonious discrete-time model to study hedge fund managers' interim risk-shifting decisions in the context of hedge fund tournaments. Motivated by the prior empirical evidence, we assume that fund flows are an increasing and concave function of a fund's relative performance.[1] In the baseline model, there are one common risky asset and one risk free asset in the market and managers are assumed to take a random portfolio allocation strategy at the beginning of the year. In the middle of the year, managers have the opportunity to reallocate their investments after funds' mid-year performance is revealed. In particular, with year-end money flows depending on fund's relative standing, a hedge fund manager needs to take into account his competitors' performance and their portfolio strategies in addition to his own performance. We show that all of these factors have substantial influence on managerial interim risk-shifting choice. In the most simplified case, we analyze managers' risk choice when they are solely driven by the motive to win more funds. Due to the concavity of the flow-performance function, we show that a fund manager has a strong incentive to reduce the volatility of his relative performance (the tracking error of his portfolio). In the absence of a risk premium for the risky asset, it is optimal for risk neutral managers to mimic the benchmark and choose a risk level which is proportional to the industry average; and the proportion is determined by the funds' relative performance to the benchmark. In contrast, mutual fund managers who are facing a convex fund flow function tend to maximize the tracking error variance by deviating from the industry benchmark.(See Basak and Makarov [2012]). In a more realistic setting, we impose a lower bound of year-end capital flows

[1]See Goetzmann, Ingersoll, and Ross [2003], Chen [2011] and Getmansky [2012]

due to the fact that money outflow cannot exceed the value of the fund. In the presence of the lower bound, the flow-(relative)performance function has a convexity region near the lower bound, which induces the manager to deviate from the industry's portfolio in order to maximize the tracking error variance. On the other hand, when a fund is far away from the lower bound, the manager would still choose to mimic the benchmark. Therefore, the relative performance (or the distance to the industry benchmark) plays a critical role in determining a manager's optimal risk shifting strategy.

Another distinctive feature of the hedge fund industry is that most fund managers are rewarded based on an asymmetric compensation plan. They charge not only a fixed management fee based on the size of AUM, but also a performance fee based on the High-Water-Mark (HWM). Specifically, managers will receive a proportion of the increase in the net asset value. Several papers are focused on the implications of the HWM and suggest that the convex compensation structure causes excessive risk taking, especially when a fund's value is somewhat below its HWM. In this paper, we find that the high water mark and fund flow concern can separately generate two distinctive risk shifting patterns. Consistent with the existing work, the HWM provision results in a bell-shaped relation between absolute performance and risk taking.(See Hodder and Jackwerth [2007] and Buraschi, Kosowski, and Sritrakul [2013]) When combining the HWM and fund flow concerns, our model yields some interesting results. Firstly, when mid-year performance surpasses the high water mark, managers have a strong incentive to reduce risk to lock in performance fees and thus the mimicking behavior caused by the fund flow concern is substantially suppressed by the HWM effect. This result holds under all market conditions. Secondly, when fund value is below the high water mark, managers' incentive to take on more risk are replaced by the incentive to mimic the benchmark. Therefore, interim losers are relatively more concerned about possible fund outflows, while interim winners focus more on securing performance fees.

Our paper also examines the impact of potential liquidation on fund managers' risk shifting decision. According to Getmansky [2012], on average, approximately 7.1% of all hedge funds go out of business every year. During the 2008 subprime mortgage crisis, 70% of the hedge funds had negative returns, which caused

a liquidation rate of 23%, the highest in hedge fund history. To examine the effect of the threat of liquidation, we assume that a fund will be shut down automatically once the fund's running value hits the pre-specified liquidation bound, in which case fund managers will get nothing. In the absence of the fund flow concern, managers with fund values approaching the liquidation bound will take minimal risk to avoid fund closure. However, when investors can freely withdraw money at the end of the year, investing in the riskless asset is no longer a safe strategy for the under-performing managers, due to the concern that massive fund outflows will also lead to fund closure. Hence, funds ranked at the bottom in the middle of the year will try to increase the tracking error variance by choosing an opposite strategy to the industry's. Their risk choices will primarily depend on the benchmark portfolio instead of their own absolute performance. Following Hodder and Jackwerth [2007], we also analyze the case when managers have the option to shut down the fund after mid-year performance is revealed. Our model shows that an endogenous closure region appears when a fund has very poor relative performance. Furthermore, when the industry on average opts for high risk, managers with poor relative performance are more likely to liquidate their funds.

In addition, we disentangle two types of risks, market risk and idiosyncratic risk, and examine their roles in hedge fund mangers' interim risk shifting decisions. Most hedge funds bear manager-specific risks. According to Deutsche Bank's Alternative Investment Survey (2009), investors choose hedge funds largely because of their diversified or uncorrelated returns. In the extended model, we consider an economy which has multiple assets representing different sources of risks. In particular, we postulate that each fund has access to a fund-specific asset. In contrast to Basak, Pavlova, and Shapiro [2007], our model with multiple risky assets reveals that in the 'gambling' region, hedge fund managers would opt for the maximum idiosyncratic risk in order to maximize the tracking error variance, no matter whether they have alpha generating abilities or not, which are in line with the received wisdom in hedge fund tournaments.(See Chen [2011]) Moreover, by making a distinction between systematic risk and idiosyncratic risk, we uncover two distinct risk-taking patterns in different assets, which are largely supported by the extant empirical work. In a nutshell, hedge fund managers

mainly distort fund-specific risk to gamble when they are behind the benchmark and the bell-shaped risk-taking propensity induced by HWM is more pronounced in the fund-specific asset than in the market asset when the manager has alpha generating skills.

Our paper is the very first to theoretically explore the combined effects of tournaments and typical compensation contracts on hedge fund managers' risk-taking behavior. Compared with existing papers which are focused on HWM, our model provides a more complete picture on hedge fund managers' incentives and a richer set of predictions on their investment decisions as funds' absolute performance, relative performance and the benchmark's portfolio strategy in our model all have significant influences on managers's risk shifting decisions. Furthermore, our model can better explain some stylized facts of hedge fund risk shifting patterns than the existing models. Hodder and Jackwerth [2007] resort to a multi period model where they show that a long investment horizon mitigates manager's aggressive risk-taking near the HWM as it would adversely affect the fund manager's compensation in the long run. Similarly, our model points out that the desire to attract new investors would also temper the excess risk entailed by the HWM.

Our model setup is similar in spirit to Taylor [2003] and Basak and Makarov [2012] who examine mutual funds' tournament behavior. It is worth mentioning that Basak and Makarov [2012] and Taylor [2003] both argue that interim winners in equilibrium would increase the volatility of their investments while interim losers tend to reduce risk. Nevertheless, this prediction does not appear to hold for hedge funds as Brown, Goetzmann, and Park [2001] and other papers on hedge fund tournaments all suggest the opposite pattern in reality. In contrast to Basak and Makarov [2012] and Taylor [2003]'s findings, our model shows that interim hedge fund winners do not necessarily increase risk due to fundflow concerns and HWM effects. Firstly, interim winners have a strong incentive to mimic the industry benchmark, which leads to low risk taking if the industry's average risk level is low; Secondly, the HWM-induced lock-in behavior leads to moderate risk taking when the fund value is above HWM. Hence, the hedge funds' unique flow-performance relation and asymmetric payoffs cause managers' different risk shifting pattern from mutual fund managers'.

The rest of the paper proceeds as follows. Section 2 reviews the most related work in the literature. Sections 3 and 4 present the economic setup, solutions to the baseline model and interpretations of the model. Sections 5 and 6 analyze the extended model with exogenous and endogenous fund closures, respectively. Section 7 discusses the multiple-asset scenario. Section 8 summarizes the main findings of the paper as well as future research directions. The appendix contains proofs, additional figures and numerical procedures.

## 4.2 Literature Review

Our work is related to four streams of the theoretical literature. First, the most related to ours are Taylor [2003] and Basak and Makarov [2012], who examine the tournament effect on mutual fund managers' investment behavior. Taylor [2003] is the first theoretical paper which models mutual fund tournaments. He studies how fund managers adjust their risk taking according to their mid-year performance when they compete for cash inflows. He distinguishes between scenarios with a passive benchmark (e.g., market index) and with an active benchmark (peers in the industry). When one of the managers is an exogenous benchmark, the winning manager indexes and the losing manager gambles; however, when both managers are active, the winning manager is more likely to gamble, especially when the midyear performance gap is high and meanwhile stocks offer high returns and low volatilities. The tournament model of Basak and Makarov [2012] is the closest one to ours in the literature. They investigate managers' equilibrium portfolios in the context of mutual fund tournaments and predict that the portfolio volatility of an interim winner is higher than that of an interim loser. The intuition is that the convexity of the flow-performance relation leads to the convexity of a manager's objective function, implying that a manager seeks to maximize the volatility of her tracking error (the difference between her own and industry-average returns). Moreover, since the year-end return volatility is proportional to its corresponding interim performance, the interim winner would invest in risky assets to leverage her high interim performance. This drives the interim loser into bonds. One of the main departures of our model from theirs is that hedge fund industry has been found to have a concave flow-performance

relationship, which should significantly affect fund managers' objective function.

The literature related to fund tournaments also includes Chevalier and Ellison [1997], Berk and Green [2004], Palomino [2005], Basak, Pavlova, and Shapiro [2007], Christoffersen and Musto [2008], Chen and Pennacchi [2009] and etc. Chevalier and Ellison [1997] study the agency conflict between money managers and investors. They suggest that mutual fund managers have a strong incentive to attract inflow of investments, which undermines investors' interest as managers would shift the riskiness of the portfolio in response to the fund's past returns rather than to maximize the risk adjusted returns. They empirically estimate the flow-performance relationship of the mutual fund industry and provide evidence that managers would alter the volatility of the portfolio at the end of the year to increase capital inflows. Berk and Green [2004] study the relationship between endogenous fund flows and mutual fund performance. All investors in the model are assumed to earn zero expected excess returns in the equilibrium with perfect competition. In their belief-updating process, the duration between time 0 and time $t$ matters. In other words, flows to younger funds respond much more dramatically to performance than flows to more mature funds. They conclude that investors chase high-performance funds, which, together with decreasing returns to scale, make superior fund performance unpredictable. Christoffersen and Musto [2008] focus on the effect of HWM on investors' equilibrium investment levels, which determines the fund flows or fund size. Like Berk and Green [2004], they adopt decreasing returns to scale and extend their baseline model to a model with a continuous distribution of returns to analyze the cross-section of returns. Their model incorporates Bayesian updating as investors' learning processes of managers' abilities. They find that the confidence in a manager's ability is crucial to the provision effect, and this effect is to boost the initial fund size and to depress initial expected returns while increasing subsequent expected returns. Palomino [2005] aims to investigate how the entry and investment decisions of fund managers are affected by their relative performance objectives. Their main difference from Taylor [2003] is that they assume that some managers have superior information, and for this reason, the difference in interim performance of different funds are no longer exogenously-specified. Compared with the objective of absolute performance maximization, relative performance objectives

increase managers' risk taking level and reduce the number of low-quality funds. Basak, Shapiro, and Teplá [2006] argue that money managers in reality are usually evaluated relative to a benchmark. They demonstrate that in the absence of benchmarking, a risk averse managers optimal portfolio decision is purely driven by his risk aversion level. In contrast, when the manager is evaluated based on his relative performance, the manager exhibits a variety of economic behavior in choosing his optimal investment strategies. Basak, Pavlova, and Shapiro [2007] investigate a mutual fund manager's risk taking incentives induced by a piecewise convex relationship between money flows and fund's relative performance. The optimal risk exposure results from the tradeoff between managers' risk aversion and the risk-shifting incentive due to potential fund flows. Similarly, Chen and Pennacchi [2009] model a manager's portfolio choice by assuming that the compensation scheme can be either a concave, linear or convex function of the fund's performance relative to a benchmark. Both Basak, Pavlova, and Shapiro [2007] and Chen and Pennacchi [2009] find that poor-performing funds would increase their tracking error volatility, but not necessarily the volatility of the fund's return.

A second stream of the literature studies the role of incentive contracts in hedge fund risk taking strategies. Our model setup is most related to Hodder and Jackwerth [2007] who study the incentive effects of a typical hedge fund contract with HWM and liquidation barrier for a manager with power utility. Their main finding is that with a one-year horizon, the manager displays risk taking that varies dramatically with fund value. However, when the model is extended to multiple valuation periods, the manager's risk taking is rapidly moderated. Although our model only involves one-year period, the fund outflow concern also mitigates the excess risk taking that the HWM entails. Panageas and Westerfield [2009] also tackles a similar problem by theoretically model the optimal risk choice of risk-neutral hedge fund managers in a dynamic setting in order to better understand the incentives provided by the widely-used high-water mark contracts. They argue that a HWM contract is essentially a call option to managers, with the HWM as the strike price. Nevertheless, with an indefinite investment horizon, the contract should not be viewed as a single option but as a sequence of call options with a changing strike price. A decrease in fund value today will reduce the

values of future options. Therefore, even a risk neutral manager would not take take an unboundedly large position in the risky asset. Specifically, they solve the optimal portfolio choice of a risk-neutral hedge fund manager who aims to maximize the expected present value of her compensation fees and they demonstrate that she would allocate a constant fraction of wealth on the risky asset just like a risk averse manager would do. Goetzmann, Ingersoll, and Ross [2003] provide a closed-form solution to the cost of the high-water mark contract to investors under certain conditions. Also they argue that the pervasive use of the HWM in the hedge fund industry might be due to the diminishing returns to scale of hedge fund technologies. The reason is that most mutual funds can compensate their managers for past performance with a fixed percentage fee on assets, since good performance will attract new money; In contrast, hedge fund managers may not be able to take or even want new funds. However, this argument contradicts the empirical findings on the existence of tournament behavior in the hedge fund industry; hedge fund managers do compete for money flows (see Brown, Goetzmann, and Park [2001], Chen [2011], Getmansky [2012] and Aragon and Nanda [2012] ). Carpenter [2000] investigates if a convex compensation scheme would increase a managers' risk appetite. Specifically, she solves the dynamic investment problem of a risk averse manager when the mangers is compensated based on a option-like contract on the fund's asset value. She suggests that the option-like contract does not necessary result in a greater level of risk taking when he cannot hedge the option. Moreover, when the manager is given more options, he would actually decrease the riskiness of the fund's asset as these options increase the volatility of his personal portfolio. Chakraborty and Ray [2008] study an intricate set of risk, effort and walkaway decisions, which are driven by the HWM feature of the hedge fund contract depending on how far the fund is from the previous watermark. They find that, funds' expected future returns fall as the fund value drops below the HWM, while the volatility of future returns and the probability of fund liquidation increases. In addition, all of these effects are most stark for funds near the HWM and are considerably reduced when the funds are far from the HWM.

Additionally, some existing papers tackle the dynamic optimal investment problems of hedge fund managers. For example, Lan, Wang, and Yang [2013]

investigate the optimal leverage that hedge fund managers would choose to maximize the expected present value of their management fees and incentive fees. They assume that hedge managers are risk neutral in a multiple-period setup with path-dependent HWMs and a downside exogenous liquidation bound. Their results show that a fund's leverage increases with alpha (which is a manager's ability to generate abnormal returns) and decreases with volatility and the manager's endogenous effective risk attitude. However, they do not consider tournament behavior or investors' fund flow decisions. Buraschi, Kosowski, and Sritrakul [2013] study the dynamic optimal investment problem of hedge fund managers who face non-linear incentives. In particular, the compensation function of managers consists of three parts: performance fee (a call option on fund value), management fee and deadweight cost, which is incurred if the fund's value drops below a certain threshold. Their theoretical results show that the optimal leverage depends on the distance of the net asset value from HWM and they documented a bell-shaped risk taking pattern of hedge fund managers.

Third, our paper also contributes to the literature regarding how fund managers shift risk loadings between systematic risks and idiosyncratic risks. Basak, Pavlova, and Shapiro [2007] examine this issue in the context of mutual fund tournaments. They use two risky assets representing systematic risk and idiosyncratic risk respectively to see whether managers would take on idiosyncratic risk to win more fund inflow or not. They show that managers would choose to have zero exposure to the idiosyncratic risk and only adjust the exposure to systematic risk based on their relative performance when there is no risk premium for the idiosyncratic asset. Also, Chen and Pennacchi [2009] study mutual fund managers' risk shifting problems with their compensation depending on their performance relative to the benchmark. They assume a smooth fund flow function, and study two correlated assets, one benchmark asset and one alternative asset. Ozdenoren and Yuan [2012] seek to explain why compensation contracts would encourage mangers to take on excessive systematic as opposed to idiosyncratic risks.

More broadly, our paper is also related to the work on optimal contracts. Aggarwal and Samwick [1999] derive the optimal contract in a principal-agent model of strategic competition in which managers can be compensated on both their own profits and their rivals' profits. They argue that strategic interac-

tion among firms can explain the lack of relative-performance-based incentives in which compensation decreases with rival firm performance. Biais and Casamatta [1999] analyze the optimal financing of investment projects when managers must exert unobservable effort and also engage in value-reducing risk shifting. They argue that if the risk-shifting problem is dominant, then the optimal financing scheme is a combination of debt and outside equity; when the effort problem is the major source of moral hazard, stock options should be awarded to the managers. Makarov and Plantin [2010] develop a model of active portfolio management in which fund managers may secretly gamble in order to manipulate their reputation and attract more funds. They study the optimal long-term contract that deters this risk shifting behavior, and show that contracts that simultaneously increase and defer the managers' expected fee after abnormally high returns eliminate risk-shifting incentives. DeMarzo, Livdan, and Tchistyi [2011] try to solve the two-dimensional moral hazard problem- managers' risk shifting problem and cashflow diversion (stealing) at the same time. First of all, any incentive compatible contract must reward the agent for reporting high cashflow, otherwise, they would steal the cash or shirk. However, this type of contract also creates incentives for managers to take on disaster risk. For this reason, they argue that this extreme risk taking can be mitigated if disaster states can be identified ex-post by paying the manager a large bonus if the firm survives. But when the performance is sufficiently weak, the manager will give up the bonus, and take on disaster risk. Their model explains why suboptimal risk taking can emerge even when investors are fully rational and managers are compensated optimally.

**Empirical flow-performance relation**: Some recent empirical papers suggest that tournament behavior exists in the hedge fund industry and that the risk-shifting decisions of hedge fund managers depend upon relative rather than absolute fund performance. Brown, Goetzmann, and Park [2001] is the first to document hedge funds' tournament behavior. They find that performance relative to peer funds is important in managers' strategic use of variance, while performance relative to the HWM is not. Specifically, mid-year winning funds significantly reduce portfolio variance while mid-year losing funds tend to increase their risk exposures. Moreover, their survival analysis suggests that hedge fund managers are seriously concerned with fund closure, as opposed to maximiz-

ing the option-like feature of their incentive contracts. Consistent with Brown, Goetzmann, and Park [2001], Chen [2011] finds that annual net fund flows are positively related to last year's fund performance, indicating that investors make investment decisions based on funds' past performance. Specifically, hedge funds which have poor relative performance in the 1st half of a year exhibit greater risk increase propensity in the 2nd half of the year.

Getmansky [2012] examines how the life cycle of hedge funds is affected by fund characteristics (such as age, asset size, fund returns, and fund flows) and industry characteristics (such as favorable positioning and competition). They find a concave relationship between hedge fund's past relative performance and year-end fund flows. Aragon and Nanda [2012] analyze if a hedge fund's risk shifting is related to the manager's incentive contract, personal capital stake and the possibility of fund closure. They document that the HWM provision, managerial stake in the fund, and low risk of fund closure appear to make a hedge fund manager more conservative with regard to risk shifting. It is worth noting that their results indicate that the HWM can actually reduce the propensity of losing hedge fund managers to increase risk in tournaments. The intuition is that a hedge fund manager is essentially given a sequence of options given a long investment horizon. While a riskier portfolio can increase the probability of crossing the current HWM, it also increases the probability that the assets will be worth less, causing the future options to be even more out of the money.

Ding, Getmansky, Liang, and Wermers [2009] investigate the impacts of share restrictions (including lockup period, redemption, advance notice and so on) on the fundflow-performance relation of hedge funds. They find a convex flow-performance relation in the absence of share restrictions and a concave flow-performance relation in the presence of significant share restrictions. They also document that funds with more volatile returns tend to be smaller and younger, as these funds are more aggressive and competing more vigorously for money inflows. Also, these funds in general impose looser share restrictions. In addition, their test results suggest a concave flow-performance relation for live funds and a convex relation for defunct funds. Moreover, they relate share restrictions with 'Smart money' effect and find that funds which experienced prior net inflow outperform funds which experienced prior net outflow only when they have no share

restrictions. Hence, they conclude that restrictions on fundflow prevent investors from shifting money to better funds.

## 4.3 The Setup

We assume that the economy is populated by n hedge funds indexed by $i$, and denote the industry average by $j$. Hereafter, we utilize the terms 'fund', 'manager' and 'fund manager' interchangeably. Financial investment opportunities are given by a riskless asset and a risky asset. The properties of asset returns are public knowledge. The riskless asset yields a constant return $r$, and the risky asset yields return $x$, depending on the state of the world. Return $x$ is normally distributed with mean $\mu > r$ and volatility $\sigma$, where $\mu$ and $\sigma$ are constant as well. Manager i invests $\theta \in [0, \overline{\theta}]$ portion of the wealth in the risky asset, and $1 - \theta$ in the riskless asset, where $\overline{\theta}$ is the upper bound of allowed leverage.

Past literature on mutual fund tournaments posits that fund flows occur at the end of a calendar year after investors observe funds' performances. Following Taylor [2003],Basak and Makarov [2012], we assume that there are three dates, $t = 0$, $t = 1$ and $t = 2$, which are referred to as year-start, mid-year and year-end. At time 0, all the funds start with the same size but different pre-determined investment strategies. A manager receives a management fee at a given rate $k$ before he allocates assets, and thus the fund's initial wealth is expressed as $W_{i,0} = (1 - k)I_0$. Without the loss of generality, we assume that a fund has a unit wealth at year-start, $W_{i,0} = 1$.

At time 1, mid-year performances $m_i$ and $m_j$ are revealed; and funds' mid-year wealth is $W_{i,1} = m_i$ and $W_{j,1} = m_j$ given their year-start strategies. Manager $i$ is to be in a winning (losing) position if $m_i > m_j$ ($m_i < m_j$ ). Based on the interim performance, a risk averse manager needs to decide on how much to invest in the risky asset in order to maximize his expected utility. The benchmark $j$'s portfolio strategy is assumed to be public knowledge since it is regarded as an exogenously specified industry index.

At time 2, funds' year-end wealth is realized based on $\theta_i$ and the realization of x, i.e., $W_{i,2} = W_{i,0} \times m_i \times [1 + r + \theta_{i,1}(x - r)]$ and the industry average wealth is $W_{j,2} = W_{j,0} \times m_j \times [1 + r + \theta_{j,1}(x - r)]$. Fund $i$ will experience fund inflow or

outflow, denoted as $F_i$, based on the fund's performance relative to the industry average. Given the fund's total wealth including the fund flow $F_i$, manager $i$ will receive a year-end compensation $C_i$, which consists of three components, namely the management fee from the old investors, the management fee from the new investment (which could be negative due to fund outflow), and the performance fee if fund value exceeds the High Water Mark(HWM). Manager i's objective function is written as follows:

$$\max_{\theta_i^*} E[U] = E[\frac{C_i^{1-\gamma}}{1-\gamma}] \tag{4.1}$$

where $C_i = kW_{i,2} + kF_i + y\max\{W_{i,2} - W_{i,0}, 0\}$.

We assume that a manager face a standard $2-20$ hedge fund contract and hence $k = 2\%$ and $y = 20\%$. More importantly, we assume that the year-end fund flow $F_i$ is subject to a concave function of fund's relative performance, i.e., $F_i = f(\Delta W) = a(\Delta W)^2 + b\Delta W + c$, where $\Delta W = W_{i,2} - W_{j,2}$ represents the fund's relative performance. We assume that managers have common knowledge of the function. Specifically, the fund flow function is expressed as follows:

$$F_i = \begin{cases} c - \frac{b^2}{4a} & \text{if } \Delta W > -\frac{b}{2a}, \\ a(\Delta W)^2 + b\Delta W + c & \text{Otherwise.} \end{cases} \tag{4.2}$$

where $a < 0$ and $b > 0$ and $c$ is the fund flow for the fund which has the same performance as the industry average. This assumption of the fund flow function is consistent with empirical findings. Brown, Goetzmann, and Park [2001] provides the evidence that managers pay more attention to their performance relative to peer funds than the traditional market index such as $S\&P500$ index, which justifies our choice of benchmark. Additionally, Chen [2011] and Getmansky [2012] document that there exists a concave relationship between individual net fund flow and individual fund performance in excess of the industry's average performance. Chen [2011] estimates the impacts of the relative performance and its square term on net fundflow. His estimated coefficients will be used to numerically solve the model in later sections in our paper.

Additionally, we assume that, at $t_1$ and $t_2$, investors will withdraw all the

money from the fund if the fund value drops below a threshold. In other words, the fund will be exogenously liquidated, and thus the manager's compensation is nil in this case. Following Lan, Wang, and Yang [2013], we set the liquidation bound as a fraction of HWM, i.e., $\underline{W} = p \times H$, where $H$ is the high water mark. Like Hodder and Jackwerth [2007], we will also analyze the endogenous shutdown scenario in which managers could choose to close the fund at time $t_1$ voluntarily and take outside opportunities.

## 4.4 The Concave Flow-Performance Relationship

In order to examine the pure tournament effect, we first assume that the manager is solely driven by the incentive to maximize the expected fund flow:

$$\max_{\theta_i \in [0,\bar{\theta}]} \{E[f(\Delta W)] \tag{4.3}$$

Given the industry average portfolio strategy, $\theta_j$, and industry average interim performance $m_j$, the manager chooses the optimal $\theta_i$ at time $t_1$ to maximize the expected fund flow:

$$\begin{aligned}
\theta_i^* &= \arg \max_{\theta_i \in [0,\bar{\theta}]} \; E[f(\Delta W)] \\
&= \arg \max_{\theta_i \in [0,\bar{\theta}]} \; E[f(\Delta W) | \Delta W < -\frac{b}{2a}] P(\Delta W \leq -\frac{b}{2a}) + (c - \frac{b^2}{4a}) P(\Delta W > -\frac{b}{2a}) \\
&= \arg \max_{\theta_i \in [0,\bar{\theta}]} \; E[a\Delta W^2 + b\Delta W + c | \Delta W < -\frac{b}{2a}] P(\Delta W \leq -\frac{b}{2a}) + (c - \frac{b^2}{4a}) P(\Delta W > -\frac{b}{2a})
\end{aligned} \tag{4.4}$$

where $\Delta W = (m_i\theta_i - m_j\theta_j)(x - r) + (m_i - m_j)(1 + r)$ is normally distributed with mean

$$E[\Delta W] = (m_i\theta_i - m_j\theta_j)(\mu - r) + (m_i - m_j)(1 + r) \tag{4.5}$$

and variance

$$Var[\Delta W] = (m_i\theta_i - m_j\theta_j)^2\sigma^2 \tag{4.6}$$

For easy notation, we refer to $\Delta W$ as $w$. The standard deviation of the relative wealth is denoted by $\sigma_w = |m_i\theta_i - m_j\theta_j|\sigma$, and the mean is $\mu_w$. The expected fund flow can be rewritten as follows (See Proof 1 in Appendix C.1):

$$\begin{aligned} E[f(\Delta W)] &= E[a\Delta W^2 + b\Delta W + c|\Delta W < -\frac{b}{2a}]P(\Delta W \leq -\frac{b}{2a}) + (c - \frac{b^2}{4a})P(\Delta W > -\frac{b}{2a}) \\ &= -(a\mu_w + \frac{1}{2}b)\sigma_w\phi(d) + [a(\mu_w^2 + \sigma_w^2) + b\mu_w + \frac{b^2}{4a}]\Phi(d) + c - \frac{b^2}{4a} \end{aligned} \tag{4.7}$$

where $\phi(.)$ and $\Phi(.)$ are the standard normal distribution and standard cumulative normal distribution respectively and $\mu_w = (m_i\theta_i - m_j\theta_j)(\mu - r) + (m_i - m_j)(1+r)$, $\sigma_w = |m_i\theta_i - m_j\theta_j|\sigma$ and $d = -\frac{-b/2a - \mu_w}{\sigma_w}$ [1]

The first derivative of $E[f(w)]$ with regard to $\theta_i$ is given by (See Proof 2 in Appendix C.1)[2]

$$\begin{aligned} \frac{\partial E[f(w)]}{\partial \theta_i} &= m_i\sigma\{-2a\frac{\mu - r}{\sigma}\phi(d)\sigma_w + [(2a\mu_w + b)\frac{\mu - r}{\sigma} \pm 2a\sigma_w]\Phi(d)\} \\ &= m_i\sigma\{\frac{\mu - r}{\sigma}\Phi(d)[b + 2a(1+r)(m_i - m_j)] + 2a\sigma_w[\pm\Phi(d)(\frac{(\mu - r)^2}{\sigma^2} + 1) - \frac{\mu - r}{\sigma}\phi(d)] \end{aligned} \tag{4.8}$$

In order to examine the incentives of hedge fund managers, we analyze the sign of each term in Equation 4.8

1. The first term in Equation 4.8 : Given the empirical values of parameter$a$ and $b$, we assume that $m_i - m_j < -\frac{b}{2a(1+r)}$ always hold.[3] Hence, the first term is always positive. In this case, the manager will always have the incentive to increase his holdings in the risky asset in order to maximize the fund flow.

[1] $\mu_w$ can be expressed as a function of $\sigma_w$, i.e., $\mu_w = \pm\frac{\mu - r}{\sigma}\sigma_w + (m_i - m_j)(1 + r)$.

[2] When $m_i\theta_i - m_j\theta_j > 0$, $\frac{\partial E[f(w)]}{\partial \theta_i} = m_i\sigma\{\frac{\mu - r}{\sigma}\Phi(d)[b + 2a(1 + r)(m_i - m_j)] + 2a\sigma_w[\Phi(d)(\frac{(\mu - r)^2}{\sigma^2} + 1) - \frac{\mu - r}{\sigma}\phi(d)]\}$; When $m_i\theta_i - m_j\theta_j < 0$, $\frac{\partial E[f(w)]}{\partial \theta_i} = m_i\sigma\{\frac{\mu - r}{\sigma}\Phi(d)[b + 2a(1 + r)(m_i - m_j)] + 2a\sigma_w[-\Phi(d)(\frac{(\mu - r)^2}{\sigma^2} + 1) - \frac{\mu - r}{\sigma}\phi(d)]\}$

[3] According to Chen [2011]'s estimates, $a = -0.196$, $b = 1.088$ and $r = 0.02$. Hence, we can obtain that $-\frac{b}{2a(1+r)} = 2.72$. Moreover, the average mid-year return of the hedge fund industry is 1.054 based on Getmansky [2012]. Therefore, it is reasonable to assume that $m_i - m_j < -\frac{b}{2a(1+r)}$

2. The second term in Equation 4.8:

   - When $\theta i > \frac{m_j}{m_i}\theta_j$ , $2a\sigma_w[\Phi(d)(\frac{(\mu-r)^2}{\sigma^2}+1) - \frac{\mu-r}{\sigma}\phi(d)] < 0$[1].
     In this case, the manager will have incentive to reduce risk. As a consequence, the tracking error variance will decrease.
   - When $\theta i < \frac{m_j}{m_i}\theta_j$ , $-2a\sigma_w[\Phi(d)(\frac{(\mu-r)^2}{\sigma^2}+1) + \frac{\mu-r}{\sigma}\phi(d)] > 0$
     In this case, the manager is prone to increase risk, which also lowers the tracking error variance as $\sigma_w = |m_i\theta_i - m_j\theta_j|\sigma$.

From the above analysis on the second term of the derivative, we can see that fund manager would always try to minimize the tracking error volatility due to the concavity of the fund flow function. Moreover, these two terms of the derivative function, Equation 4.8, reveal two motives of managers when they make the optimal risk taking decision. On the one hand, they are prone to take high risk to win more money flow at year end; On the other hand, they have incentive to minimize the volatility of their relative performance to their peers.

Moreover, by combining the two terms mentioned above, we can find the lower bound of the optimal risk level chosen by fund managers. The optimal risk $\theta_i^*$ must satisfy the following inequality (See Proof 3 in Appendix C.1):

$$\begin{cases} \theta_i^* > \frac{m_j}{m_i}\theta_j & \text{if } \frac{m_j}{m_i}\theta_j < \overline{\theta} \\ \theta_i^* = \overline{\theta} & \text{if } \frac{m_j}{m_i}\theta_j > \overline{\theta} \end{cases} \tag{4.9}$$

It is worth noting that, we also solve the case with $\mu = r$ (no risk premium for the risky asset), the optimal risk level for fund managers is:

$$\begin{cases} \theta_i^* = \frac{m_j}{m_i}\theta_j & \text{if } \frac{m_j}{m_i}\theta_j < \overline{\theta} \\ \theta_i^* = \overline{\theta} & \text{if } \frac{m_j}{m_i}\theta_j > \overline{\theta} \end{cases} \tag{4.10}$$

The only motive for them is to minimize tracking error variance in the absence of risk premium.(See Proof 4 in Appendix C.1) Moreover, we assume that $m_i - m_j < -\frac{b}{2a(1+r)}$ always holds throughout the rest of the paper. Therefore, when we introduce risk premium to the model, hedge fund manager's optimal risk taking

[1] $\Phi(d)(\frac{(\mu-r)^2}{\sigma^2}+1) - \frac{\mu-r}{\sigma}\phi(d) = \Phi(d) - \frac{\mu-r}{\sigma}\phi(d) + \frac{(\mu-r)^2}{\sigma^2}\Phi(d) > 0$

level is adjusted upward compared to the case of no risk premium.(see Equations 4.9 and 4.10)

**Proposition 4** *In order to maximize the expected fund flow, a hedge fund manager has incentives to maximize the expected relative performance as well as to minimize the tracking error variance. The manager's optimal risk taking decision in the middle of the year, $t_1$, is the tradeoff between these two concerns.*

### 4.4.1 Fund flow with a lower bound

It is worth noting that many models in the literature assume that there is no lower bound of fund value (For example, Taylor [2003]), which is not realistic as fund wealth can never go below 0, and fund managers will never receive negative compensation. To account for this, we modify the piecewise fund flow function by adding a lower bound for the fund value. We assume that the fund flow will not go below the year-end wealth, i.e., $F_i \geq -W_{i,2}$, where $W_{i,2} = \max\{m_i[\theta_{i,1}(x - r) + 1 + r], 0\}$. Thus, the fund flow function can be expressed as follows.

$$F_i = \begin{cases} c - \frac{b^2}{4a} & \text{if } \Delta W > -\frac{b}{2a}, \\ a(\Delta W)^2 + b\Delta W + c & \text{if } a(\Delta W)^2 + b\Delta W + c > -W_{i,2}, \\ -W_{i,2} & \text{otherwise,} \end{cases} \tag{4.11}$$

Figure 4.1 depicts the fund flow function with a lower bound, which will be used for the remainder of the paper. In order to illustrate the tournament behavior, we solve numerically for the optimal portfolios of managers who aim to maximize the expected fund flow. We will frequently refer to a standard set of parameters as displayed in Table 4.1. Given the values of the parameters, the manager's relative interim performance is always smaller than the threshold $-\frac{b}{2a(1+r)} = 2.72$ and thus the sign of the first term of Equation 4.8 is always positive.

Figure 4.2 shows that this adjustment leads to a very different risk taking choice when the fund has poor interim performance. When the year-end fund flow approaches its lower bound, the fund manager has an incentive to increase the variance of his relative performance as he is essentially facing a call option. The

Table 4.1: Standard Parameters

| | | |
|---|---|---|
| Mean | $\mu$ | 0.05 |
| Volatility | $\sigma$ | 0.10 |
| Interest rate | r | 0.02 |
| Industry mid-year performance | $m_j$ | 1.054 |
| Individual mid-year performance | $m_i$ | [0.1,2] |
| Industry risk-taking | $\theta_j$ | [0,5] |
| Risk Aversion | $\gamma$ | 4 |
| The coefficient of squared relative performance | a | -0.196 |
| The coefficient of relative performance | b | 1.088 |
| The average net fund flow | c | 0.0568 |
| Management fee | k | 0.02 |
| Incentive fee | y | 0.2 |
| Initial fund value | $W_0$ | 1 |
| Current HWM | H | 1 |
| Liquidation boundary | B | 0.5 |
| Outside compensation | $C_{out}$ | 0.005 |

*Note*: we assume the risky asset has a mean return of $\mu = 0.05$ and a standard deviation of $\sigma = 0.10$. The riskless asset yields $r = 0.02$. Based on Chen [2011]'s empirical findings, we assume that $a = -0.196$, $b = 1.088$. According to Getmansky [2012], the average net flows into hedge funds is 5.68% and the average monthly return of the industry is 0.9%. Thus we set $c = 0.0568$ and the average industry mid-year performance of hedge funds as $mj = 1.054$. The basic management fee and incentive performance fee are set as the standard rate of 2% and 20% respectively. The risk aversion coefficient of the manager's power utility is $\gamma = 4$. In addition, the starting fund value of 1 equals the current high water mark and the liquidation boundary is set as $B = 0.5$.

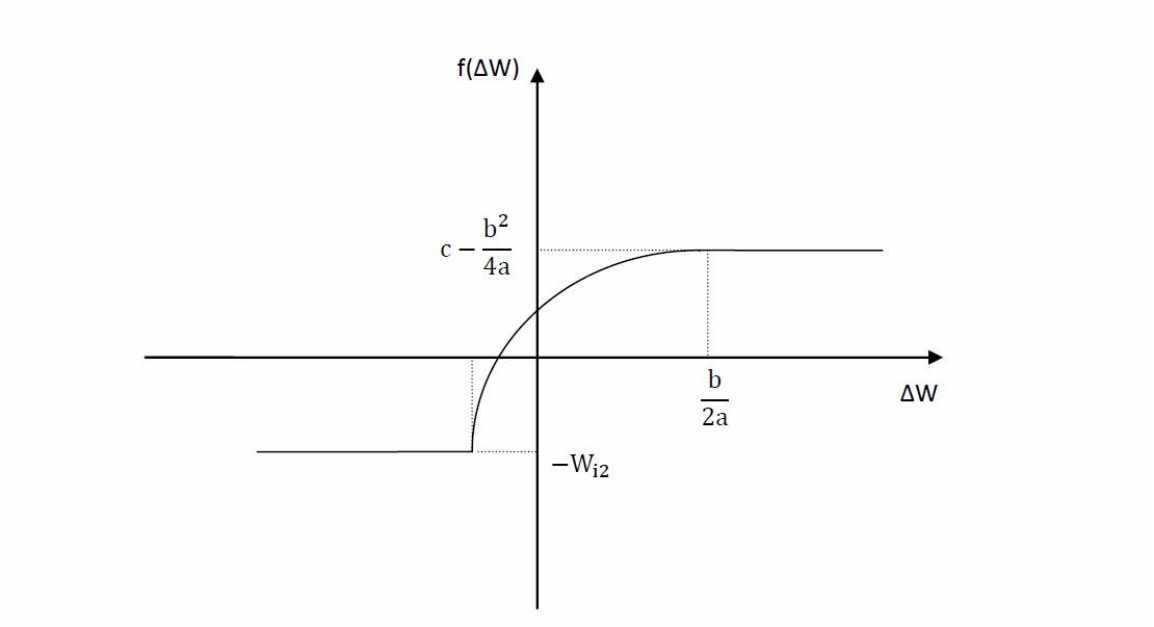



Figure 4.1: Manager i's fund flow function

fund flow function thus exhibits both concavity and convexity features as shown in Figure 4.1. For this reason, hedge fund managers' risk taking choice depends on the interplay of these two opposing effects. Specifically, when a fund is far behind the industry, convexity dominates concavity and the fund manager would optimally choose to increase the tracking error variance. When the concavity of the fund flow function dominates over convexity, managers would mimic the benchmark to decrease the variance of their performance relative to the industry average.

In Figure 4.2, we identify two regions where managers would opt for completely different risk shifting strategies. Given the value of $m_j$, when $m_i$ drops below a threshold $M$, managers would try to maximize the tracking error variance, and we label the region where $m_i < M$ as 'contrarian' region. As we know, the volatility of the relative performance is $\sigma_w = |\theta_i - \frac{m_j}{m_i}\theta_j|m_i\sigma$. To maximize $\sigma_w$, managers would take either the highest risk $\overline{\theta}$ when $\frac{m_j}{m_i}\theta_j$ is small or no risk when $\frac{m_j}{m_i}\theta_j$ is too high. When $m_i > M$, managers would mimic the benchmark, and we call it 'mimicking' region. To better illustrate the mimicking behavior of

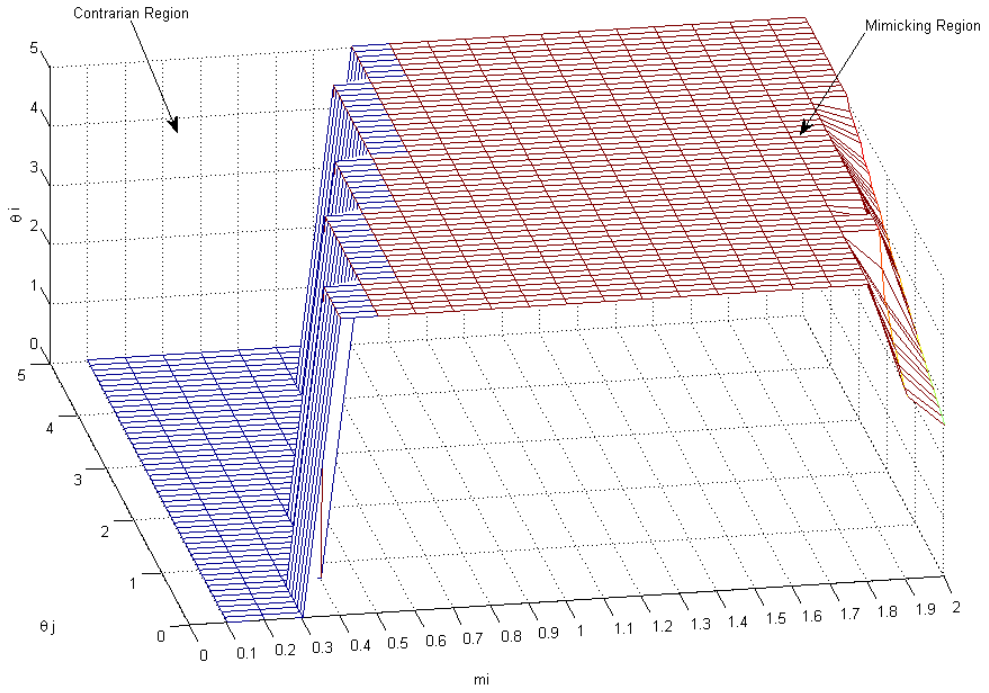



Figure 4.2: Risk-neutral manager i's optimal portfolio choice to maximize the expected fund flow (with lower fund flow boundary)

managers, we also solve the case when there is no risk premium.(See Figure 18 in Appendix C.2). Basak, Pavlova, and Shapiro [2007] provide similar insights- the better-performing fund follow the benchmark while the under-performing funds choose to deviate away from the benchmark.

Since relative performance plays a critical part in the manager's risk shifting decision, we alter the value of mid-year industry average performance $m_j$ to see how it would change the manager's optimal risk choice. Figure 4.3 reveals that with increasing $m_j$ (decreasing interim relative performance $m_i - m_j$), the 'contrarian' region widens, which means that with poor interim performance, managers are more likely to allocate all the money to the riskless asset in order to maximize their tracking error variance instead of minimizing it. This is because with lower relative performance $m_i - m_j$, they are closer to the lower bound of the fund flow function. On the other hand, the optimal risk level is more likely to hit the upper bound $\overline{\theta}$ when $m_j$ is higher in the mimicking region. This is

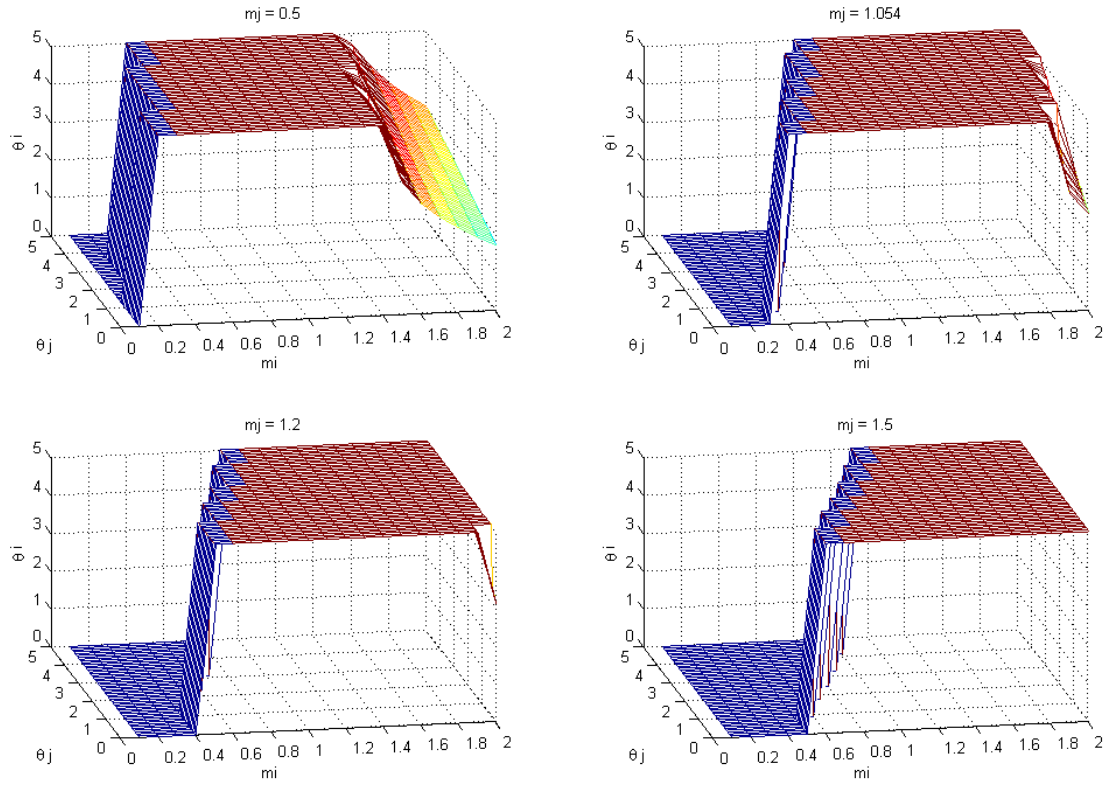



Figure 4.3: Sensitivity analysis of the industry's interim performance $m_j$

because managers need to take on more risk in order to mimic the benchmark as $\frac{m_j}{m_i}$ increases.

In Figure 4.4, we show the effect of concavity of the fund flow function. As we know, the concavity feature of fund flow controls manager's mimicking behavior. When the concavity is dominant, the more concave of the fund flow function is, the closer the optimal risk $\theta_i^*$ is to $\frac{m_j}{m_i}\theta_j$, as the manager would have a stronger incentive to minimize the tracking error variance and exhibit stronger mimicking propensity. However, when the convexity of the fund flow is dominant, parameter $a$ does not affect manager's risk choice. As shown in Figure 4.4, the 'contrarian' region remains unchanged when we increase the value of $a$.

**Proposition 5** *The convexity feature of the fund flow function dominates over the concavity when a fund's relative performance is close to the lower bound of*

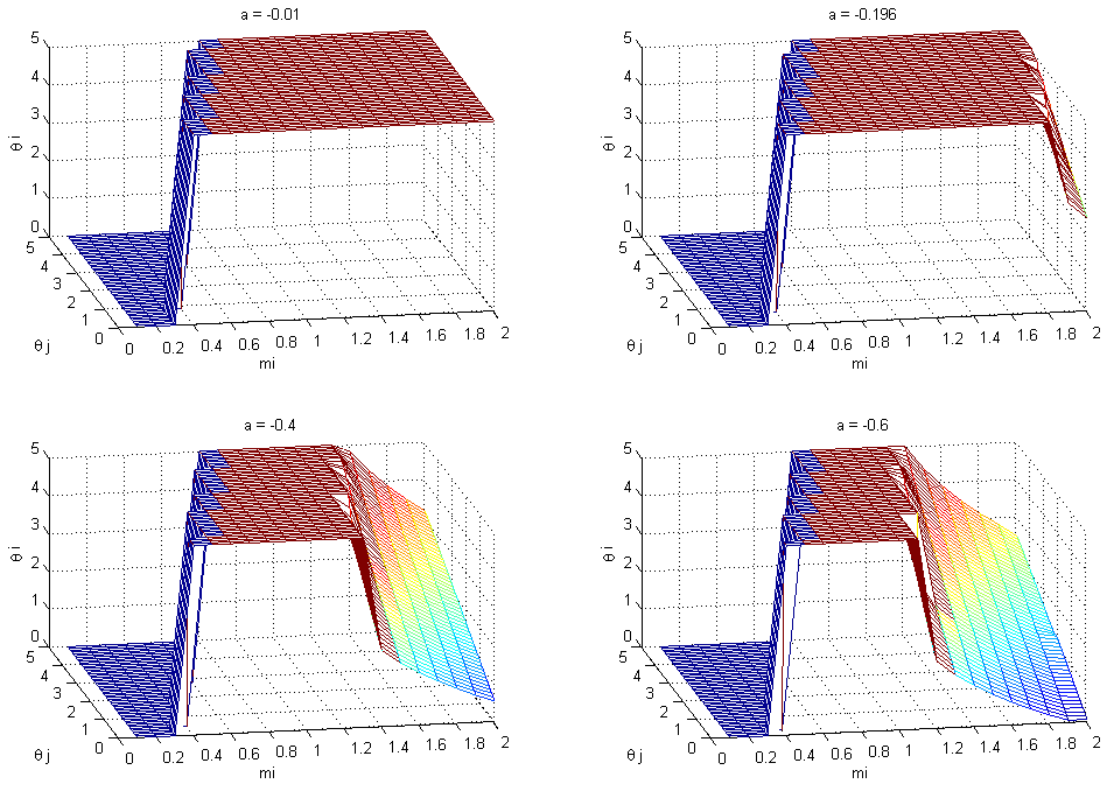



Figure 4.4: Sensitivity analysis of the concavity, $a$, of the fund flow function.

*the money flow and the hedge fund manager would shift risk to increase tracking error variance. As the relative performance improves, the concavity of the fund flow function becomes dominant and the manager would mimic the industry to minimize the tracking error variance. Based on the relative interim performance, hedge fund managers choose one of these two opposite risk shifting strategies.*

## 4.5 Solutions to the Baseline Model

In this section, we will firstly focus on the tournament behavior of risk averse hedge fund managers and then introduce the high-water-mark provision to examine the combined effects of fund flow and HWM on managers' risk shifting decisions.

### 4.5.1 Tournament Behavior

A hedge managers is assumed to have a standard constant relative risk aversion (CRRA) utility function defined over his compensation at the end of year. In the absence of the HWM, the objective of a manager is

$$\max_{\theta_i \in [0,\bar{\theta}]} E[U(C_i)] \tag{4.12}$$

where $U(C_i) = \frac{C_i^{1-\gamma}}{1-\gamma}$ and $C_i = kW_{i,2} + kf(\Delta W)$. The introduction of risk aversion results in a concave objective function over both absolute performance $W_{i2}$ and fund flow $f(\Delta W)$.

With our standard parameters, we present the numerical solution to the manager's optimal risk taking in Figure 4.5.[1] Without the fund flow concern, Merton [1969] predicts that one's risk taking level should be constant and equal to $\frac{\mu - r}{\gamma \sigma^2}$. Figure 4.5 reveals that the potential money flow induces a manager's risk choice to deviate from Merton's prediction. As analyzed before, the interplay of the convexity of fund flow function and the concavity of the objective function largely affects fund managers' risk shifting decisions. The 'contrarian' region appears when a fund has poor interim performance (when $m_i < 0.5$). When the fund moves out

[1] See Appendix C.3 for details of the numerical procedure

of the 'contrarian' region (when $m_i > 0.5$), hedge fund managers would closely follow the industry benchmark and the optimal risk level is strongly depressed due to risk aversion. To see if our results are robust, we have also used the exponential utility function and the optimal risk shifting strategies (mimicking and contrarian strategies) for hedge fund managers remain the same. Numerical results are shown in Figure 19 in Appendix C.2.

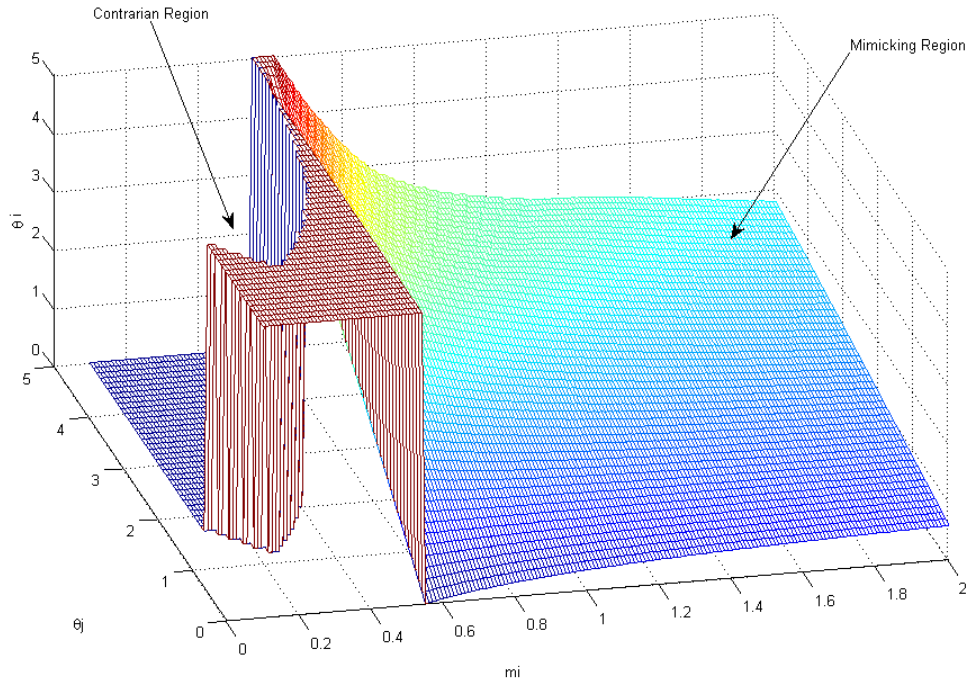



Figure 4.5: Risk-averse manager's optimal portfolio choice(standard parameters are used)

Figure 4.6 shows the sensitivity analysis of the industry's interim performance. As $m_j$ goes up, the 'contrarian' region enlarges. Intuitively speaking, the fund manager is more likely to take the opposite strategy to the industry average when other funds' mid-year return increases. In addition, since the slope $\frac{m_j}{m_i}$ increases in general, hedge fund managers' risk shifting decision becomes more sensitive to the industry's average risk level $\theta_j$. This trend can be identified by comparing the 'mimicking' regions of the four sub-figures in Figure 4.6: as $m_j$ rises, the surface of the 'mimicking' area becomes steeper.

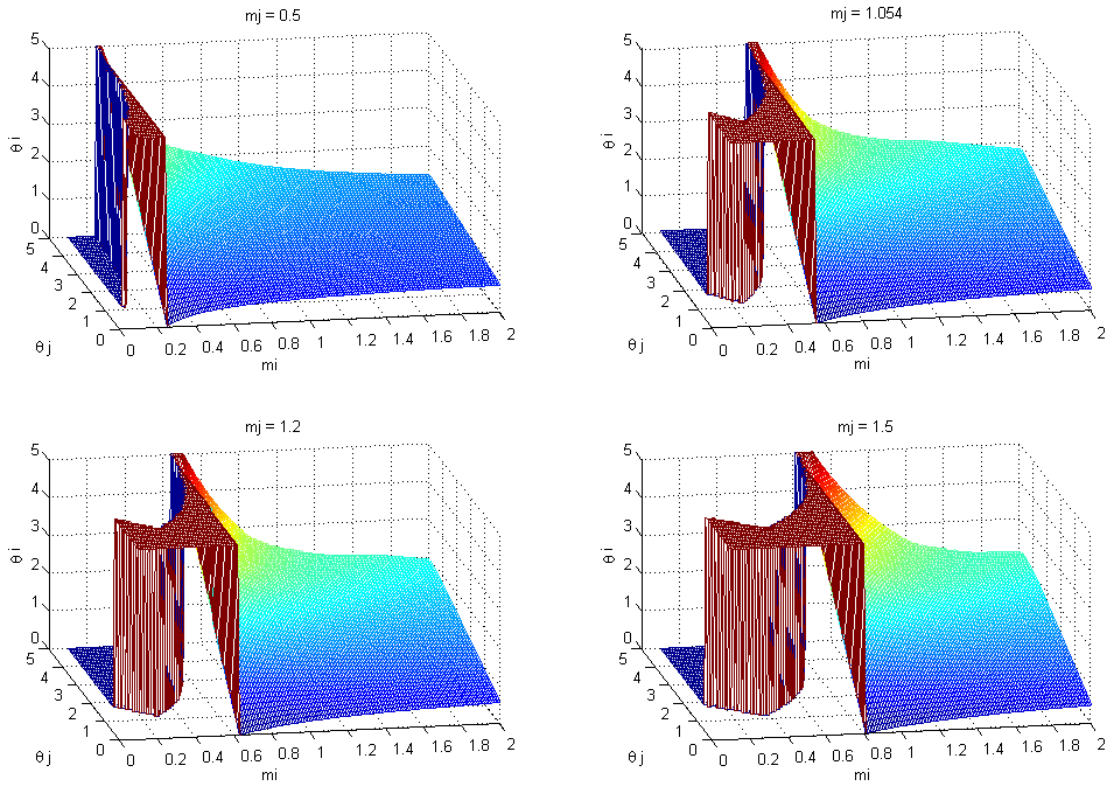



Figure 4.6: Sensitivity analysis of the interim industry performance

In order to study the effect of risk aversion, we solve the optimal portfolio allocations with different $\gamma$ and present the results in Figure 4.7. We find that the behavior of an interim loser with $m_i < 0.5$ is almost unaffected by changing the coefficient of risk aversion. This also confirms that the effect of fund flow convexity outweighs the effect of risk aversion when the manager's interim performance is far behind his peers. Nevertheless, the value of $\gamma$ largely affects the manager's mimicking behavior when $m_i > 0.5$. A more risk averse manager would take on less risk in order to reduce the volatility of the fund value as well as his own compensation.

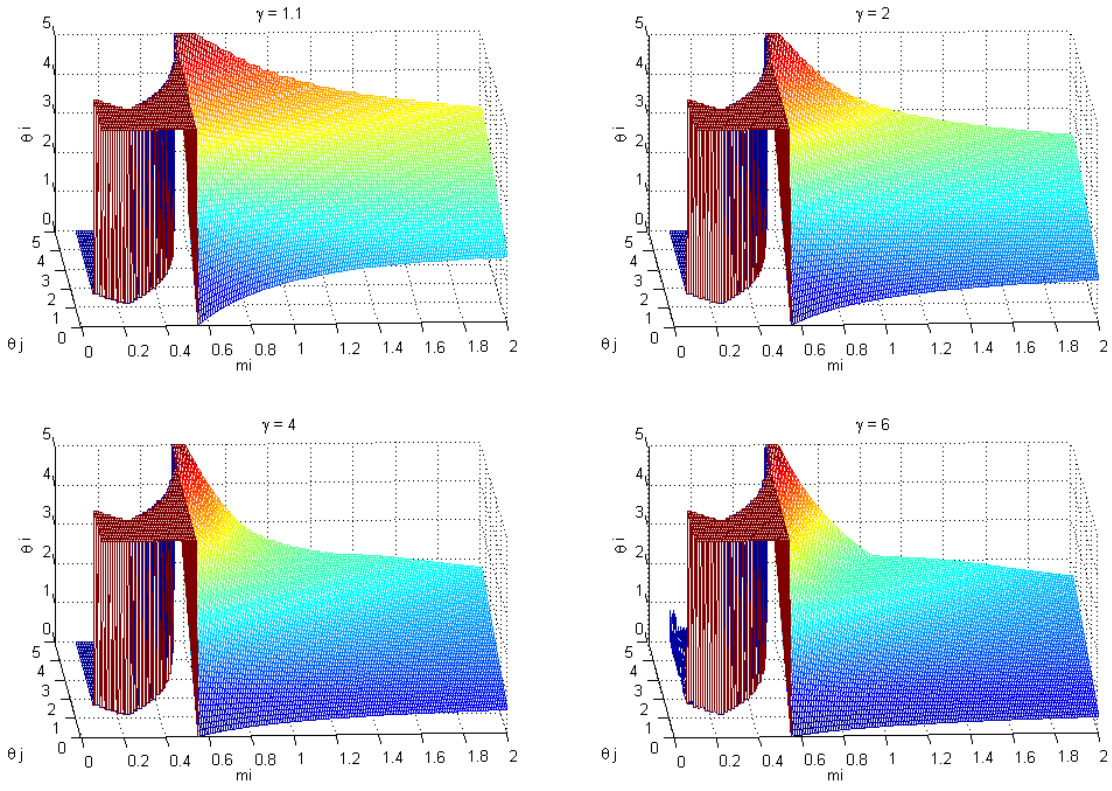
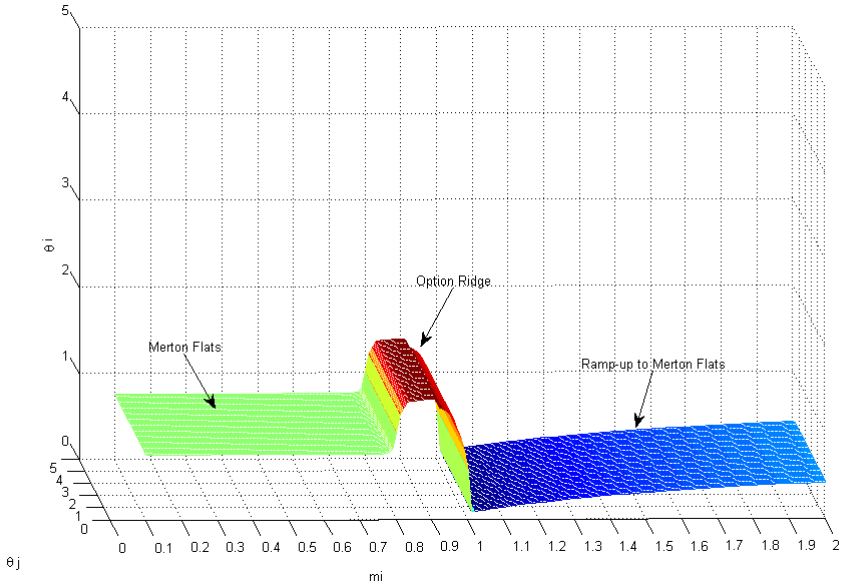


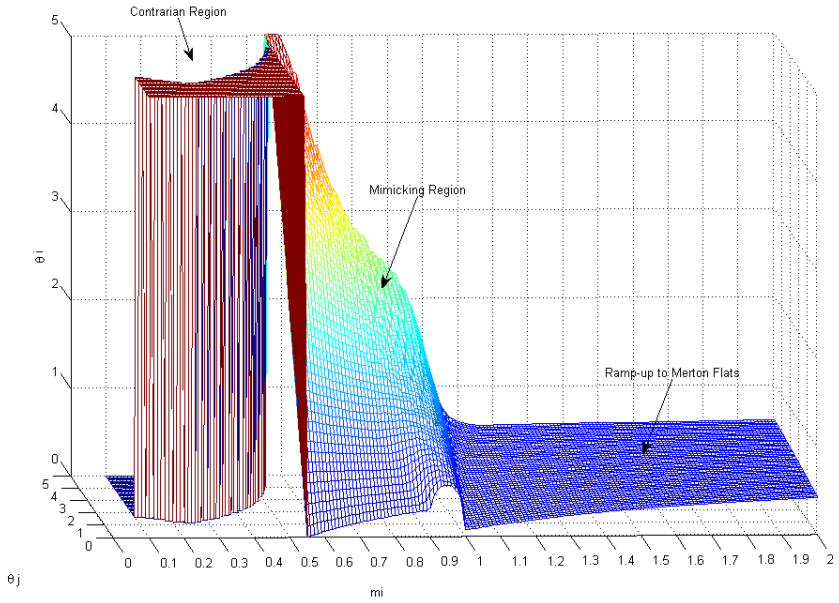

Figure 4.7: Sensitivity analysis of the coefficient of risk aversion

### 4.5.2 Tournament Behavior and Incentive Contracts

The prevalent use of the High-Water-Mark provision has raised concerns about the inappropriate risk taking incentive it brings about. Under HWM, a manager not only receives the management fee based on the size of assets under management (AUM), but also gets rewarded if the fund value exceeds the pre-determined HWM. Thus the manager's compensation equals the management fee based on the fund's year-end wealth and fund inflows/outflows plus a call option struck at the HWM (which equals $W_{i2}$ in our setting).




(a) HWM only




(b) HWM and fund flow

Figure 4.8: Risk-averse manager's optimal portfolio strategy

Figure 4.8(a) depicts the pattern of how a hedge fund manager shifts his risk taking when no money flow is allowed at year end. When a fund's interim value

is far below the HWM (i.e. $m_i = 0.1 \sim 0.8$), the manager's portfolio strategy would be mostly driven by his risk aversion propensity, and thus the optimal risk level can be characterized by Merton's prediction $\frac{\mu - r}{\gamma \sigma^2}$. Following Hodder and Jackwerth [2007], we label it as 'Merton's flat'. When the fund value approaches the HWM (i.e.$m_i = 0.8 \sim 1$), the manager would rapidly increase the volatility of his portfolio by investing more in the risky asset, but this incentive tails off rapidly when the fund value is very close to the HWM (i.e., $m_i = 1$). This is because the manager wants to play safe to lock in the performance fee and hence the risk level he chooses will be much lower than the Merton's level. This pattern is shown as an 'Option ridge' between $m_i = 0.8$ and $m_i = 1$ in the figure. As the mid-year performance $m_i$ crosses the HWM, the manager's risk taking level will go up gradually until it reaches Merton's flat again. These findings are consistent with the existing studies in the literature.(e.g. Hodder and Jackwerth [2007]).

By comparing Figure 4.8(a) and Figure 4.8(b), we can see the influence of relative performance concern when fund flow enters the manager's compensation function. Firstly, when $m_i$ is very low (i.e., $m_i = 0.1 \sim 0.6$), the manager would choose an opposite strategy to the benchmark to maximize the tracking error volatility instead of choosing the Merton's level of risk. Moreover, the manager's risk taking behavior is primarily driven by the industry's portfolio strategy $\theta_j$ due to his fund flow concern when the fund value is below HWM. Therefore, the manager would not take on high risk if the industry's average risk level is low. Secondly, When $m_i$ surpasses the HWM, the manager's portfolio strategy is almost not affected by $\theta_j$. This is due to his stronger desire to secure performance fee than to win more fund.

**Proposition 6** *In the presence of hedge fund tournaments and the High-Water-Mark provision, a hedge fund manager's incentive to increase risk is largely mitigated by his fund flow concern when fund value is somewhat below HWM. In the meanwhile, the HWM-induced lock-in behavior suppresses mimicking behavior when fund value is above HWM.*

## 4.6 Liquidation Threat

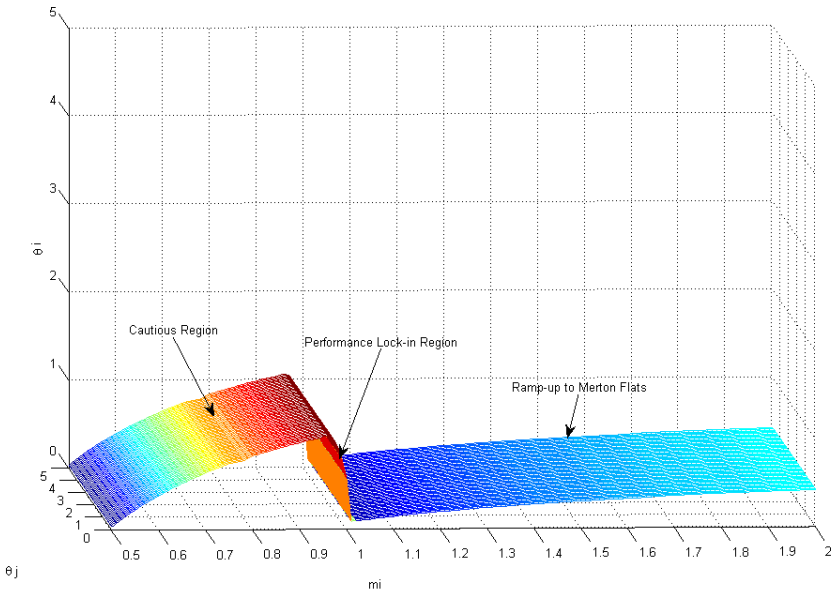
### 4.6.1 Exogenous fund closure

As suggested by empirical studies, hedge funds have higher attrition rates (8% per year) than mutual funds. Therefore, it is natural to consider the liquidation possibility and its impact on fund managers' risk shifting decisions. Following Lan, Wang, and Yang [2013], we set the liquidation bound as a fraction of HWM, i.e., $\underline{W} = p \times H$, where $H$ is the high water mark and $p$ equals 0.5 throughout this paper. Once the fund value hits the bound, the fund will be liquidated, and hedge fund manager will take nothing. Thus, the manager's compensation at $t_2$ becomes:

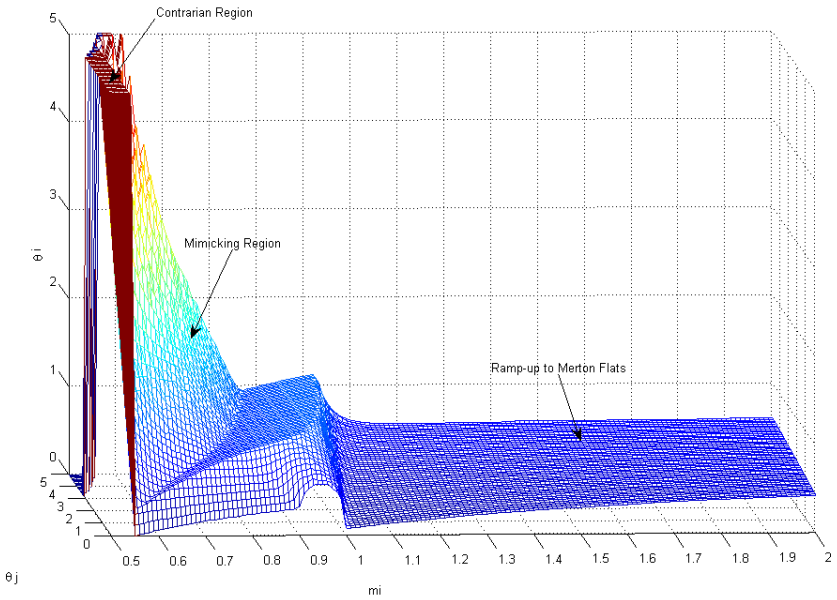
$$C_i = \begin{cases} kW_{i,2} + kF_i + y \max\{W_{i,2} - W_{i,0}, 0\} & \text{if } W_{i,2} > 0.5, \\ 0 & \text{Otherwise} \end{cases} \tag{4.13}$$

We obtain the numerical solution to the optimal risk taking decision in the presence of exogenous fund closure (see Figure 4.9).[1] Comparing Figures 4.8(a) and 4.9(a), we can observe the manager's different behavior due to managers' liquidation concern. In order to avoid hitting the liquidation bound, the manager becomes very cautious as $m_i$ approaches 0.5. Specifically, he would choose to gradually lower his risk exposure rather than taking the Merton's predicted level as soon as $m_i$ is away from the HWM level.

[1] Since we assume that the liquidation bound is 0.5, the manager's interim performance $m_i$ starts from 0.5 rather than 0.1.




(a) HWM only




(b) HWM and fund flow

Figure 4.9: Risk-averse manager's optimal portfolio strategy with exogenous fund closure

Comparing Figures 4.9(a) and 4.9(b), we find that facing potential money

withdrawals, managers with poor interim performance (i.e., $m_i = 0.5 \sim 0.8$) does not necessarily reduce risk even when the fund is close to the liquidation bound. For example, when $m_i < 0.6$ and $\theta_j < 3$, managers would actually take the highest risk. Moreover, for a wide range of mid-year performance ($0.55 < m_i < 0.8$), managers would closely follow the industry benchmark in choosing their portfolio weights. In the 'mimicking region'(i.e., $0.55 < m_i < 0.8$) shown in Figure 4.9(b), the average risk taking level is higher than that in 4.9(a).

It is worth mentioning that our results are different from Hodder and Jackwerth [2007] who focus on funds' absolute performance and argue that managers with poor interim performance would play safe to avoid hitting the bound (which is similar to the pattern in Figure 4.9(a)), while this strategy is not optimal anymore when we consider hedge fund tournaments. When the fund's interim performance is far behind his peers, investors would withdraw money from the fund and in the worst case, investors would withdraw all the investments, which would effectively liquidate the fund.

**Proposition 7** *Facing a liquidation bound, a hedge fund manager without tournament incentive will considerably reduce risk as his interim performance is close to the bound, while a manager with tournament concerns will maximize the tracking error volatility to avoid potential fund outflows.*

#### 4.6.1.1 Sensitivity Analysis

Figure 4.10 shows the sensitivity analysis of the industry's interim performance $m_j$. As shown before, interim losers are mostly driven by their fund flow concerns. To see how the change of winning/losing position affects risk shift decisions, we examine fund managers' risk taking choices with different market average performance $m_j$.

Intuitively, $m_j$ can be considered as an indicator of the overall market condition. During recession (e.g., mj=0.5), managers do not worry about fund outflow too much as the whole industry performed poorly. Hence their main incentive is to avoid hitting the liquidation bound or to lock in performance fees. As $m_j$ increases, the 'contrarian' region enlarges and more manager will try to maximize their tracking error variance by deviating from the industry benchmark. More-

over, as long as the fund value is above the HWM level, the relative standing in the industry has little effect on the manager's risk shifting decision as he would take low risks to avoid the call option falling out of the money.

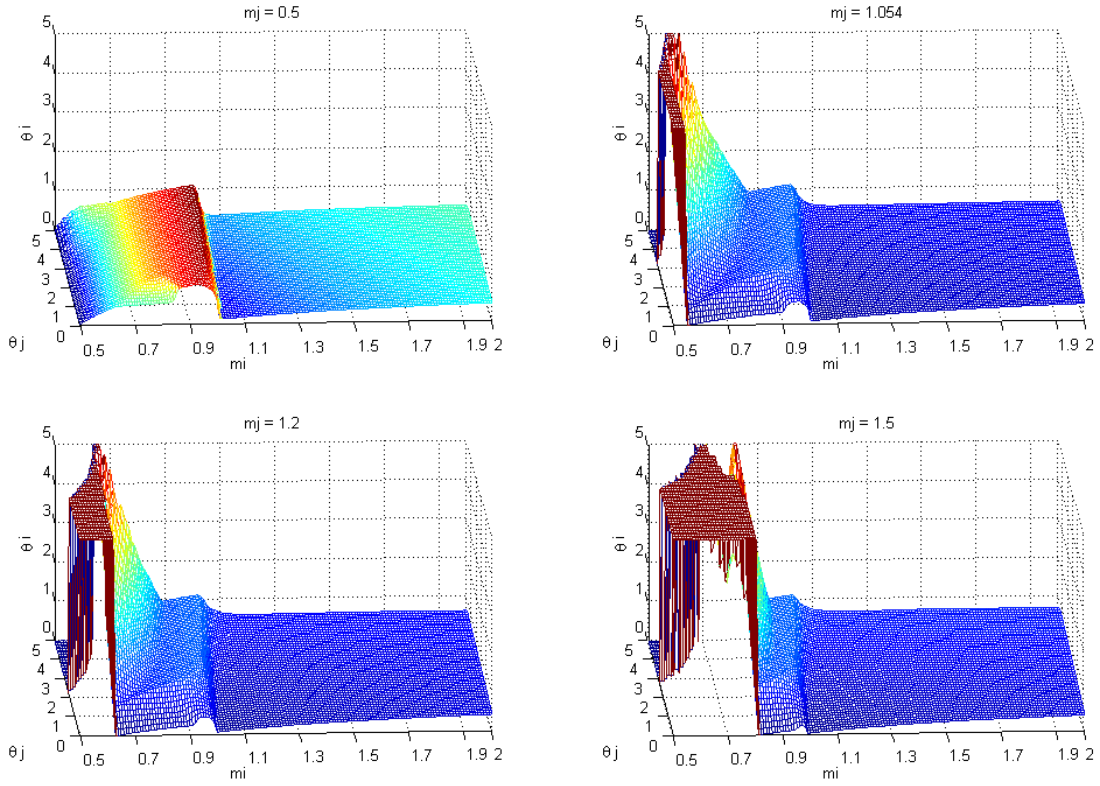



Figure 4.10: Sensitivity analysis of the industry's interim performance

#### 4.6.1.2 Equilibrium with Exogenous Fund Closure

In this subsection, we analyze the manager's equilibrium portfolio strategy. Suppose there are n funds indexed by $i$ in the market with mid-year performance $m_i$, and the industry average mid-year performance can be computed as $m_j = \frac{\sum_{i=1}^{n} m_i}{n}$, and the benchmark risk level is $\theta_j = \sum_{i=1}^{n} \frac{m_i}{\sum_{i=1}^{n} m_i} \theta_i$, a weighted average of $\theta_i$. (See ***proof 5***)

**Definition 2** *The equilibrium of the model arises if given the industry average risk level $\theta_j^*$, hedge fund manager $i$'s best risk shifting response is $\theta_i^*$, and given*

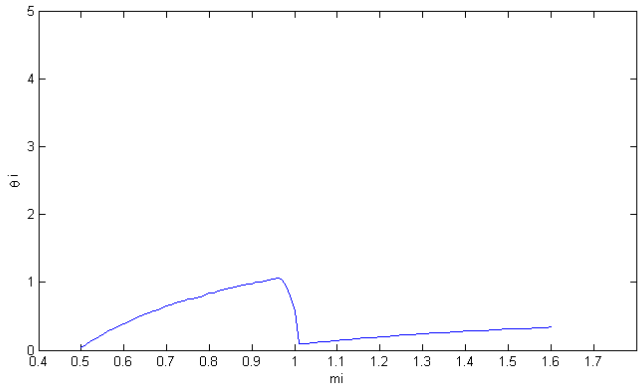
*individual fund's optimal choice $\theta_i^*$, the industry weighted average risk level is* $\theta_j^* = \sum_{i=1}^{n} \frac{m_i}{\sum_{i=1}^{n} m_i} \theta_i^*$.

We numerically solve for the equilibrium of the model. The procedure is the following: Firstly, we make assumptions on the distribution of interim performance $m_i$. To simplify our analysis, we assume that $m_i$ is uniformly distributed between$[0.5, 1.6]$, and the average mid-year performance $m_j$ is thus equal to 1.05 in this case.[1] Secondly, we compute the optimal risk taking choice $\theta_i$ for each possible value of $\theta_j$ (which lies in $[0, 5]$), and then the implied $\theta_j$ which is the weighted average of optimal $\theta_i$ across different funds. The computation continues until it reaches the point when the given value of $\theta_j$ equals the weighted average of the optimal $\theta_i$.

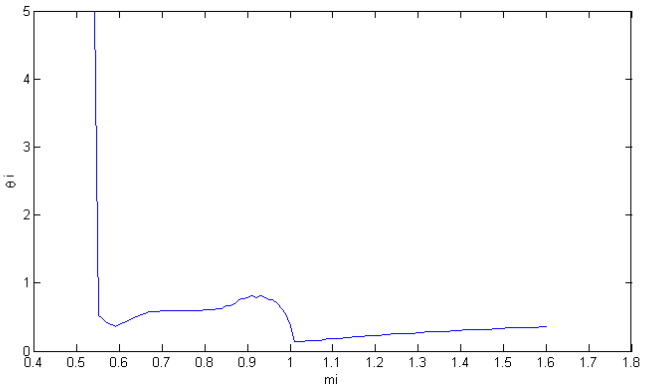
A standard hedge fund contract with the high water mark provision is in effect a call option for hedge fund managers. Figure 4.11(a) presents the optimal risk shifting pattern in equilibrium, which is consistent with Hodder and Jackwerth [2007]. Hedge fund managers would substantially increase portfolio risks when the fund value approaches the HWM and gradually reduce risk when the fund value is close to the liquidation bound. The combined effects of the HWM and fund flows is shown in Figure 4.11(b). By comparing Figure 4.11(a) and Figure 4.11(b), we can see that the option ridge induced by the HWM is significantly mitigated by managers' fundflow concern. Also, the optimal risk level around the HWM with potential year-end capital flows is in general considerably lower than in the case without capital flows.

Moreover, in contrast to mutual fund tournaments, our paper suggests that hedge fund managers who are facing a concave flow-performance function and are compensated based on the HWM contract would not increase risks when they outperform the peers as they have a strong incentive to secure performance fee. In the equilibrium shown in Figure 4.11(b), hedge fund interim winners would actually choose small risk exposures while interim losers who are close to the liquidation bound would increase risks. This finding is consistent with the empirical studies on hedge fund tournaments. (See Brown, Goetzmann, and Park [2001] and Aragon and Nanda [2012].)

[1] This is approximately equal to our standard parameter, $m_j = 1.054$, when we assume that industry level is exogenously given.




(a) Equilibrium with HWM only




(b) Equilibrium with HWM and fund flows

Figure 4.11: Risk-averse manager i's equilibrium portfolio strategy with exogenous fund closure

### 4.6.2 Endogenous Fund Closure

Instead of using a predetermined liquidation boundary, we employ a managerial shutdown option in this subsection following Hodder and Jackwerth [2007] as many hedge fund managers choose to close their funds voluntarily. An endogenous fund closure option in our model is essentially an American option where managers can choose to liquidate their funds whenever the fund is above the pre-specified liquidation boundary. After comparing the value of their outside opportunities and the expected value of continuing to run the funds, managers

decide whether they will exercise the option or not.

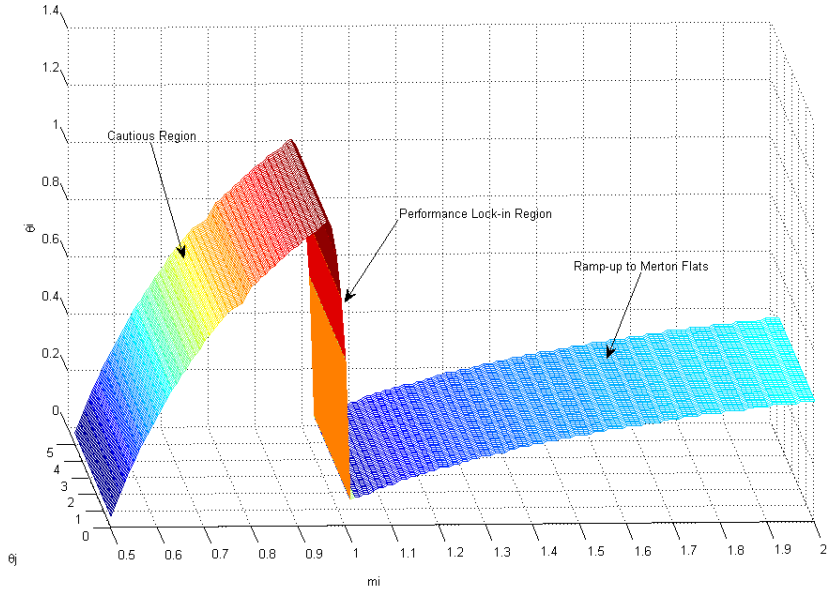
Specifically, we assume that at time $t_1$, the manager can choose between shutting down the fund to take the outside opportunity $C_{out}$ and continuing running the fund.[1] When mid-year performance is revealed, if a manager expects that the value of his outside opportunity is higher than the compensation from running the current fund, he will opt to close the fund at $t_1$ rather than waiting until $t_2$. The manager's compensation at $t_2$ for continuing running the fund is the same as shown by Equation 4.13. If the manager chooses to close the fund at $t_1$, she receives $C_{out}$:

$$C_i = C_{out} \tag{4.14}$$

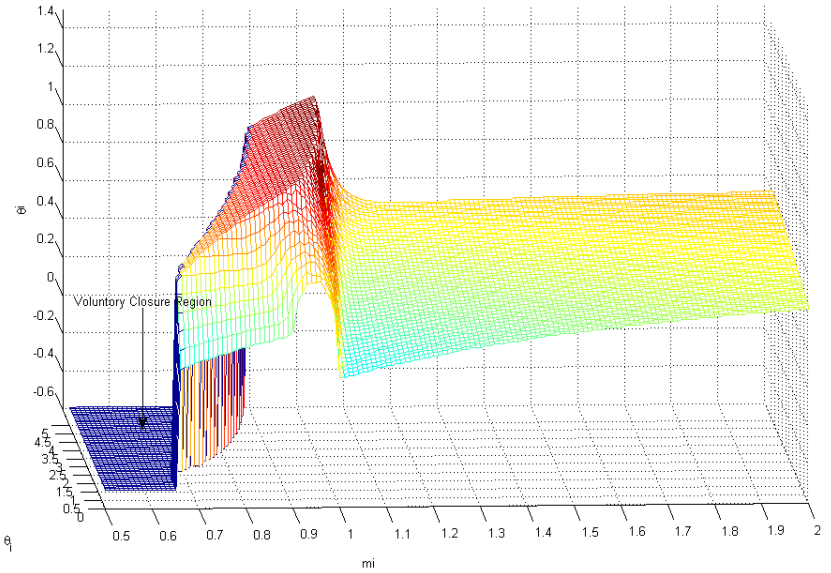
Figures 4.12(a) and 4.12(b) present hedge fund managers' optimal risk choices with and without fund flow concerns, respectively. Comparing Figure 4.9(a) with Figure 4.12(a), we find that the pattern of managers' risk taking behavior is not changed when we only consider HWM. This is because the benefit of outside opportunity is smaller than that of continuing the current fund and thus the manager would lower the portfolio risk to avoid hitting the liquidation bound.

In order to distinguish between the extreme risk taking 0 and fund closure, we use the risking taking $-0.5$ to represent the fund closure decision. In Figure 4.12(b), we can see that the 'contrarian' region disappears. Moreover, fund closure decision is affected not only by fund's interim performance $m_i$, but also by other funds' average risk taking level, which is different from Hodder and Jackwerth [2007] who suggest that hedge fund managers would prefer to close the fund only when the fund value is far below the high water mark. Due to the fund outflow concern, the fund closure region is larger than that in Hodder and Jackwerth [2007]. Moreover, managers' endogenous fund closure decision is largely affected by the industry's risk level. when the industry on average takes extreme risk, funds with mid-year performance $m_i < 0.9$ would be closed; When the industry takes modest risk (i.e., $\theta_j < 1$), only funds with $m_i < 0.7$ would exit the market.

[1] This is similar to Lan, Wang, and Yang [2013]'s setting, which assume that (1) the restart boundary to be 80% of the fund (2) the subsequent fund's to be 75% of the previous funds and (3) the new fund's size is zero when the manager is forced to liquidate. Our assumption is also similar to Hodder and Jackwerth [2007] who assume that the manager will receive a prorated fraction management fee plus an prorated annual compensation rate.




(a) HWM only




(b) HWM and fund flow

Figure 4.12: Risk averse manager's optimal portfolio strategy with endogenous fund closure option ($C_{out} = 0.005$)

#### 4.6.2.1 Sensitivity Analysis

Next we are also going to examine how the fund manager's decision changes in response to different outside compensation, different industry performance and different levels of risk aversion. By comparing the four sub-figures in Figure 4.13 below, we can see that the outside opportunity has effects mainly on interim losers while risk aversion and benchmark performance can influence both mid-year winning funds and mid-year losing funds.

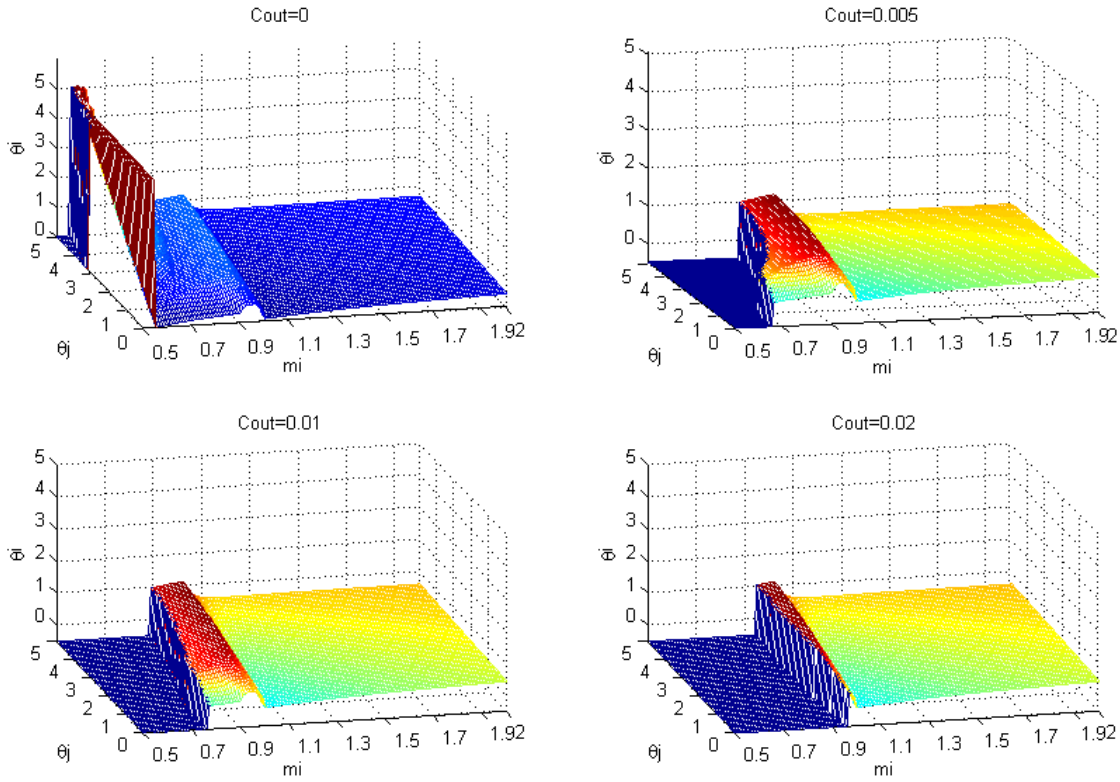



Figure 4.13: Sensitivity analysis of the outside opportunity(manager's optimal portfolio choice with endogenous fund closure)

Figure 4.14 shows that with poor industry average performance ($m_j = 0.5$), fund manager will shut down the fund only when the fund is on the verge of liquidation and the industry as a whole opts for highly risky position (i.e., $\theta_j > 2$). As $m_j$ increases, the relative interim performance of the fund worsens and

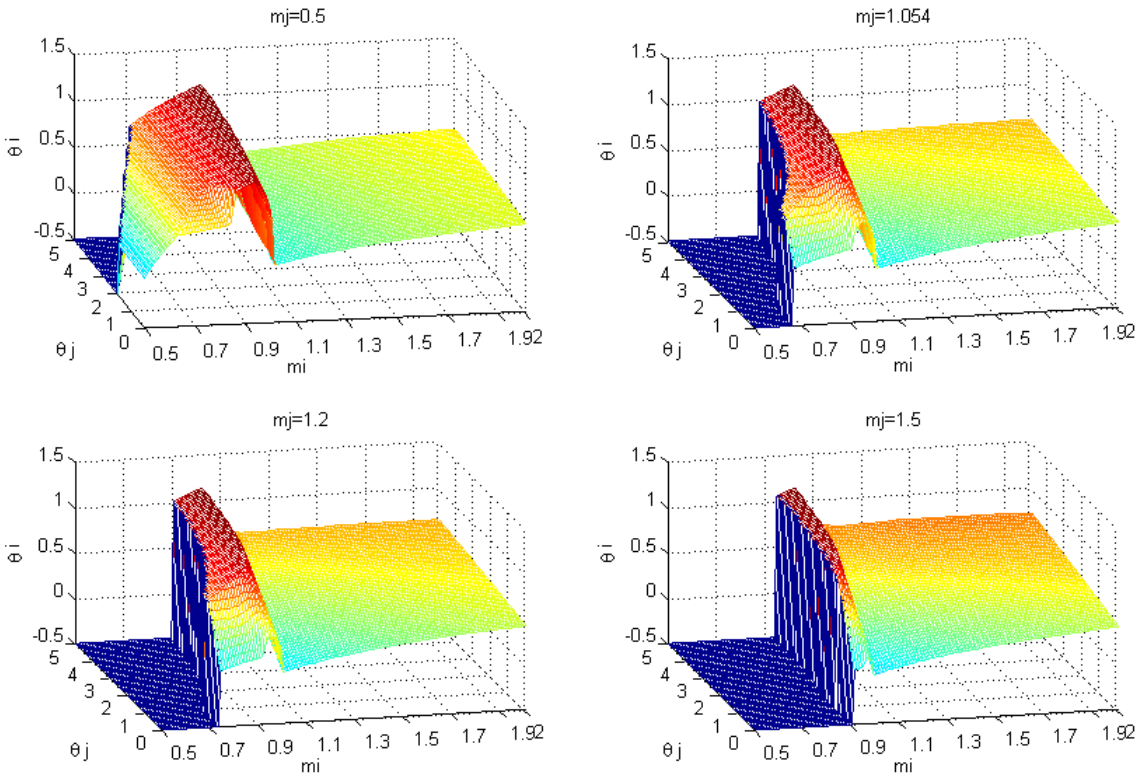



Figure 4.14: Sensitivity analysis of the industry's average performance(manager's optimal portfolio choice with endogenous fund closure)

fund managers are more likely to close the fund due to possible fund outflow at year end. This is similar to the effect of increasing $C_{out}$. In the meantime, the mimicking tendency of managers is more prominent when the industry on average has better mid-year performance.

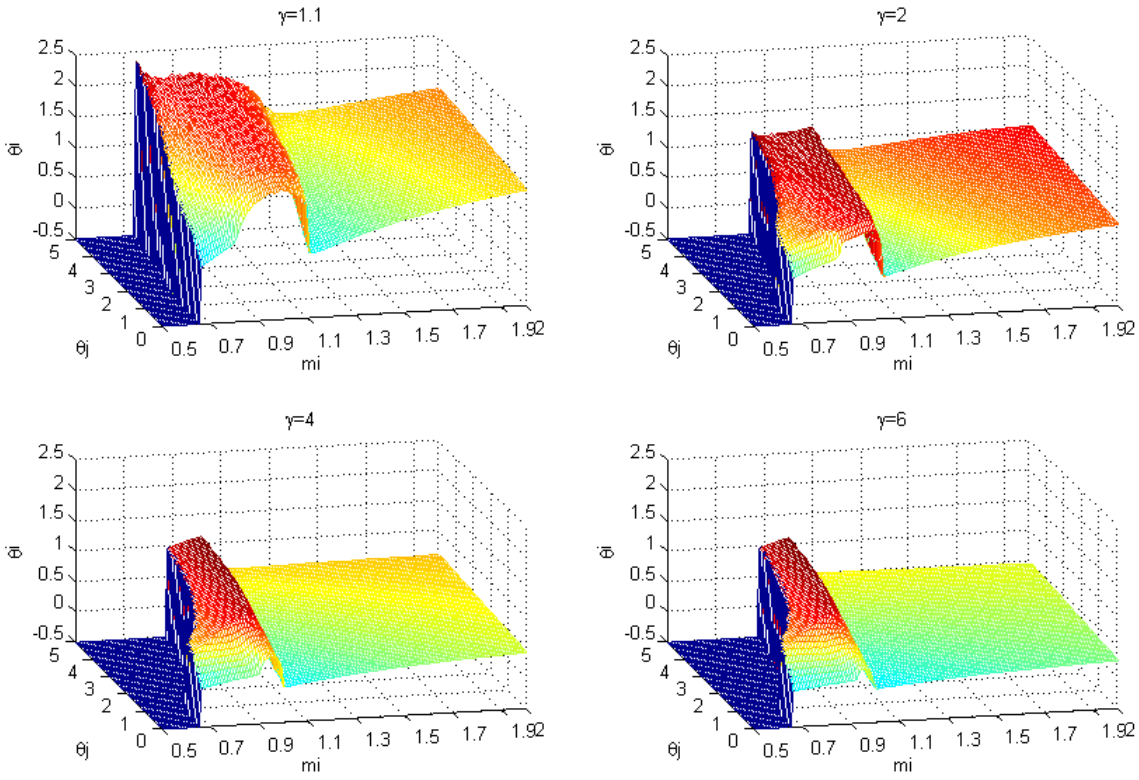



Figure 4.15: Sensitivity analysis of the coefficient of risk aversion (manager's optimal portfolio choice with endogenous fund closure)

Figure 4.15 suggests that the endogenous fund closure region is widened when hedge fund managers become more risk averse, the reason being that risk averse managers would prefer certain outside compensation over uncertain compensation from managing the fund. As can be seen from Figure 4.15, risk aversion level also influence the risk levels in general. As $\gamma$ goes up, the optimal risk is decreased for all the funds.

**Proposition 8** *Given a shutdown option, a hedge fund manager with poor in-*

*terim performance would close the fund, especially when the industry on average takes high risk. Moreover, the voluntary closure region enlarges with the value of the manager's outside opportunity and his risk aversion level as well as the industry's average interim returns.*

## 4.7 Systematic Risk versus Idiosyncratic Risk

Chen [2011] documents that (relatively) poor-performing funds increase both market risk and idiosyncratic risk and the magnitude of risk shifting in the idiosyncratic risk is much larger than that in the market risk.[1] In order to examine how fund managers choose their risk profiles by taking on different types of risks, we introduce another risky asset to our previous model. We postulate that each fund has access to a fund-specific asset which has a random return $x_{id}$, independent from the return of the market asset, and is assumed to be normally distributed with mean $\mu_{id}$ and variance $\sigma_{id} = \sigma^2$.[2] Moreover, managers who face leverage constraints invest $\theta_s$ portion of the money in the systematic-risk asset, and $\theta_{id}$ in the idiosyncratic-risk asset, and the sum of $\theta_s$ and $\theta_{id}$ cannot exceed $\overline{\theta}$.

In the literature, this additional risky asset is widely regarded as manager-specific investment technology and the risk premium $\mu_{id} - r$ is interpreted as manager's skills.[3] In the presence of two risky assets, fund i's wealth at year end becomes $W_i = W_{i,0} \times m_i \times [1 + r + \theta_s(x - r) + \theta_{id}(x_{id} - r)]$. In the meanwhile, the industry's year end wealth is not affected by individual funds' exposures to idiosyncratic risks as the fund-level uncertainty can be canceled out when we compute the industry's average performance. Hence, $W_j = W_{j,0} \times m_j \times [1 + r + \theta_j(x - r)]$. The optimal risk allocation should yield the highest expected utility for a fund manager:

$$\max_{\theta_s, \theta_{id}} E[U(C_i)] \tag{4.15}$$

s.t. $\theta_s + \theta_{id} \leq \overline{\theta}$

[1] This is shown by the results in Table 9 and Table 10 in his paper.

[2] We also examine the case in which $\sigma_{id} > \sigma$ and the results are almost identical to the case $\sigma_{id} = \sigma$, given the same mean $\mu_{id}$ of the fund-specific asset.

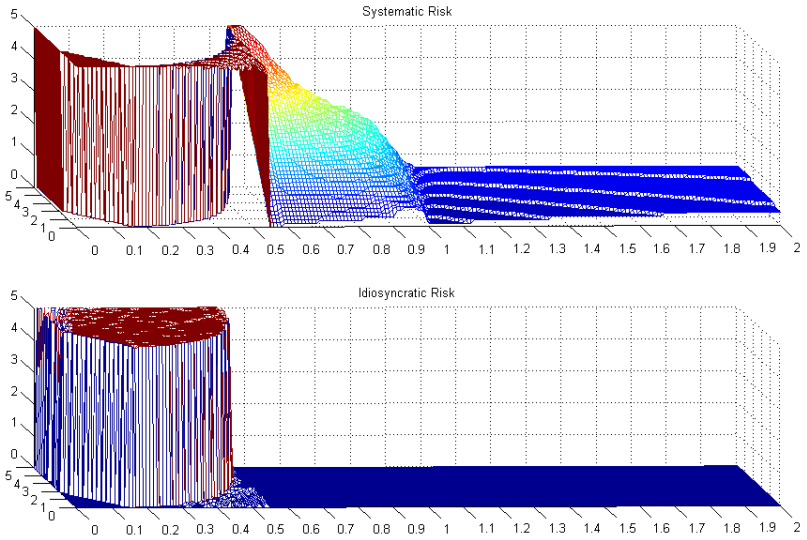
[3] See Buraschi, Kosowski, and Sritrakul [2013] for instance.

where $U(C_i) = \frac{C_i^{1-\gamma}}{1-\gamma}$ and $C_i = kW_{i,2} + kf(\Delta W) + y\max\{W_{i,2} - W_{i,0}, 0\}$

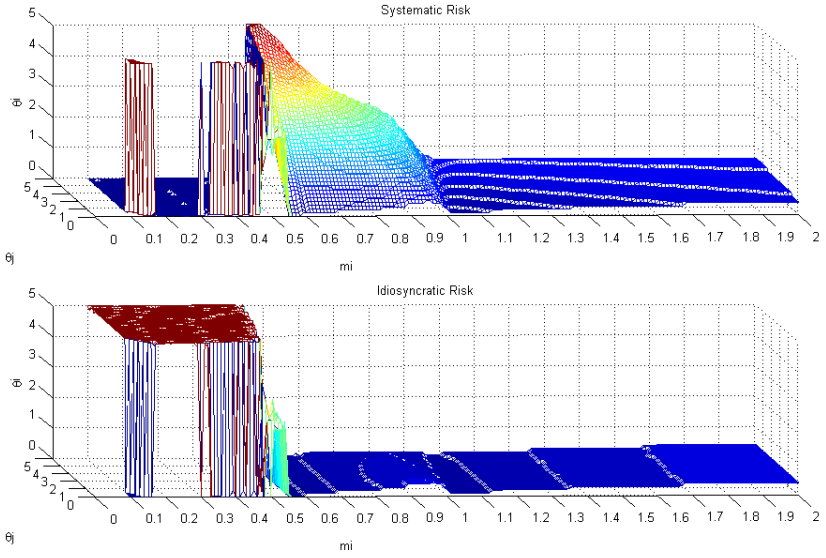
Intuitively speaking, risk averse agents would not invest in the fund-specific asset if it had no risk premium. In the context of hedge fund tournaments, however, hedge fund managers might have the incentive to take on idiosyncratic risk in order to maximize the tracking error variance. To provide more insights on this issue, we analyze two cases with and without risk premium. Figure 4.16 illustrates manager's optimal asset allocations on the two risky assets respectively. Figure 4.16(a) has $\mu_{id} = r$ and Figure 4.16(b) is for $\mu_{id} = 0.1 > \mu$. We do not consider fund closure here.[1]

It is evident from Figure 4.16 that: (I) In the 'contrarian' region, hedge fund managers would invest almost nothing in the market asset, while they would opt for the maximum idiosyncratic risk no matter whether they have alpha generating abilities or not in the presence of leverage constraint. Consistent with our prior conjecture, hedge fund managers would not invest in the fund-specific asset outside the 'gambling' region when $\mu_{id} = r$. This finding echoes Chen [2011] in that hedge funds mainly increase idiosyncratic risk when they fall behind the peers. (II) In the presence of alpha generating abilities (as in Figure 4.16(b)), the bell-shaped risk shifting pattern around HWM is more pronounced for the fund-specific asset than the market asset and the volatility shifting in the market asset is more strongly driven by fund flow concerns than before. (III) Although fund's performance relative to the industry plays a key role in determining the portion of money invested in the fund-specific asset, $\theta_{id}$ is almost not affected by the risk level of the industry $\theta_j$.

[1]Introducing fund closure will not qualitatively change the results.




(a) without alpha generating abilities: $\mu = 0.05$, $\mu_{id} = 0.02$




(b) with alpha generating abilities: $\mu = 0.05$, $\mu_{id} = 0.1$

Figure 4.16: Risk averse manager's optimal choices on systematic and idiosyncratic risks

## 4.8 Conclusion

In this paper, we suggest a role for the theory of tournaments in studying hedge funds' risk taking behavior. A typical compensation contract for hedge funds would induce managers to pursue high absolute performance, while the year-end competition for new capitals among managers also generates relative performance objectives. We characterize the managers' portfolio strategies in a two-period (one-year) model where the managers' compensation depends on both their absolute and relative performance to examine the interplay of tournament concerns, incentive contracts and liquidation threats.

Our paper extend the work of Basak and Makarov [2012] on mutual funds by explicitly modeling hedge funds' features such as (i) high water marks; (ii) the concave fundflow-performance relation; (iii) and high attribution rates. Different from Basak and Makarov [2012]'s results for mutual funds that interim winners opt for a higher portfolio volatility than interim losers, we find that (i) hedge fund interim winners will mimic the benchmark to minimize the portfolio's tracking error volatility and due to the HWM provision, they would only take moderate risk; (ii) the interim losers managers have strong incentives to maximize their tracking error variance and their risk choice largely depends on other managers' risk taking decision.

In addition, we disentangle the idiosyncratic risk from the fund's total risk and relate this fund-specific risk to the manager's alpha generating ability. We confirm Chen [2011]'s empirical finding that hedge funds mainly shift idiosyncratic risk in response to their poor performance relative to peer funds and distort both systematic and idiosyncratic risks when their option-like fee contracts are out of the money.

Finally, our results indicates a different portfolio strategy when the manager faces a liquidation bound from Hodder and Jackwerth [2007]: the manager with the fund flow concern might choose to gamble to avoid fund outflows rather than playing safe; Given an outside opportunity, the manager's endogenous fund closure largely depends on the benchmark's portfolio choice and they might voluntarily shut down the fund even when the fund value is still far away from the liquidation bound.

Nevertheless, we might have lost some interesting results by only considering a short(one year) investment horizon. Since investors enter the funds at different points in time, hedge fund managers in reality face multiple HWMs. Due to the fact that old investors always have a higher HWM level than new investors, new coming funds will lower the average HWM. Thus, for the future research, our one-year model can be extended to a multi-period one to examine the impact of new funds on the option value of the contract and thus on managerial risk choices. In addition, another assumption in our paper that the initial fund size is the same for all funds can be relaxed, as empirical evidence suggests that managers with larger assets under management will be more cautious and less prone to take high risk compared with smaller and younger funds. Therefore, it is also worth investigating whether the manager's risk shifting decision is affected by the size of assets under management or not. Additionally, in our paper the tournament behavior is subject to a given concave fund flow function. In contrast, Berk and Green [2004] examine the endogenous fund flows in their model by assuming that investors use past returns to update their beliefs about managers' abilities. Thus, it will be more fruitful for future work to consider investors' endogenous fund flow decisions in the context of hedge fund tournaments.

# Appendix A

## A.1 Robustness Check: Timing of Earnings Announcements

## Table 2: Robustness Check: Timing of Earnings Announcements

FE is the earnings surprise decile. FE1 refers to stocks which have the lowest forecast errors. FE10 refers to stocks which have the highest forecast errors. Panel A presents the test results of the effects of macroeconomic announcements on the frequency of earnings news release, which is the daily number of earnings announcement divided by the total number of announcements made in the calendar quarter. Macro Dummy is an indicator variable, which equals 1 when there is at least one of the 7 macro announcements, and 0 otherwise. Indicator variables for days and months are also included in the regressions. Announcements made on Saturdays or Sundays are excluded from the sample. In Panel B, we replace the Macro Dummy with 7 indicator variables for the macro announcements of interest. A Tobit regression is employed to estimate the models and standard deviations are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A. Regression Analysis on the Frequency of Earnings Announcements

| | FN | FFE1 | FFE2 | FFE3 | FFE4 | FFE5 | FFE6 | FFE7 | FFE8 | FFE9 | FFE10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Macro Dummy** | **-0.0021**** | -0.0016 | **-0.0034***** | -0.0016 | **-0.0021*** | -0.0011 | 0.0004 | -0.0011 | **-0.0028**** | **-0.0039***** | **-0.0045***** |
| | (0.0009) | (0.0011) | (0.0012) | (0.0012) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 |

Panel B. Regression Analysis on the Frequency of Earnings Announcements

| | FN | FFE1 | FFE2 | FFE3 | FFE4 | FFE5 | FFE6 | FFE7 | FFE8 | FFE9 | FFE10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CPI | -0.0025 | -0.0022 | **-0.0056**** | -0.0007 | -0.0027 | -0.0023 | -0.0007 | -0.0037 | -0.0038 | **-0.0047*** | **-0.0075***** |
| | (0.0018) | (0.0022) | (0.0025) | (0.0025) | (0.0026) | (0.0027) | (0.0026) | (0.0026) | (0.0027) | (0.0027) | (0.0027) |
| Housing | 0.0002 | -0.0031 | 0.0003 | 0.0017 | **0.0042*** | **0.0045*** | **0.0063**** | **0.0044*** | -0.0005 | -0.0016 | -0.0033 |
| | (0.0018) | (0.0022) | (0.0025) | (0.0025) | (0.0025) | (0.0026) | (0.0025) | (0.0025) | (0.0026) | (0.0026) | (0.0026) |
| Newhome | **0.0040**** | 0.0027 | 0.0028 | **0.0049**** | 0.0011 | **0.0072***** | **0.0068***** | **0.0091***** | **0.0055**** | **0.0058**** | 0.0040 |
| | (0.0017) | (0.0021) | (0.0024) | (0.0024) | (0.0025) | (0.0025) | (0.0025) | (0.0024) | (0.0025) | (0.0026) | (0.0025) |
| PPI | **-0.0051***** | -0.0033 | **-0.0094***** | **-0.0059**** | **-0.0059**** | **-0.0062**** | **-0.0045*** | **-0.0069***** | **-0.0072***** | **-0.0086***** | **-0.0084***** |
| | (0.0017) | (0.0021) | (0.0025) | (0.0025) | (0.0027) | (0.0026) | (0.0026) | (0.0026) | (0.0027) | (0.0027) | (0.0027) |
| Trade | **-0.0046***** | -0.0002 | -0.0023 | **-0.0062**** | **-0.0074***** | **-0.0066**** | **-0.0051**** | **-0.0044*** | **-0.0083***** | **-0.0078***** | **-0.0068***** |
| | (0.0017) | (0.0021) | (0.0024) | (0.0025) | (0.0025) | (0.0026) | (0.0025) | (0.0025) | (0.0027) | (0.0026) | (0.0026) |
| Unem | -0.0014 | -0.0016 | -0.0015 | **-0.0054*** | -0.0018 | -0.0026 | -0.0019 | -0.0026 | -0.0026 | -8.82e-05 | -0.0013 |
| | (0.0019) | (0.0025) | (0.0028) | (0.0030) | (0.0030) | (0.0032) | (0.0032) | (0.0031) | (0.0032) | (0.0031) | (0.0030) |
| GDP | -0.0030 | -0.0015 | -0.0006 | -5.12e-05 | 0.0013 | -0.0063 | -0.0043 | **-0.0086*** | -0.0018 | -0.0070 | **-0.0078*** |
| | (0.0029) | (0.0037) | (0.0042) | (0.0043) | (0.0043) | (0.0049) | (0.0047) | (0.0048) | (0.0046) | (0.0048) | (0.0047) |
| Indicators of Day of week | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Indicators of Months | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 | 2515 |

# Appendix B

## B.1 Proof of the optimal fraction of loans that banks would sell in the secondary market

**Proof** The necessary condition for banks to sell the loan is that $P\max(1, R_1) > R_0$. Suppose banks choose to sell $\alpha_1$ portion of the assets to outside investor, where $\alpha_1 < \alpha$, the payoff from selling is $\alpha_1 P\max(1, R_1) + (1-\alpha_1)R_0$, which can be written as $\alpha_1(P\max(1, R_1) - R_0) + R_0$. Since $P\max(1, R_1) > R_0$, the payoff is increasing in $\alpha_1$, and should reach the maximum at $\alpha$. Therefore, we have proved that the optimal fraction of loans at which banks should sell is the upper bound $\alpha$ set by government.

□

## B.2 Proof of the existence of a solution to Equation (3.4)

**Proof**

i. when $R^* = R$, the domain of $P$ is $[1, R]$ Since $\widetilde{R}_0 \geq R^* = R$, and $\widetilde{R}_0 \in [0, R]$, $\widetilde{R}_0$ must be equal to $R$ regardless of P. Hence, $h(P, R) = E[\widetilde{R}_0] = R$ for any $P \in [1, R]$. The equation $h(P, R) = P$ holds only when $P = R$, which is the unique solution of $P$ in this case.

ii. when $0 < R^* < R$, we can show two inequalities that $h(\frac{R^*}{R}, R) > \frac{R^*}{R}$, and $h(R, R^*) < R$. As is illustrated before, function $h(P, R^*)$ is continuous and

increases with $P$, which together with $h(\frac{R^*}{R}, R) > \frac{R^*}{R}$, and $h(R, R^*) < R$ implies that $h(P, R^*) = P$ has at least one solution of $P$ within $[\frac{R^*}{R}, R]$. As shown in the graph, when $P = \frac{R^*}{R}$, the curves of $h(R, R^*)$ are always above the 45 degree line while $h(R, R^*)$ is always below it. Since the curves increase with regard to the horizontal axis, there must exist at least one intersection point of the curve and the 45 degree line, which solves the equation. Derivation of the two inequalities is as follows.

(a) $h(\frac{R^*}{R}, R) > \frac{R^*}{R}$ As is known, $P\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*$. When $P = \frac{R^*}{R}$, we have $\frac{R^*}{R}\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*$. Since $\frac{\max(1,\widetilde{R}_1)}{R} \leq 1$, we can obtain $\widetilde{R}_0 = R^*$. Accordingly, function $h(\frac{R^*}{R}, R^*) = E[\widetilde{R}_0] = R^*$. Therefore, $h(\frac{R^*}{R}, R^*) \geq \frac{R^*}{R}$.

(b) It has been proved that $h(R, R^*) = R$ when $R^* = R$. Since $\frac{\partial h}{\partial R^*} > 0$, we get $h(R, R^*) < R$ when $R^* < R$.

iii. when $R^* = 0$, the inequality $h(\frac{R^*}{R}, R^*) \geq \frac{R^*}{R}$ still holds. Hence, $h(0, R^*) = 0$. In this case, $P = 0$ is one of the solutions.

□

## B.3 Proof of Figure 3.9.2

**Proof** We prove that the curve of $k(P)$ shifts to the right as $R$ increases. In other words, we need to show that for a given $R^*$, the corresponding price $P$ is higher with $R^H$ than with $R^L$.

Recall investors' rational expectation on loan quality, $h(P, R^*) \equiv E_{\widetilde{R}_0, \widetilde{R}_1}(\widetilde{R}_0 | P\max(1, \widetilde{R}_1) \geq \widetilde{R}_0 \geq R^*)$. With a given $R^*$ and a greater $R$, to maintain the same level of expectation as with $R^L$ , the price P should be lowered. This together with the fact that $h(P, R^*)$ is an increasing function in $P$ suggests that the curve of $h(P|R^*, R^H)$ should lie above the curve $h(P|R^*, R^L)$. Therefore, the intersection point of the 45 degree line and $h(P|R^*, R^H)$ should be higher than that for $h(P|R^*, R^L)$, as shown in Figure 18 ($P_H > P_L$ for the same lending standard $R^*$), which completes our proof.

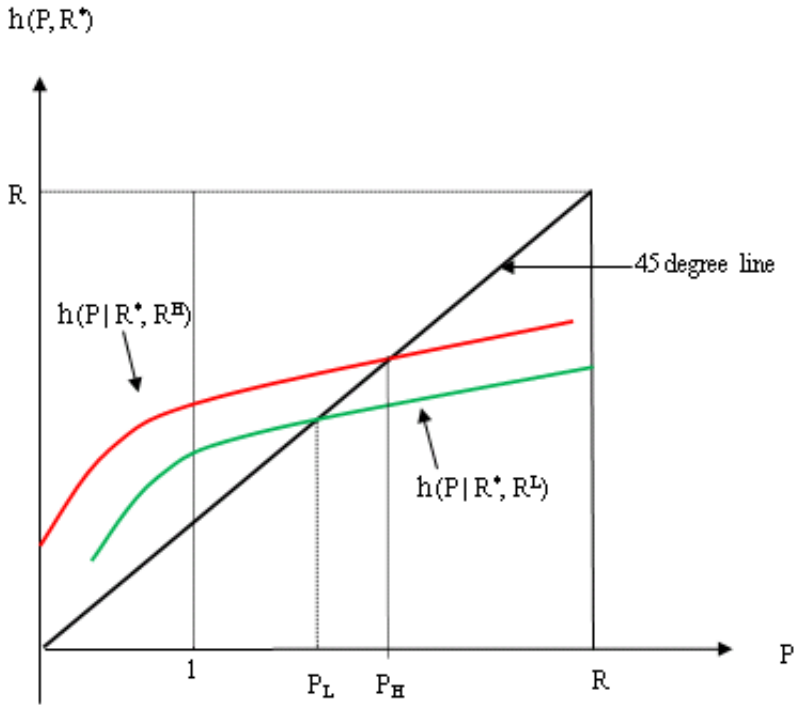



Figure 17: Investors' expected loan return $h(P, R^*)$ under different economic prospects

□

## B.4 Proof of the extended model with liquidity shock

**Proof**

1. When $\alpha = 0$ (there is no secondary market),
   If the bank issued loan at $t_0$, the expected future cashflow can be calculated as $(1-\lambda)(R_0 - L)$ when $R_0 \geq L$ and 0 when $R_0 < L$. If the bank held cash till $t_1$, then the expected future cashflow will be $\lambda(1-L)E_{\widetilde{R}_1}\max(1, \widetilde{R}_1) + (1-\lambda)[E_{\widetilde{R}_1}\max(1, \widetilde{R}_1) - L]$, which can be expressed as $\lambda(1-L)C + (1-\lambda)(C-L)$ where $C = E_{\widetilde{R}_1}\max(1, \widetilde{R}_1)$. Since $(1-\lambda)(R_0 - L) > 0$ and $\lambda(1-L)C + (1-\lambda)(C-L) > 0$ , banks will never underwrite when $R_0 < L$. Therefore, banks' underwriting standard will not be smaller than $L$ when $\alpha = 0$. Moreover, banks are indifferent between holding cash and issuing loan when the following equation holds:

$$(1-\lambda)(R_0 - L) = \lambda(1-L)C + (1-\lambda)(C-L) \tag{16}$$

   Solving the above equation yields $R_0 = \frac{C(1-\lambda L)}{1-\lambda}$.

2. When $\alpha = 1$,
   First of all, it is easy to show that banks' participation condition in the secondary market is that $P \geq L$. Otherwise, banks would never sell loans to outside investors. The reason is the following. If the bank issued loan at $t_0$ and encountered liquidity shock at $t_1$, selling the loan at $P \geq L$ is not sufficient for the bank to pay back depositors. If the bank did not encounter liquidity shock at $t_1$, it would not sell the loan either because it would be better to simply hold cash till $t_1$. Hence, $P \geq L$ must hold.
   If the bank issued loan at $t_0$, then its expected cashflow is $\lambda[(1-\frac{L}{P})E_{\widetilde{R}_1}\max(R_0, P, P\widetilde{R}_1)]) + (1-\lambda)[E_{\widetilde{R}_1}\max(R_0, P, P\widetilde{R}_1) - L]$, which can be rewritten as $\lambda[(1-\frac{L}{P})\max(R_0, PC)]) + (1-\lambda)[\max(R_0, PC) - L]$, where $C = E_{\widetilde{R}_1}\max(1, \widetilde{R}_1)$ ; If the bank held

cash till $t_1$, the expected future cashflow will be $\lambda(1-L)E_{\widetilde{R}_1}\max(1,\widetilde{R}_1) + (1-\lambda)[E_{\widetilde{R}_1}\max(1,\widetilde{R}_1) - L]$.

(a) When $R_0 > PC$, the expected cashflow from issuing loan becomes $\lambda[(1-\frac{L}{P})R_0]) + (1-\lambda)[R_0 - L]$ and the condition of bank being indifferent is the following:

$$\lambda[(1-\frac{L}{P})R_0]) + (1-\lambda)[R_0 - L] = \lambda(1-L)C + (1-\lambda)(C-L) \quad (17)$$

Solving the above condition yields $R_0 = \frac{C(1-\lambda L)}{1-\frac{L}{P}\lambda}$. Since $R_0 > PC$, we must have $\frac{1-\lambda L}{1-\frac{L}{P}\lambda} > P$. Hence, $L < P < 1$.

(b) When $R_0 \leq PC$, bank's expected future cashflow from issuing loan is $\lambda[(1-\frac{L}{P})PC]) + (1-\lambda)[PC - L]$ and the condition of bank being indifferent is the following:

$$\lambda(1-\frac{L}{P})PC) + (1-\lambda)(PC-L) = \lambda(1-L)C + (1-\lambda)(C-L) \quad (18)$$

from which, we can derive that $P = 1$. Since $R_0 \leq PC$, now we have $R_0 \leq C$

□

# Appendix C

## C.1 Proofs

**Proof 1: The expected fund flow**

**Proof** The expected the fund flow $E[f(\Delta W)] = E[a\Delta W^2 + b\Delta W + c|\Delta W < -\frac{b}{2a}]P(\Delta W \leq -\frac{b}{2a}) + (c - \frac{b^2}{4a})P(\Delta W > -\frac{b}{2a})$ is equivalent to

$$E[f(\Delta W)] = \{aE[\Delta W^2|\Delta W < -\frac{b}{2a}] + bE[\Delta W|\Delta W < -\frac{b}{2a}] + c\}P(\Delta W \leq -\frac{b}{2a}) + (c - \frac{b^2}{4a})P(\Delta W > -\frac{b}{2a}) \tag{19}$$

Recall that we assume $\mu_w = (m_i\theta_i - m_j\theta_j)(\mu - r) + (m_i - m_j)(1 + r)$, $\sigma_w = |m_i\theta_i - m_j\theta_j|\sigma$ and $d = -\frac{-b/2a-\mu_w}{\sigma_w} \sim [0, 1]$, we can rewrite the following argument.

$$P(\Delta W \leq -\frac{b}{2a}) = \Phi(d) \tag{20}$$

$$E[\Delta W|\Delta W < -\frac{b}{2a}] = \frac{-\sigma_w\phi(d) + \mu_w\Phi(d)}{\Phi(d)} \tag{21}$$

$$E[\Delta W^2|\Delta W < -\frac{b}{2a}] = \frac{(b/2a - \mu_w)\sigma_w\phi(d) + (\mu_w^2 + \sigma_w^2)\Phi(d)}{\Phi(d)} \tag{22}$$

where $\phi(.)$ and $\Phi(.)$ is the standard normal density and cumulative distribution respectively. Insert equation (19),(20) and (21) into equation (18) we can obtain Equation 4.8. □

**Proof 2: The derivatives of the fund flow with regard to $\theta_i$**

**Proof** Given the expression of the expected fund flow function in 4.8, we can write the first derivative of the expected fund flow with regard to $\theta_i$ as follows.

$$\begin{aligned}\frac{\partial E[f(\Delta W)]}{\partial \theta_i} &= \frac{\partial\{-(a\mu_w + \frac{1}{2}b)\sigma_w\phi(d) + [a(\mu_w^2 + \sigma_w^2) + b\mu_w + \frac{b^2}{4a}]\Phi(d)\}}{\partial \theta_i} \\ &= -[(a\mu_w + \frac{1}{2}b)\sigma_w]'\phi(d) - (a\mu_w + \frac{1}{2}b)\sigma_w\frac{\partial\phi(d)}{\partial\theta_i} + [a(\mu_w^2 + \sigma_w^2) + b\mu_w + \frac{b^2}{4a}]\frac{\partial\Phi(d)}{\partial\theta_i} \\ &+ [(2a\mu_w + b)\frac{\partial\mu_w}{\partial\theta_i} + 2a\sigma_w\frac{\partial\sigma_w}{\partial\theta_i}]\Phi(d)\end{aligned} \tag{23}$$

Insert the derivatives of the following argument into (30),

$$\frac{\partial\mu_w}{\partial\theta_i} = m_i(\mu - r) \tag{24}$$

$$\frac{\partial\sigma_w}{\partial\theta_i} = \pm m_i\sigma \tag{25}$$

$$\frac{\partial d}{\partial\theta_i} = \frac{m_i}{\sigma_w^2}[\pm(\mu_w + b/2a)\sigma - (\mu - r)\sigma_w] \tag{26}$$

$$\frac{\partial\phi(d)}{\partial\theta_i} = -d\phi(d)\frac{\partial d}{\partial\theta_i} \tag{27}$$

$$\frac{\partial\Phi(d)}{\partial\theta_i} = \phi(d)\frac{\partial d}{\partial\theta_i} \tag{28}$$

we can obtain Equation 4.9. □

**Proof 3: The lower bound of the optimal risk level $\theta_i^*$:**

**Proof**

- When $\frac{m_j}{m_i}\theta_j \leq \overline{\theta}$:
  When $0 \leq \theta_i \leq \frac{m_j}{m_i}\theta_j$, the first derivative of $E[f(w)]$ with regard to $\theta_i$ is positive. Therefore, the optimal $\theta_i^*$ can only be $\frac{m_j}{m_i}\theta_j$; When $\frac{m_j}{m_i}\theta_j \leq \theta_i \leq \overline{\theta}$, the first derivative of $E[f(w)]$ with regard to $\theta_i$ is positive at $\theta_i = \frac{m_j}{m_i}\theta_j$, and decreasing in $\theta_i$. Hence, the optimal point when $\theta_i \in [\frac{m_j}{m_i}\theta_j, \overline{\theta}]$ must be

higher than $\frac{m_j}{m_i}\theta_j$. Therefore, when $\theta_i \in [0, \overline{\theta}]$, the optimal risk level $\theta_i^*$ must be higher than $\frac{m_j}{m_i}\theta_j$

- When $\frac{m_j}{m_i}\theta_j > \overline{\theta}$:
  The first derivative of $E[f(w)]$ with regard to $\theta_i$ is positive. Thus, the optimal $\theta_i^* = \overline{\theta}$.

□

**Proof 4: The manager's optimal risk taking when risk premium equals 0**

**Proof** Recall that Equation 4.8 gives the derivatives of the fund flow with regard to $\theta_i$, i.e., $\frac{\partial E[f(w)]}{\partial \theta_i} = m_i\sigma\{\frac{\mu-r}{\sigma}\Phi(d)[b+2a(1+r)(m_i-m_j)] + 2a\sigma_w[\pm\Phi(d)(\frac{(\mu-r)^2}{\sigma^2}+1) - \frac{\mu-r}{\sigma}\phi(d)]\}$. In the case without risk premium, *i.e.*, $\mu - r = 0$, the equation (9) can be written as

$$\frac{\partial E[f(w)]}{\partial \theta_i} = \pm 2am_i\Phi(d)\sigma\sigma_w \tag{29}$$

- When $\frac{m_j}{m_i}\theta_j \leq \overline{\theta}$:
  When $\theta i \geq \frac{m_j}{m_i}\theta_j$, we have $\frac{\partial E[f(w)]}{\partial \theta_i} \leq 0$ and thus the manager will decrease risk. When $\theta i \leq \frac{m_j}{m_i}\theta_j$, $\frac{\partial E[f(w)]}{\partial \theta_i} \geq 0$ and thus the manager will increase the risk taking. In both cases, the manager's optimal risk level $\theta_i^* = \frac{m_j}{m_i}\theta_j$, which also minimizes the tracking error volatility.

- When $\frac{m_j}{m_i}\theta_j > \overline{\theta}$:
  $\theta i \leq \overline{\theta} < \frac{m_j}{m_i}\theta_j$. $\frac{\partial E[f(w)]}{\partial \theta_i}$ is always positive. Hence, $\theta_i^* = \overline{\theta}$

□

**Proof 5: the equilibrium portfolio strategy in the case with exogenous fund closure**

**Proof** For each hedge fund, its year end wealth $W_{i,2} = m_i[\theta_i(x-r)+1+r]$, and industry average year end wealth can be expressed by:

$$W_{j,2} = \frac{\sum_{i=1}^{n} W_{i,2}}{n} = \frac{\sum_{i=i}^{n} m_i[\theta_i(x-r)+1+r]}{n} \tag{30}$$

$$= \frac{\sum_{i=1}^{n} m_i\theta_i(x-r) + \sum_{i=1}^{n} m_i(1+r)}{n} \tag{31}$$

$$= \frac{\sum_{i=1}^{n} m_i}{n}(1+r) + \frac{\sum_{i=1}^{n} m_i\theta_i}{n}(x-r) \tag{32}$$

Let $\overline{m} = \frac{\sum_{i=1}^{n} m_i}{n}$ and $\overline{\theta} = \sum_{i=1}^{n} \frac{m_i}{\sum_{i=1}^{n} m_i}\theta_i$

Then

$$W_{j,2} = \overline{m_i}(1+r) + \overline{\theta}\sum_{i=1}^{n} m_i(x-r) \tag{33}$$

$$= \overline{m}[\overline{\theta}(x-r)+1+r] \tag{34}$$

Therefore, $\overline{m}$ can be regarded as industry average mid-year performance and $\overline{\theta}$ is the average risk taking level of all the funds. □

## C.2 Figures

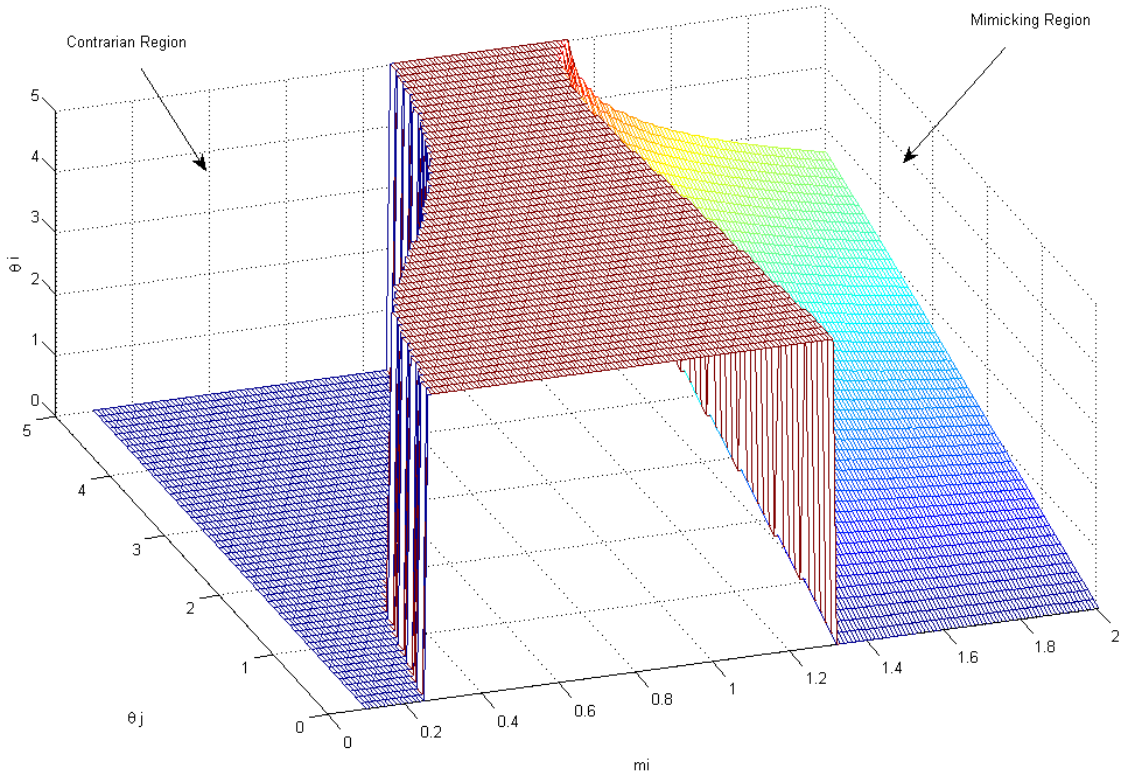



Figure 18: Risk-neutral manager's optimal portfolio choice to maximize the expected fundflow with lower bound (no risk premium)

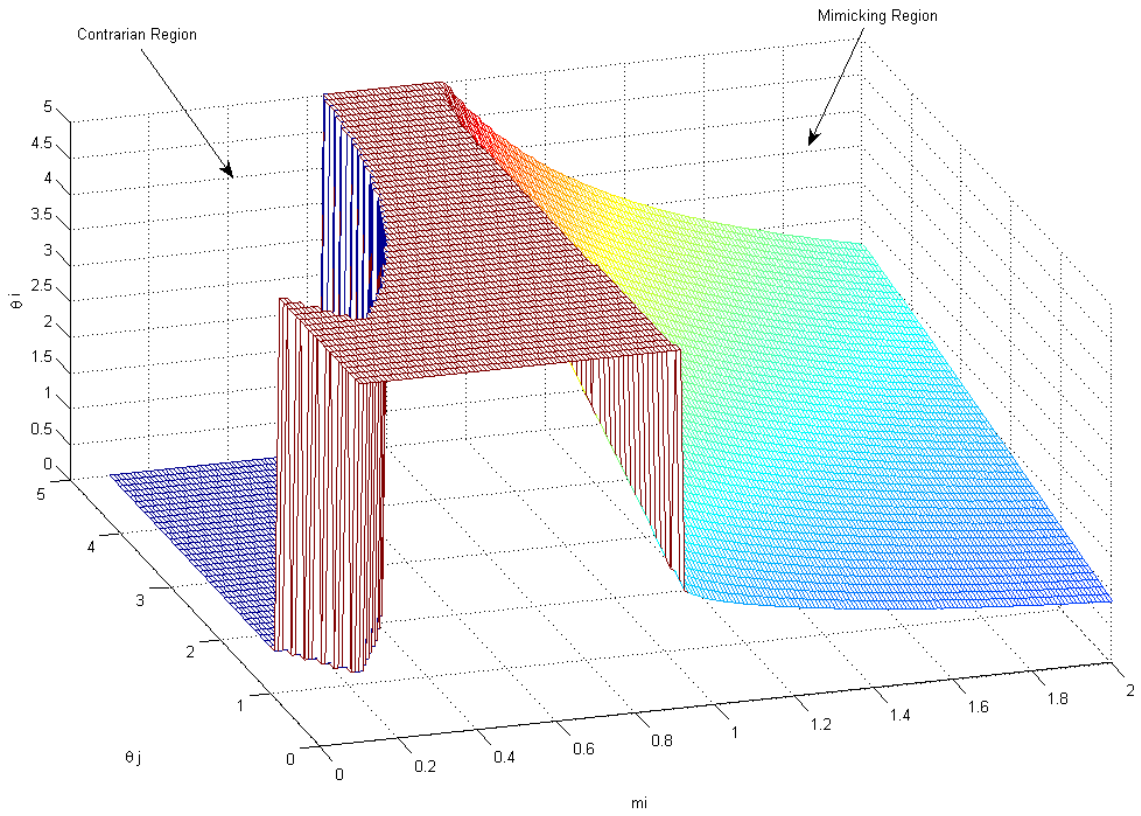



Figure 19: Risk-averse manager's optimal portfolio choice in mutual fund tournaments(with exponential utility function)

## C.3 Numerical Procedures

When an analytical solution cannot be obtained, we implement numerical procedure to solve the model. The method that we use is in spirit similar to the one in Hodder and Jackwerth [2007]. The major difference is that our model is a discrete-time model while Hodder and Jackwerth [2007] utilize a continuous time framework. The result of the model is presented in a three-dimensional plot with a grid of mid-year performance $m_i$ and industry average new risk level $\theta_j$, and the variable of interest if the optimal risk level $\theta_i$, which is shown in the $Z$ axis. The range of $m_i$ is $[0.1, 2]$ with step 0.01, and with the assumption of leverage constraint, the range of risk level is $[0, 5]$ with step 0.01.

First of all, we need to approximate the distribution of the random return $x$. The range of $x$ we choose is $[-0.45, 0.55]$ and the step is 0.01. Our results are not affected by different choices of the range of $x$. Given the industry mid-year performance $m_j$, industry average risk $\theta_j$ and manager's new risk level $\theta_i$, all the possible fund value $W_{i,2}$, fundflow $f(\Delta W)$, and compensation $C_i$ can be calculated according to their formulas:

$$W_{i,2} = W_{i,0} \times m_i \times [1 + r + \theta_{i,1}(x - r)] \tag{35}$$

$$F_i = \begin{cases} c - \frac{b^2}{4a} & \text{if } \Delta W > -\frac{b}{2a}, \\ a(\Delta W)^2 + b\Delta W + c & \text{Otherwise.} \end{cases} \tag{36}$$

$$C_i = kW_{i,2} + kF_i + y \max\{W_{i,2} - W_{i,0}, 0\} \tag{37}$$

In addition, we assume that $x$ follows a normal distribution with mean $\mu$ and volatility $\sigma$. To calculate the expected fund value, we use the discrete normal distribution. Specifically, we compute the probability for each point of $x$ indexed by $i$ using the density function of normal distribution $p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$, and then divide the probabilities by their sum such that they will add up to 1.

$$P(x_i) = \frac{\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}}{\sum_{x_i=-0.45}^{0.55} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}} \tag{38}$$

Since $W_{i,2} = W_{i,0} \times m_i \times [1 + r + \theta_{i,1}(x - r)]$, applying the probabilities $P(x_i)$ for each possible $W_{i,2}$, we can obtain the expected fund value $E[W_{i,2}]$. Similarly, we can calculate the expected fundflow and expected compensation values. ( In the case of risk averse investors, we calculate the expected utilities instead based on $U(C_i) = \frac{C_i^{1-\gamma}}{1-\gamma}$)

Second of all, with $\theta_i$ varying between 0 and 5 in the steps of 0.01, we calculate the expected compensation/utilities (depending on manager's objective function) for each point of $\theta_i$. The one which yields the highest $E[C_i]$ or $E[U(C_i)]$ is the optimal risk level $\theta_i^*$ that the manager should choose.

Thirdly, we change the values of $m_i$ and $\theta_j$ and find the optimal risk $\theta_i^*$ for each combination of these two variables. In Matlab, we use the command mesh$(m_i, \theta_j, \theta_i^*)$, which produces the desired optimal trading strategy $\theta_i^*$ as a function of $m_i$ and $\theta_j$.

The above procedures are adjusted for the following extensions of the model:

- *Fund closure*: When exogenous fund closure is considered in the model, we change the wealth function by setting the fund value as 0 when $W_{i,2} = W_{i,0} \times m_i \times [1 + r + \theta_{i,1}(x - r)]$ hits the liquidation bound 0.5. In the event of fund closure, managers will get nothing; When endogenous fund closure is considered, we need to compare the expected utility from taking the optimal risk $\theta_i$ and the expected utility from outside opportunity. If the former is higher than the latter, the manager would continue running the fund taking the optimal risk $\theta_i^*$. Otherwise, he would close the fund voluntarily.

- *Equilibrium*: To find the optimal risk shifting choice in equilibrium, we implement the above procedures to find the optimal proportion of money invested in the risky asset $\theta_i^*$ given a $\theta_j$, and we also compute the implied $\theta_j^* = \sum_{i=1}^{n} \frac{m_i}{\sum_{i=1}^{n} m_i} \theta_i^*$, which is equal to the weighted average of optimal $\theta_i^*$. We repeat this process with different $\theta_j$ until the given $\theta_j$ equals the implied $\theta_j^*$, which is the industry average risk in equilibrium. The situation with endogenous fund closure option is a bit more complicated, as we need to take into account the number of managers who choose to close down the business.

- *Two risky assets*: For the case of two risky assets, we add one more random variable $x_{id}$ as the return of the second asset. Moreover, we assume that this second asset is independent from the first asset ($Cov(x, x_{id}) = 0$), and has mean $\mu_{id} = r$, and volatility $\sigma_{id}$. Firstly , we need to find the joint distribution of the two random variable. With the $x$ lying between -0.45 and 0.55 in the steps of 0.01 and $x_{id}$ lying between -0.5 and 0.5 in the steps of 0.01, we obtain 10201 pairs of $(x, x_{id})$. As shown before, we need

to calculate the probability of each possible $x$ and $x_{id}$. With index j, the probability of $x_{id_j}$ can be computed as:

$$P(x_{id_j}) = \frac{\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_{id_j}-\mu)^2}{2\sigma^2}}}{\sum_{x_{id_j}=-0.5}^{0.5} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_{id_j}-\mu)^2}{2\sigma^2}}} \tag{39}$$

For each pair of asset returns, we calculate the probability as $P(x_i, x_{id_j}) = P(x_i)P(x_{id_j})$. We denote the risk loading in the first asset as $\theta_{i,1}$ and the risk loading in the second asset as $\theta_{i,2}$. $\theta_{i,1}$ and $\theta_{i,2}$ both lie between 0 and 5 in the steps of 0.01. With leverage constraint, $\theta_{i,1} + \theta_{i,2}$ must not exceed 5. Given the values of $m_i$, $m_j$ and $\theta_j$, we can calculate the expected compensation or expected utility for each pair of $\theta_{i,1}$ and $\theta_{i,2}$. The optimal trading strategy is the pair of $(\theta_{i,1}, \theta_{i,2})$ which brings the highest expected utility.

# References


Aboody, D., and R. Kasznik (2000): "CEO stock option awards and the timing of corporate voluntary disclosures," *Journal of Accounting and Economics*, 29(1), 73 – 100. 23

Acharya, V., and H. Naqvi (2012): "The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle," *Journal of Financial Economics*, 106(2), 349 – 366. 95

Acharya, V. V., P. Schnabl, and G. Suarez (2013): "Securitization without risk transfer," *Journal of Financial Economics*, 107(3), 515 – 536. 71

Aggarwal, R. K., and A. A. Samwick (1999): "Executive compensation, strategic competition, and relative performance evaluation: Theory and evidence," *The Journal of Finance*, 54(6). 109

Aghion, P., P. Bolton, and J. Tirole (2004): "Exit Options in Corporate Finance: Liquidity versus Incentives," *Review of Finance*, 8(3), 327–353. 65

Alevy, J. E., M. S. Haigh, and J. A. List (2007): "Information Cascades: Evidence from a Field Experiment with Financial Market Professionals," *The Journal of Finance*, 62(1), 151–180. 4

Allen, F., S. Morris, and H. S. Shin (2006): "Beauty Contests and Iterated Expectations in Asset Markets," *Review of Financial Studies*, 19(3), 719–752. 5

Amihud, Y. (2002): "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets*, 5(1), 31 – 56. 50, 51

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2007): "Real-time price discovery in global stock, bond and foreign exchange markets," *Journal of International Economics*, 73(2), 251 – 277. 24, 53

Aragon, G. O., and V. Nanda (2012): "Tournament Behavior in Hedge Funds: High-water Marks, Fund Liquidation, and Managerial Stake," *Review of Financial Studies*, 25(3), 937–974. 108, 111, 133

Ball, R., and P. Brown (1968): "An Empirical Evaluation of Accounting Income Numbers," *Journal of Accounting Research*, 6(2), pp. 159–178. 3, 13, 20

Barber, B. M., and T. Odean (2008): "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Review of Financial Studies*, 21(2), 785–818. 21, 27, 35

Barberis, N., M. Huang, and T. Santos (2001): "Prospect Theory and Asset Prices," *The Quarterly Journal of Economics*, 116(1), 1–53. 20

Basak, S., and D. Makarov (2012): "Difference in interim performance and risk taking with short-sale constraints," *Journal of Financial Economics*, 103(2), 377 – 392. 101, 104, 105, 112, 143

Basak, S., A. Pavlova, and A. Shapiro (2007): "Optimal Asset Allocation and Risk Shifting in Money Management," *Review of Financial Studies*, 20(5), 1583–1621. 103, 106, 107, 109, 120

Basak, S., A. Shapiro, and L. Teplá (2006): "Risk management with benchmarking," *Management Science*, 52(4), 542–557. 107

Begley, J., and P. Fischer (1998): "Is there Information in an Earnings Announcement Delay?," *Review of Accounting Studies*, 3(4), 347–363. 23

Berk, J. B., and R. C. Green (2004): "Mutual Fund Flows and Performance in Rational Markets," *Journal of Political Economy*, 112(6), pp. 1269–1295. 106, 144

Bernard, V. L., and J. K. Thomas (1989): "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?," *Journal of Accounting Research*, 27, pp. 1–36. 20, 40, 45

Berndt, A., and A. Gupta (2009): "Moral hazard and adverse selection in the originate-to-distribute model of bank credit," *Journal of Monetary Economics*, 56(5), 725 – 743. 8

Biais, B., and C. Casamatta (1999): "Optimal leverage and aggregate investment," *The Journal of Finance*, 54(4), 1291–1323. 110

Bord, V., and J. Santos (2012): "The rise of the originate-to-distribute model and the role of banks in financial intermediation," *Economic Policy Review*, 18(2), 21–34. 79

Brown, S. J., W. N. Goetzmann, and J. Park (2001): "Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry," *The Journal of Finance*, 56(5), 1869–1886. 100, 101, 104, 108, 110, 111, 113, 133

Brunnermeier, M. K. (2009): "Deciphering the Liquidity and Credit Crunch 2007-2008," *Journal of Economic Perspectives*, 23(1), 77–100. 7, 61

Buraschi, A., R. Kosowski, and W. Sritrakul (2013): "Incentives and Endogenous Risk Taking: A Structural View of Hedge Funds Alphas," . 6, 102, 109, 140

Buraschi, A., F. Trojani, and A. Vedolin (2013): "When uncertainty blows in the orchard: Comovement and equilibrium volatility risk premia," . 6

Campbell, J. Y., and R. J. Shiller (1998): "Valuation Ratios and the Long-Run Stock Market Outlook," *Journal of Portfolio Management*, pp. 11–26. 2

Carpenter, J. N. (2000): "Does option compensation increase managerial risk appetite?," *The journal of finance*, 55(5), 2311–2331. 108

Chakraborty, I., and S. Ray (2008): "Effort, Risk and Walkaway Under High Water Mark Contracts," . 108

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok (1996): "Momentum Strategies," *The Journal of Finance*, 51(5), 1681–1713. 3, 20, 47

Chan, N., M. Getmansky, S. M. Haas, and A. W. Lo (2005): "Systemic risk and hedge funds," Discussion paper, National Bureau of Economic Research. 9

Chemla, G., and C. Hennessy (2013): "Skin in the Game and Moral Hazard," *Journal of Finance, forthcoming*. 65, 69

Chen, H.-l., and G. G. Pennacchi (2009): "Does Prior Performance Affect a Mutual Funds Choice of Risk? Theory and Further Empirical Evidence," *Journal of Financial and Quantitative Analysis*, 44, 745–775. 106, 107, 109

Chen, Y. (2011): "Derivatives Use and Risk Taking: Evidence from the Hedge Fund Industry," *Journal of Financial and Quantitative Analysis*, 46(04), 1073–1106. 9, 101, 103, 108, 111, 113, 115, 118, 140, 141, 143

Chevalier, J. A., and G. D. Ellison (1997): "Risk taking by mutual funds as a response to incentives," . 106

Chordia, T., and B. Swaminathan (2000): "Trading Volume and Cross-Autocorrelations in Stock Returns," *The Journal of Finance*, 55(2), 913–935. 27

Christoffersen, S. E., and D. K. Musto (2008): "High water marks in competitive capital markets," *Unpublished working paper*. 106

Cooper, M. J., R. C. Gutierrez, and A. Hameed (2004): "Market States and Momentum," *The Journal of Finance*, 59(3), 1345–1365. 14, 30, 36

Corwin, S. A., and J. F. Coughenour (2008): "Limited Attention and the Allocation of Effort in Securities Trading," *The Journal of Finance*, 63(6), 3031–3067. 4, 21

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers (1997): "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *The Journal of Finance*, 52(3), 1035–1058. 38

Degeorge, F., J. Patel, and R. Zeckhauser (1999): "Earnings Management to Exceed Thresholds," *The Journal of Business*, 72(1), pp. 1–33. 23

Dellavigna, S., and J. M. Pollet (2009): "Investor Inattention and Friday Earnings Announcements," *The Journal of Finance*, 64(2), 709–749. 12, 15, 22, 26, 34, 38, 45

DeMarzo, P. M., D. Livdan, and A. Tchistyi (2011): "Risking Other Peoples Money: Gambling, Limited Liability, and Optimal Incentives," *University of California, Berkeley*. 110

Demyanyk, Y., and O. Van Hemert (2011): "Understanding the Subprime Mortgage Crisis," *Review of Financial Studies*, 24(6), 1848–1880. 7, 61, 71

Didier, T., I. Love, and M. S. Martnez Pera (2012): "What explains comovement in stock market returns during the 20072008 crisis?," *International Journal of Finance and Economics*, 17(2), 182–202. 6

Ding, B., M. Getmansky, B. Liang, and R. Wermers (2009): "Share restrictions and investor flows in the hedge fund industry," *SSRN eLibrary*. 111

Faure-Grimaud, A., and D. Gromb (2004): "Public Trading and Private Incentives," *Review of Financial Studies*, 17(4), 985–1014. 65

Feldman, D. (2007): "Incomplete information equilibria: Separation theorems and other myths," *Annals of Operations Research*, 151(1), 119–149. 5

Flannery, M. J., and A. A. Protopapadakis (2002): "Macroeconomic Factors Do Influence Aggregate Stock Returns," *Review of Financial Studies*, 15(3), 751–782. 24, 53

Gande, A., and A. Saunders (2012): "Are Banks Still Special When There Is a Secondary Market for Loans?," *The Journal of Finance*, 67(5), 1649–1684. 61, 87

Gervais, S., and T. Odean (2001): "Learning to be overconfident," *Review of Financial Studies*, 14(1), 1–27. 5

Getmansky, M. (2012): "The Life Cycle of Hedge Funds: Fund Flows, Size, Competition, and Performance," *The Quarterly Journal of Finance*, 2(01). 9, 100, 101, 102, 108, 111, 113, 115, 118

Gilbert, T., S. Kogan, L. Lochstoer, and A. Ozyildirim (2012): "Investor inattention and the market impact of summary statistics," *Management Science*, 58(2), 336–350. 21

Goetzmann, W. N., J. E. Ingersoll, and S. A. Ross (2003): "High-Water Marks and Hedge Fund Management Contracts," *The Journal of Finance*, 58(4), 1685–1718. 9, 101, 108

Gorton, G., and A. Metrick (2012): "Securitized banking and the run on repo," *Journal of Financial Economics*, 104(3), 425 – 451. 7, 65, 70, 95, 98

Gorton, G. B., and G. G. Pennacchi (1995): "Banks and loan sales Marketing nonmarketable assets," *Journal of Monetary Economics*, 35(3), 389 – 411. 62, 65, 66

Grossman, S. J., and J. E. Stiglitz (1980): "On the impossibility of informationally efficient markets," *The American economic review*, 70(3), 393–408. 3

Hautsch, N., and D. Hess (2007): "Bayesian learning in financial markets: Testing for the relevance of information precision in price discovery," *Journal of Financial and Quantitative Analysis*, 42(1), 189. 1

Hirshleifer, D., S. S. Lim, and S. H. Teoh (2009): "Driven to Distraction: Extraneous Events and Underreaction to Earnings News," *The Journal of Finance*, 64(5), 2289–2325. 13, 22, 26, 30, 37, 40, 43

Hirshleifer, D., and S. H. Teoh (2003): "Limited attention, information disclosure, and financial reporting," *Journal of Accounting and Economics*, 36(13), 337 – 386, ¡ce:title¿Conference Issue on¡/ce:title¿. 34

Hirshleifer, D. A., J. N. Myers, L. A. Myers, and S. H. Teoh (2008): "Do Individual Investors Cause Post-Earnings Announcement Drift? Direct Evidence from Personal Trades," *The Accounting Review*. 35

Hodder, J. E., and J. C. Jackwerth (2007): "Incentive contracts and hedge fund management," *Journal of Financial and Quantitative Analysis*, 42(4), 811. 6, 9, 102, 103, 104, 107, 114, 128, 131, 133, 134, 135, 143, 157

Hoerova, M., C. Holthausen, and F. Heider (2009): "Liquidity hoarding and interbank market spreads: the role of counterparty risk," in *2009 Meeting Papers*, no. 929. Society for Economic Dynamics. 65, 68

Holmstrom, B., and J. Tirole (1997): "Financial Intermediation, Loanable Funds, and The Real Sector," *The Quarterly Journal of Economics*, 112(3), 663–691. 67

Hördahl, P., and M. King (2008): "Developments in repo markets during the financial turmoil," *BIS Quarterly Review*, pp. 37–53. 65

Hou, K., L. Peng, and W. Xiong (2008): "A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum," Working paper. Available at SSRN: http://ssrn.com/abstract=890875 or http://dx.doi.org/10.2139/ssrn.890875. 20, 30

Huang, J., K. D. Wei, and H. Yan (2007): "Participation Costs and the Sensitivity of Fund Flows to Past Performance," *The Journal of Finance*, 62(3), 1273–1311. 4, 12

Jegardeesh, N., and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48(1), 65–91. 47

Kahneman, D. (1973): *Attention and Effort*. Prentice-Hall Inc., Englewood Cliffs, New Jersey. 17

Karlsson, N., G. Loewenstein, and D. Seppi (2009): "The ostrich effect: Selective attention to information," *Journal of Risk and Uncertainty*, 38(2), 95–115. 13, 19, 20, 24, 41

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010): "Did Securitization Lead to Lax Screening? Evidence from Subprime Loans," *The Quarterly Journal of Economics*, 125(1), 307–362. 7, 8, 61, 62, 70, 74

Kyle, A. S. (1985): "Continuous Auctions and Insider Trading," *Econometrica*, 53(6), pp. 1315–1335. 2

Lan, Y., N. Wang, and J. Yang (2013): "The economics of hedge funds," *Journal of Financial Economics*. 108, 114, 129, 135

Maćkowiak, B., and M. Wiederholt (2010): "Business cycle dynamics under rational inattention," . 12

Makarov, I., and G. Plantin (2010): "Rewarding trading skills without inducing gambling," *Unpublished working paper. London Business School*. 110

Malkiel, B. G., and E. F. Fama (1970): "Efficient Capital Markets: A Review Of Theory And Empirical Work," *The journal of Finance*, 25(2), 383–417. 2

Mendenhall, R. R. (2004): "Arbitrage Risk and Post-Earnings Announcement Drift," *The Journal of Business*, 77(4), pp. 875–894. 21

Merton, R. C. (1969): "Lifetime Portfolio Selection under Uncertainty: The Continuous-Time Case," *The Review of Economics and Statistics*, 51(3), pp. 247–257. 123

Mian, A., and A. Sufi (2009): "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," *The Quarterly Journal of Economics*, 124(4), 1449–1496. 61, 69

Mitchell, M. L., and J. H. Mulherin (1994): "The Impact of Public Information on the Stock Market," *The Journal of Finance*, 49(3), 923–950. 24

Ozdenoren, E., and K. Yuan (2012): "Stock Market Tournaments," . 109

Palomino, F. (2005): "Relative performance objectives in financial markets," *Journal of Financial Intermediation*, 14(3), 351 – 375. 106

Panageas, S., and M. M. Westerfield (2009): "High-Water Marks: High Risk Appetites? Convex Compensation, Long Horizons, and Portfolio Choice," *The Journal of Finance*, 64(1), 1–36. 107

Parlour, C. A., and G. Plantin (2008): "Loan Sales and Relationship Banking," *The Journal of Finance*, 63(3), 1291–1314. 65, 67, 98

Pashler, H., and J. C. Johnston (1998): "Attentional limitations in dual-task performance.," *attention*, 1(1), 155–189. 17

Pastor, L., and R. F. Stambaugh (2003): "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111(3), pp. 642–685. 50, 51

Pastor, L., and P. Veronesi (2009): "Learning in financial markets," Discussion paper, National Bureau of Economic Research. 3, 5

Peng, L., and W. Xiong (2006): "Investor attention, overconfidence and category learning," *Journal of Financial Economics*, 80(3), 563 – 602. 6, 12, 13, 17, 19, 24

Peng, L., W. Xiong, and T. Bollerslev (2007): "Investor Attention and Time-varying Comovements," *European Financial Management*, 13(3), 394–422. 19, 43

Penman, S. H. (1987): "The distribution of earnings news over time and seasonalities in aggregate stock returns," *Journal of Financial Economics*, 18(2), 199 – 228. 23

Pennacchi, G. G. (1988): "Loan Sales and the Cost of Bank Capital," *The Journal of Finance*, 43(2), 375–396. 65, 66

Peress, J. (2008): "Media Coverage and Investors Attention to Earnings Announcements," Working paper. Available at http://www.lse.ac.uk/fmg/researchProgrammes/paulWoolleyCentre/pdf/Firstnference 21

Rajan, U., A. Seru, and V. Vig (2010): "The failure of models that predict failure: distance, incentives and defaults," *Chicago GSB Research Paper*, (08-19). 62

Sadka, R. (2006): "Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk," *Journal of Financial Economics*, 80(2), 309 – 349. 16, 50, 51

Shin, H. S. (2009): "Securitisation and Financial Stability," *The Economic Journal*, 119(536), 309–332. 62, 68

Sims, C. A. (2003): "Implications of rational inattention," *Journal of Monetary Economics*, 50(3), 665 – 690. 4, 12

Sims, C. A. (2005): "Rational inattention: a research agenda," Discussion paper, Discussion paper Series 1/Volkswirtschaftliches Forschungszentrum der Deutschen Bundesbank. 4

Taylor, J. (2003): "Risk-taking behavior in mutual fund tournaments," *Journal of Economic Behavior and Organization*, 50(3), 373 – 383. 9, 104, 105, 106, 112, 117

Welch, I. (1992): "Sequential Sales, Learning, and Cascades," *The Journal of Finance*, 47(2), pp. 695–732. 4

Yantis, S. (1998): "Control of visual attention," *attention*, 1(1), 223–256. 17