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Essays on Empirical Asset Pricing

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ESSAYS ON EMPIRICAL ASSET PRICING

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
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in partial fulfillment of the
requirements for the degree of
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Table of Contents

| | |
|---|-----|
| Acknowledgments | ii |
| List of Tables | v |
| List of Figures | vi |
| Abstract | vii |
| Chapter 1: Introduction | 1 |
| Chapter 2: Illiquidity and Volatility Timings of Mutual Fund Managers: Holding Based Evidence | 4 |
| 2.1 Introduction | 4 |
| 2.2 Measuring Market Timing | 7 |
| 2.2.1 Return-based measures | 7 |
| 2.2.2 Artificial timing bias | 8 |
| 2.2.3 The Holding-based Measure | 11 |
| 2.2.4 Estimation of Holdings Beta | 12 |
| 2.2.5 Liquidity and Volatility Measures | 14 |
| 2.2.6 Bootstrapping Approach | 15 |
| 2.3 Summary | 17 |
| Chapter 3: Illiquidity and Volatility Reactions of Mutual Fund Managers ... | 18 |
| 3.1 Introduction | 18 |
| 3.2 The Model | 21 |
| 3.2.1 The Reaction Measures | 22 |
| 3.2.2 Market Illiquidity Measure | 26 |
| 3.2.3 Market Volatility Measures | 27 |
| 3.3 Motivation of Managers' Reaction and Reaction Shift | 29 |
| 3.4 Trading Costs and Liquidity Concerns | 30 |
| 3.5 Conclusion | 30 |
| Chapter 4: Equity Duration and Stock Market Volatility | 32 |
| 4.1 Introduction | 32 |
| 4.2 Methodology | 33 |
| 4.2.1 Equity Duration and Idiosyncratic Volatility | 33 |
| 4.2.2 Equity Duration and Systemic Risks | 35 |
| 4.3 Empirical Evidences | 36 |
| 4.3.1 Data and Descriptive Statistics | 36 |
| 4.3.2 Idiosyncratic Volatility and Equity Duration | 39 |
| 4.3.3 Predictability Test | 43 |

| | |
|---------------------------------|----|
| 4.4 Summary | 47 |
| Chapter 5: Conclusion | 49 |
| Vita | 56 |

List of Tables

| | | |
|-----|---|----|
| 4.1 | Correlation Coefficients | 38 |
| 4.2 | Summery Statistics | 39 |
| 4.3 | Determinates of Idiosyncratic Volatiltiy | 42 |
| 4.4 | In-sample Predictability using $g_{dur,t}$ as predictor | 46 |
| 4.5 | In-sample Predictability using $Shock_{dur,t}$ as predictor | 46 |

List of Figures

| | | |
|-----|--|----|
| 3.1 | Time-series Pattern of Volatility and Illiquidity Measures | 28 |
| 4.1 | Market Duration | 40 |
| 4.2 | Growth and Shocks of Market Duration | 40 |
| 4.3 | Market Duration and Idiosyncratic Volatility | 43 |
| 4.4 | Market Excess Return and Duration Growth | 44 |
| 4.5 | Market Excess Returns and Duration Shocks | 45 |

Abstract

This work contains three essays on empirical pricing. In the first essay, I propose to re-examine the evidence on mutual fund managers' illiquidity and volatility timing ability by using a holdings-based approach, which is free from the artificial timing bias occurred in the traditional return-based timing method. Through testing the timing evidence by the holdings approach, I am able to know to what degree the results in the literature are biased by no-information reasons. In the second essay, I investigate mutual fund managers' skills from their reactions to the observable market condition, which is a relatively overlooked dimension in the literature. I propose to distinguish managers' economic motives from their reaction behavior to the public market illiquidity and volatility condition, which brings us new insight into how managers' private incentive affects their investment behaviors. In the third essay, I try to solve the idiosyncratically puzzle in the literature. I show that equity duration plays as a multiple of discount rate news shock and, therefore, affects equity return volatility. I show that the trend of the implied market duration is consistent with the trend of market idiosyncratic volatility as addressed in Campbell et al. (2001).

Chapter 1

Introduction

This work contains three essays on empirical pricing. In the first essay, I propose to re-examine the evidence on mutual fund managers' illiquidity and volatility timing ability by using a holdings-based approach.

The rapid growth of mutual fund market since 1980s has shown people's belief in sophisticated investors' ability to exploit market conditions. Whether fund managers can allocate assets more efficiently than naive investors thus attracts great academic interest. To evaluate managers' skills to exploit information about future market condition, also known as timing abilities, the leading research Treynor and Mazuy (1966) propose a return-based regression model. The idea is to capture the non-linear relationship between portfolio returns and market returns as the proxy for manager's operating of portfolio exposure. This study initiate a stream of researches exploring managers' timing ability (for example, Henriksson and Merton (1981), Becker et al. (1999), and Jiang (2003)).

However, the timing evidences of these return-based researches could be biased when the non-linearity is due to non-information-based strategy. Such strategies as option holding or dynamic trading naturally create a significant interaction term in a return regression, which results in a false timing (artificial timing) problem. These aforementioned issues naturally cast doubt on past liquidity and volatility timing evidence. It is important to know whether the conclusions still hold after correcting these biases.

In the late 1990s, a holding-based alternative timing measure becomes feasible when managers' holdings data becomes available. Through observing managers'

portfolio holdings, it is easily to examine whether managers adjust their portfolio exposures based on their forecast for market conditions. Most importantly, the holding-based method uses only ex ante holding information on portfolio formation and therefore does not biased by the non-information-based return non-linearity occurred during a holding period.

In the first essay, I propose to re-examine liquidity/volatility timing evidences through a holding-based approach. I investigate whether managers utilize liquidity/volatility information to adjust their portfolio. I try to answer to what extent the artificial timing problem biases our knowledge of liquidity/volatility timing.

The second essay focuses on how managers' illiquidity/volatility reactions reflect their private incentives and how the reactions predict future fund performance. At first thought, no relation should be expected since public information to which fund managers react cannot generate any rent to funds. However, managers could react very differently to the market condition based on their perspectives. A fund manager could take actions that are consistent with the rational risk-averse models because of his rigorous training. However, he could also do so for the lack of skills. Similarly, a manager could increase risk exposure during market turmoil to explore his private information, or to maximize his personal benefit, which is known for as the agency problem. It is not clear what kind of reaction reflect managers' skills and add value to funds, and the performance consequences of managers' reactions are still unanswered in the literature.

I propose to construct new reaction measures by using the mutual fund holding data, which provides us direct information about managers' optimal asset allocation. The new measure contains forward-looking information and, therefore, better captures managers' investment decision.

The third essay try to solve the idiosyncratically puzzle in the literature. Campbell et al. (2001) documented a significant positive slope idiosyncratic volatility trend from 1962 to 1997, whereas the aggregate market volatility seems to be constant during this period. This puzzling result initiates a stream of active asset pricing studies trying to explain the upward trend. Some of the studies explore the phenomena from the perspective of investor composition. Other studies put their emphasis on the angle of fundamental changes. While these studies provide different angles to explore the dynamic of market idiosyncratic volatility, most of them fail to explain the downward idiosyncratic volatility trend after year 2000.

I propose a new explanation based on the cash flow horizon of stocks for to the idiosyncratic volatility puzzle. I demonstrate that stock volatility can be viewed as a function of equity duration. The implied equity duration plays a role as a multiple, whose change amplifies the shock of discount rate. I consider the dynamic of stock duration as an alternative explanation for the upward trend through late 1990s. Moreover, market equity duration explains the ups and downs of market idiosyncratic volatility after year 2000. Given the positive relationship between equity duration and market volatility, I further investigate whether market equity duration is associated with positive market returns. I complement the literature by showing a time-series relationship between the aggregate market duration and the market risk premium.

Chapter 2

Illiquidity and Volatility Timings of Mutual Fund Managers: Holding Based Evidence

2.1 Introduction

The rapid growth of mutual fund market since 1980s has shown people's belief in sophisticated investors' ability to exploit market conditions. Whether fund managers can allocate assets more efficiently than naive investors thus attracts great academic interest. To evaluate managers' skills to exploit information about future market condition, also known as timing abilities, the leading research Treynor and Mazuy (1966) propose a return-based regression model. They measure the non-linear relationship between portfolio returns and market returns as the proxy for manager's operating of portfolio exposure. This research initiates a stream of literature discussing managers' ability to time market returns (see Henriksson and Merton (1981), Becker et al. (1999), and Jiang (2003)), market liquidity (see Cao et al. (2013a), Cao et al. (2013b)), and market volatility (see Busse (1999)) under similar return-based framework.

However, the timing evidences of these return-based researches could be biased when the non-linearity is due to non-information-based strategy. Such strategies as option holding or dynamic trading naturally create a significant interaction term in a return regression, which results in a false timing (artificial timing) problem. Traditional return-based liquidity/volatility timing researches in the literature use regressions with interaction terms between market returns and market liquidity/volatility to capture managers' timing ability. Therefore, any non-information-based strategy that could induce such a non-linearity would be identified as false liquidity/volatility timing. For instance, the well-documented interim trading prob-

lem, which means the frequency of evaluating a fund's performance is lower than a manager's trading frequency. In this case, even though managers react to market change after observing the market conditions, the low frequency return evaluation would not be able to distinguish between the ex anti prediction or ex post reaction of the manager and thus identify false timing. The interim trading problem has been widely discussed in the mutual fund literature (see Fama (1972), Jagannathan and Korajczyk (1986), Goetzmann et al. (2000), Ferson and Khang (2002), Ferson et al. (2006), and Ferson and Tucker (2006)).

Another means of false timing is option holding. For instance, a manager could hold an index option in his portfolio, which earns a high return in the bull market due to large underlying appreciation. At the same time, the appreciation of the underlying market attracts more investors and thus results in a more liquid option. Option increases as the liquidity increases due to the decrease of required return or due to the increase of option demand. The price appreciation that is due to above channel exactly replicates a positive interaction effect. Specifically, the option price increase given an underlying return is larger when simultaneous market liquidity is higher. This non-linearity between portfolio returns and market returns under different liquidity level is formed mechanically and has nothing to do with managers' timing ability.

These aforementioned issues naturally cast doubt on past liquidity and volatility timing evidence. It is important to know whether the conclusions still hold after correcting these biases. With the increase of data availability a holding-based alternative timing measure becomes feasible after the late 1990s. Through observing managers' portfolio holding data, it is easily to examine whether managers adjust their portfolio exposures based on their forecast for market conditions. The holding-based method uses only ex ante holding information on portfolio forma-

tion and therefore is not suffered from the artificial timing bias problem. In this study, I re-examine whether managers have superior skills to time market illiquidity/volatility than normal investors, through which we learn how important the artificial biases plays a role in timing literature. I contribute to the timing literature by providing new evidences that is not subject to false timing bias and thus can show mutual fund's genuine timing performance.

Literature on return-based market timing, such as Treynor and Mazuy (1966), Henriksson and Merton (1981), Becker et al. (1999), and Jiang (2003) , have document insignificant or even negative market timing in mutual fund market. It is hard to reconcile these results with the growing trading volume of mutual funds in recent decades. To see if these evidences are biased by the non-information-based strategy, Jiang et al. (2007) uses the holding-based method to reexplore managers' ability to time market returns and confirm positive timing evidence on actively managed U.S. equity funds. Motivated by their research, in this study, I re-examine liquidity/volatility- timing evidences in previous literature through holding-based model. I am interested in answering whether managers utilize liquidity/volatility information to adjust their portfolio, and whether the artificial timing problem biases our knowledge of liquidity/volatility timing.

I focus on the liquidity and volatility timing for several reasons. First of all, unlike market returns, market liquidity and market volatility are both persistent, which makes it more predictable. It is easier for managers to utilize these information to adjust their portfolio exposure. Secondly, liquidity and volatility are all important factors when discussing to market risk premiums. For example, during the 2008 market crash, market liquidity dried up immediately and triggered more serious depreciation of stock prices, while market volatility also surges during this period. Literature have also documented significant results between market volatility, liq-

uidity, and returns. French et al. (1987) reports a negative relationship between volatility shock and excess holding period returns. Acharya and Pedersen (2005) shows that the covariance between liquidity and market returns accounts for most part of liquidity risk and strongly affects expected returns. Positive liquidity shock brings low expected returns and thus contemporaneous price appreciation. Given these evidences, I put my emphasis on managers' ability to time market liquidity and market volatility.

I propose to use bootstrapped statistics to account for the multiple comparison problem to rule out the case that managers show timing skills by pure luck. I start our analysis from confirming the positive liquidity timing evidence on return-based method in the literature. Then I re-examine the timing abilities using the holding-based approach. The comparison between the two approaches shed lights on how strong the artificial biases are and provides us new knowledge about fund managers' skills.

2.2 Measuring Market Timing

In this section, I show the traditional return-based timing measure could be contaminated by the artificial timing bias. I start with introducing the return based timing measure proposed by the leasing research Treynor and Mazuy (1966).

2.2.1 Return-based measures

The return-based timing approach are initiated by the leading research Treynor and Mazuy (1966). This approach is built on the traditional capital asset pricing model. The intuition is to approximate managers' portfolio exposure to market risk as a linear function of his information about future market condition. Specifically, the return process follows the equation:

$$r_{pt+1} = a_p + b_{p,t}r_{mt+1} + v_{pt+1} \tag{2.1}$$

$$b_{p,t} = b_p + \gamma_t \cdot E(z_{t+1}|I_t) \quad (2.2)$$

, where r_{pt+1} denotes the excess portfolio return on time $t + 1$, r_{mt+1} is the market excess return on time $t + 1$, and $b_{p,t}$ is the market beta of the portfolio. Market beta $b_{p,t}$ can be expressed as two parts: the average portfolio exposure b_p and the exposure based on the current information I_t about future market condition z_{t+1} . The coefficient γ_t captures how the portfolio exposure changes with the forecasted condition, i.e. a manager’s timing ability. When market condition z_{t+1} captures the market return, these equations represent the timing model proposed in Treynor and Mazuy (1966). When z_{t+1} captures market liquidity, the coefficient represents managers’ liquidity-timing skills.

2.2.2 Artificial timing bias

Plugging equation (2.2) into equation (2.1), it is clear that the return-based timing measure capture managers’ timing ability through the interaction term between market return r_{mt+1} and the market condition z_{t+1} . Such an approach has a problem: any non-information-based strategy that can induce the interaction relationship would also be identified as managers’ timing ability. This problem is known as “artificial timing” or “false timing”. One example that has been widely addressed in the literature is the interim trading bias, which occurs when fund performance is evaluated at a lower frequency than that a manager can trade. This bias is very similar to the issue occurred when using unconditional asset pricing model to evaluate managers’ performance while he actually trades conditionally. Specifically, assume a fund manager, who have no timing ability, changes his portfolio exposure daily based on the public information z_t he observed. His conditional portfolio exposure could be expressed as:

$$b_{p,t} = b_p + \phi_t \cdot z_t + \gamma_t \cdot E(z_{t+1}|I_t) \quad (2.3)$$

, where z_t is the public observable information at day t , ϕ_t captures managers reaction to observable public information, and the conditional timing coefficient γ_t^c is equal to 0 since I assume the manager has no timing ability. Therefore, the true return regenerating process of the managed fund follows:

$$r_{pt+1} = a_p + b_p r_{mt+1} + \phi_t \cdot z_t \cdot r_{mt+1} + \gamma_t^c \cdot E(z_{t+1}|I_t) \cdot r_{mt+1} + v_{pt+1} \quad (2.4)$$

, with the conditional timing coefficient $\gamma_t^c = 0$. Now assume that I can only evaluate portfolio performance at a lower weekly level τ . Withing this week, I can observe nothing but the return and the market condition at the end of the week, which means we do not have any information about the simultaneous change of market condition and the reaction of manager every day in this week τ . In other words, I can only use unconditional model to evaluate the manager's timing ability at this lower frequency:

$$r_{p\tau+1} = a_p + b_p r_{m\tau+1} + \gamma_\tau^u \cdot E(z_{\tau+1}|I_\tau) \cdot r_{m\tau+1} + v_{p\tau+1} \quad (2.5)$$

Comparing equation (2.4) and equation (2.5), it is clear that the unconditional timing measure γ^u absorbs the effect of manager's reaction to public information ϕ_t and probably would result in a significant timing coefficient at the lower frequency even if there is no timing ability. A simple example in the review paper Aragon and Ferson (2006) clearly illustrates this interim bias problem. Suppose a terrorist event occurs in the middle of the day, which increase market volatility a lot in the second-half of the day. A manager observe this event and immediately reduce his portfolio exposure to reduce his volatility risk. If I can only observe daily but

not intraday data in this case, this manager's portfolio performance would be looked like the manager have foreseen the high volatility and adjusted his portfolio beforehand in a way that it is exposed less on volatility risk. The timing model at a lower frequency misidentify the higher-frequency reaction as the timing ability. This artificial timing bias the results not only in return timing, but also in liquidity and volatility timing.

Other than dynamic trading, holding options is also one means that could generate such an interaction effect in a return regression and come up with false timing. For example, Vega, which is defined as $\partial Price_{option} / \partial volatility_{underlying}$, measures the sensitivity between market return and underlying volatility, reaches its maximum when a standard option is at the money. When market goes up and a out of money call becomes at the money call due to underlying positive return, Vega rises accordingly. i.e.:

$$\frac{\partial Vega_t}{\partial r_{mt}} = \frac{\partial Price_{option} / \partial volatility_{underlying}}{\partial r_{mt}} \equiv \frac{\partial Price_{option}}{\partial volatility_{underlying} \partial r_{mt}} > 0 \quad (2.6)$$

Assuming that a manager hold a portfolio that contains this option on market index, the last tern in equation (2.6) exactly shows an interaction relationship between market return and market volatility in a return regression. The return-based timing method therefore identify false volatility timing when a fund manager simply holds an option.

Such an interaction effect of holding an option could also occurs through a demand channel when the option market and the underlying market are not perfect substitute for each other. For instance, the price of an index option increase when the underlying market experience significant appreciation. The prosperity of the underlying market results in more liquid underlying assets and therefore attracts

more investor to join the option market. The demand of the option market further pushes the option price up. In this case, option returns increases more when the underlying market is more liquid due to the increase of demand. This demand channel exactly replicate a interaction effect between market return and market liquidity and thus would results in a positive liquidity timing evidence in a return-based timing model.

2.2.3 The Holding-based Measure

The return based measure use the non-linearity of portfolio returns with regard to market condition as the evidence of timing ability. The advantage of this methodology is its minimal information requirement, which needs only fund returns, market returns, and the proxy for market conditions. However, when the portfolio holding of each fund is observable, I can directly compute fund exposure, i.e. beta, through weight-averaging individual stock betas held by the portfolio. Due to the increase of data availability, this holding-based measure has become an applicable alternative for the return-based method.

With manager’s holding data, I am able to compute fund beta as:

$$\hat{\beta}_{p,t} = \sum_{i=1}^N w_{p,it} \hat{b}_{it} \quad (2.7)$$

, where $\hat{\beta}_{p,t}$ is the estimated beta of portfolio p , $w_{p,it}$ is the portion of asset i hold in portfolio p at the end of time t , and \hat{b}_{it} is the estimated beta of asset i . The holding-based timing measure examines the correlation between portfolio exposure and the proxy for future market conditions. In other words, I examine manager’s timing ability through estimating the following regression:

$$z_{t+1} = a_p + \gamma_p \cdot \hat{\beta}_{p,t} + \varepsilon_{p,t+1} \quad (2.8)$$

, where z_{t+1} is the proxy for market condition, say liquidity or volatility, at time $t + 1$, and γ_p denotes the holding-based timing measure of portfolio p . A significant coefficient γ_p implies that a manager forecast future market condition at time $t + 1$ and adjust his exposure at the end of time t .

There are at least two strength of holding-based measure. First, holding-based method computes portfolio exposure from the estimated beta of individual stocks, which utilize the information at a higher frequency (daily return data of individual stocks are easily available). Including the information of manager's holding and the individual beta brings holding-based measure information advantage. For example, Jiang et al. (2007) use a simulation to show that the standard errors of the holding-based measure is much smaller than those of return-based measure and confirms that the holding-based measure have superior statistical power.

Secondly and most importantly, the holding-based measure looks for manager's ability to take action before any changes in value of the portfolio. It does not rely on subsequent portfolio returns that could subject to non-information-based strategies. Therefore, the holding-based measure is not subject to the artificial timing biases which provides us a nice basis to reexamine managers' timing ability. This research not only allows to know more about the timing ability, it also features the importance of artificial biases in the past return-based studies.

2.2.4 Estimation of Holdings Beta

The portfolio exposure for each mutual fund can be calculated as the weighted average beta of individual stocks held by the fund. I use 1-year historical daily stock return from CRSP data set to estimate individual stock beta following Jiang et al. (2014). Specifically, beta for each stock (\hat{b}_i) is estimate as the following equations:

$$r_{i,t} = a_i + \sum_{q=-5}^5 b_{i,q} r_{m,t-q} + e_{i,t} \quad (2.9)$$

$$\hat{b}_i = \sum_{q=-5}^5 \hat{b}_{i,q} \quad (2.10)$$

, where $r_{i,t}$ is the return of stock i at day t , $r_{m,t-q}$ denotes the market return at day $t - q$, and \hat{b}_i is the estimated beta of stock i . I include market returns up to five days leads and lags to account for the effect of nonsynchronous trading. I require stocks to have at least 60 observations during our estimation period. I assume $\beta = 1$ for these stocks that do not satisfy our requirement.

I am interested in how managers take position based on their forecast. Therefore, I control for the differences of portfolio exposures that is resulted from passive strategy. Following Daniel et al. (1997), I form the passive characteristics portfolios by sorting stocks into 5 groups according to its size based on the NYSE breakpoints. Then I sort stocks into 5 groups according to its book-to-market ratio within each size-group and then 5 momentum groups within each size-BM groups. I use market capitalization as the proxy for firm size at the end of each month. Book value of each stock is based on the most recently reported fiscal year, with at least 3-months gap to make sure the data is observable. The momentum is measured as the total stock returns during the previous six months. I rebalance our 125 passive characteristics portfolios each month and compute the average beta of each characteristics portfolio as the passive betas. Finally, I subtract the passive betas from original betas of each stocks that is in the same characteristics-matched portfolio as our characteristics-adjusted stock beta. With the adjusted-beta and managers' holding for each stock, I am able to compute weighted-averaged fund beta for each mutual fund.

2.2.5 Liquidity and Volatility Measures

Market liquidity cannot be observed directly. Past researchers have proposed proxies for different dimensions of liquidity, such as trading cost (Amihud and Mendelson (1986), turnover (Datar et al. (1998), price impact (Amihud (2002) and Pastor and Stambaugh (2003)), and trading speed (Liu (2006)). In this timing study, it is especially important to know the interaction between liquidity and stock returns. Therefore, I use Pastor and Stambaugh (2003) and Amihud (2002) measure to capture the price impact of whole market as our liquidity measure.

The monthly data for Pastor and Pastor and Stambaugh (2003) constructed as the following regression:

$$r_{i,d+1,t}^e = \theta_{i,t} + \varphi_{i,t}r_{i,d,t} + \gamma_{i,t}sign(r_{i,d,t}^e) \cdot v_{i,d,t} + \epsilon_{i,d+1,t} \quad (2.11)$$

, where $r_{i,d,t}$ is the return on stock i on day d in month t . $r_{i,d,t}^e$ is the excess stock return stock i on day d in month t , computed as $r_{i,d,t} - r_{m,d,t}$, where $r_{m,d,t}$ is the CRSP value-weighted market portfolio return. $v_{i,d,t}$ is the dollar volume for stock i on day d in month t . The intuition of Pastor and Stampburg liquidity measure is that the price reverse would be larger if a stock is more illiquid. As a result, the coefficient $\gamma_{i,t}$ captures such an effect as the liquidity measure. I compute the market liquidity as scaled equal-weighted average liquidity measures of individual stocks in our sample. The scaling factor m_t/m_1 is the total market value at the end of month of $t - 1$ divided by the total market value at the end of July 1980, and N_t is the number of stocks in month t .

$$\gamma_t = \frac{m_{t-1}}{m_1} \cdot \frac{1}{N_t} \sum_{i=1}^{N_t} \gamma_{i,t} \quad (2.12)$$

To ensure our analysis is not sensitive to the liquidity measure I choose, I also compute the Amihud (2002) illiquidity measure as an alternative measure for price impact. The Amihud illiquidity measure for stock i is computed as follows:

$$ILLIQ_t^i = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{td}^i|}{V_{td}^i} \quad (2.13)$$

, where $D_{i,t}$ denotes the trading days in month t for stock i , R_{td}^i is the return on day d in month t for stock i , and V_{td}^i is the dollar volume in millions on day d in month t . Then I construct a normalized Amihud market illiquidity measure following Acharya and Pedersen (2005) and Cao et al. (2013b) as:

$$c_t^i = \min(0.25 + 0.3ILLIQ_t^i \cdot \frac{m_{t-1}}{m_1}, 30) \quad (2.14)$$

, where m_t/m_1 is the same scaling factor I used in the Pastor and Stambaugh measure with the base period of 1980. I choose the parameters 0.25 and 30 following Cao, Simin, and Wang (2013) to normalize illiquidity measure and eliminate outliers. Based on this normalized illiquidity measure, I compute the market illiquidity measure c_t as:

$$c_t = \frac{1}{N_t} \sum_{i=1}^{N_t} c_t^i \quad (2.15)$$

where N_t is the number of stocks in month t . To match the data frequency of mutual holding, I average both Pastor and Stambaugh and Amihud monthly liquidity data into 1, 2, 3, and 4 quarterly data in the latter analysis.

2.2.6 Bootstrapping Approach

When the statistical inference is based on a large number of funds, some managers must create extreme returns by chance. They change their portfolio exposure by pure luck in a way that they seemingly to have anticipated market liquidity. This

is addressed as the multiple comparison problem in the literature. To distinguish manager's skill from luck, I randomly bootstrap our data under the null of no timing-ability while keep the cross-sectional holding of mutual funds fixed to generate pseudo-distributions of our statistics as the benchmark for comparison.

The bootstrap procedure conducted in this study follows Jiang, Yao, and Yu (2007). Let $\Gamma(\cdot)$ be the cross-sectional statistic I am interested in, which is related to the holding-based beta, the market liquidity/volatility at a specific quantile. For example, I can express $\Gamma(\cdot)$ as $\Gamma(b_t, liq_{t+1}, q)$, which denotes the liquidity timing measure $\hat{\gamma}_i$ or its t-statistic at the cross-sectional quantile q . I simulate the distribution of $\Gamma(\cdot)$ under the null of no timing ability with 2000 bootstrapped replication. To ensure the bootstrapped results is under the null of no timing-ability while maintaining the cross-sectional covariance structure of mutual fund betas, I keep the holding-beta for each fund unchanged in each simulation. I randomly draw market liquidity/volatility from our sample period to form a bootstrapped liquidity data in each simulation and match the bootstrapped data with holding-betas. In other words, I disconnect the relationship between managers' fund holding with market condition and create a distribution of $\Gamma(\cdot)$ under no timing ability.

Through comparing the empirical t-statistics and the bootstrapped t statistics, I am able to compute the bootstrapped p-values for each quantile. I compute the bootstrapped p-value as the ratio of positive-timing to the number of bootstrapping simulation, i.e. 2000 times. For example, out of 2000 times of simulation, if only 5% of the bootstrapped $\Gamma^b(\cdot)$ shows a superior timing ability than the real $\Gamma(\cdot)$ I observe in the real data, the p-value is 0.05. The bootstrapped p-value use the pseudo-distribution of estimated statistics in a world without timing ability as the benchmark. Therefore, through it I am able to evaluate the managers' timing ability that is more than by luck.

2.3 Summary

In this section, I propose to use a holdings-based approach to re-examine managers' illiquidity and volatility timing abilities. Traditional timing studies use a return-based method to estimate the non-linearity of portfolio returns as the measure of fund managers' timing abilities. However, such a measure suffers from the artificial timing bias. The holdings approach is free from such a bias and could provide as more accurate evidence about managers' skills.

Moreover, I account for the multiple comparison problem by using bootstrapping approaches, which allows us to exclude those managers who seems to be able to time market volatility and illiquidity but actually is due to luck. This study contributes to the literature by correcting the artificial bias in evaluating managers' illiquidity and volatility timing abilities and help us better understand their skills.

Chapter 3

Illiquidity and Volatility Reactions of Mutual Fund Managers

3.1 Introduction

In 2014, 15.9 trillion of assets are under active management by mutual fund managers who, on behalf of their clients, charge expense for their service. Given an average 0.70% expense fee (Investment Company Fact Book 2015), mutual fund managers extract a remarkable rent from clients. Naturally, two questions, understanding whether mutual fund managers add value to their clients to justify their fees and how to identify skilled outperforming fund managers, have long been intriguing to both academics and practitioners. This paper focuses on these two questions and shows that mutual fund managers' reaction to market-wide volatility and illiquidity can strongly predict future fund performance that no previous papers have uncovered.

It is worth discussing upfront why reaction can be related to future fund performance. At first thought, no relation should be expected since public information to which fund managers react cannot generate any rent to funds. However, managers could react very differently to the market condition based on their private information or motivation. A fund manager could take actions that are consistent with a rational risk-averse investor because of his rigorous training. However, he could also do so for the lack of skills. Similarly, a manager could increase risk exposure during market turmoil to explore his private information, or to gamble with client's money to maximize his personal benefit. It is not clear beforehand whether the cautious or aggressive reactions reflect managers' skills and can be used to predict future fund performance. If they do, what are the economic motives and the performance consequence of these reactions are still unanswered.

Although we are not the first one to consider the mutual funds' reaction to market volatility and liquidity (see Cao et al. (2013a) and Busse (1999)), none of the previous studies has found a significant relation between reaction and portfolio future performance. We differ from the previous studies by designing two new measures to better capture fund managers' reaction and differentiate two stories behind cautious and aggressive reactions. We answer the question of whether fund managers take more risk because of superior skills or ill-incentives. Specifically, we test two alternative hypotheses: (1) Cautious (aggressive) reaction to market illiquidity/volatility signifies the skill (ill-incentive) of a manager and predicts good (bad) future performance, and (2) Aggressive (cautious) reaction to market illiquidity/volatility is driven by superior skill (the lack of skills) and predicts good (bad) future performance.

When fund managers react to market conditions, their portfolio exposure would be a function of the observable market condition. Therefore, we estimate our first reaction measure using a conditional Carhart model with an interaction term between market excess return and market illiquidity/volatility following Treynor and Mazuy (1966), Ferson and Schadt (1996), and Carhart (1997). Instead of using actual fund returns, we compute the hypothetical fund returns based on mutual fund holdings data and past individual stock returns as our dependent variable. The idea is to assume that managers use past individual stock information as the expectation to the future performance of these stocks, based on which he form the optimal holdings for his fund. Therefore, the hypothetical fund return contains the forward-looking information of managers' investment decision. The coefficient of the interaction term shows the sensitivity of market beta to market condition, and captures managers' reactions. We label this coefficient of the interaction term as the 'intended reaction' measure.

There are two concerns about measure managers' reaction using the intended reaction measure. When the underlying asset react to market condition due to mechanical reasons, we might detect fake reactions even though managers actually did nothing. Moreover, the intended reaction level reflect managers' aggregate portfolio adjustment. If the adjusting cost is high, especially during volatile market, most of the information in the intended reaction measure might come form the historical adjustments. In this case, it would not be appropriate to use the intended reaction to study managers' reactions to the contemporaneous market condition.

To better understand managers' reaction to contemporaneous market information, we construct our second measure, the 'reaction shift' measure, as the difference between our intended reaction measure and funds' realized reaction measure that estimated by using actual fund returns. The reaction shift captures managers' change of reaction at each period and can provide us more clear information of managers' response to the contemporaneous market condition. Since our reaction shift is the difference between two the reaction measures during identical period, it naturally controls the exogenous changes in market conditions in different time periods. Such exogenous changes could be especially severe in episodes of market turmoil when managers react to the market condition the most. Better than the simple time difference of reaction level, our reaction shift is free of the bias resulting from exogenous market changes.

The closest related research to our study is Huang et al. (2011), which studies the motivation and the performance consequences behind managers' risk shift behavior. They construct their risk-shifting measure as the difference between funds' hypothetical holding volatility and funds' realized volatility. They find a bad performance of volatility shifters, in both positive and negative direction, and conclude that risk shifting is motivated by agency issues. Our study is different from theirs

in that I focus on managers' reactions in response to observable market illiquidity/volatility condition rather than on the change of total portfolio volatility.

3.2 The Model

Our measures of managers' illiquidity/volatility reaction are built on the pioneer timing research Treynor and Mazuy (1966). Before introducing our model, it is important to point out the main difference that distinguish our study on reaction from the past timing literature.

Past literature that study managers skills mainly focuses on their timing ability. In other words, they study whether managers can predict the future market condition and adjustment the portfolio exposure prior to the change. A rational risk-averse manager who predict good future market performance would increase his portfolio exposure before the market boom, and vice versa. Researchers identify skilled managers based on whether the portfolio beta is a function of future market condition.

Rather than focusing on managers' ability to predict the future market condition, this study looks into managers' reactions to the observable market condition. Perhaps it is not surprising that the literature did not put much emphasis on managers reactions to the market condition, since the market condition is observable to every investor and the collection of which does not require special skills. However, the heterogeneity of managers reactions could reflects their diverse perspectives and motivations. A manager who increase portfolio exposure when market is bad does not have to be a nave investor. He might be a rational skilled investor driven by private information. Similarly, a manager who behave as a rational risk-averse investor could so so because of his rigorous training. It is also possible that such an manager is simply lack of skills. Studying managers reactions allows us to explore a new dimension of managers ability, from which we can distinguish different

stories behind managers' reactions. To my knowledge, very few studies looked into managers' reactions. Even though some effort has been made, there is no conclusive result that managers' reaction can be a signal for their quality. For example, Busse (1999) study managers reaction to market volatility, and Cao et al. (2003) focus on the managers' liquidity. However, both studies did not find evidence that managers' reaction are associate with their future performance.

In this study, we use managers' holdings data, which allows us to direct observe managers' asset allocation, to construct two new reaction measures to capture managers' reactions to the observable market volatility/illiquidity condition. The holding-based measure contains forward-looking information and can better captures managers' reaction behavior. In this section, I demonstrate how we estimate our illiquidity/volatility reaction measure.

3.2.1 The Reaction Measures

We start with measuring fund managers' reaction to market liquidity. Following the widely used Carhart (1997) model in the asset pricing literature, fund return can be written as the following four-factor regression:

$$R_{pt} = \alpha_p + \beta_{mkt}R_{Mkt,t} + \beta_{smb}R_{SMB,t} + \beta_{hml}R_{HML,t} + \beta_{umd}R_{UMD,t} + \epsilon_t \quad (3.1)$$

, where R_{pt} is the portfolio(fund) return at time t, and $R_{Mkt,t}$, $R_{SMB,t}$, $R_{HML,t}$, $R_{UMD,t}$ stand for the mimicking portfolio returns of the market, size, book-to-market, and momentum factor. We can easily re-write equation 3.1 in a more compact form as equation 3.2:

$$R_{pt} = \alpha_p + \sum_{j=1}^4 [\beta_j R_{jt}] + \epsilon_t \quad (3.2)$$

When a manager changes his portfolio market exposure in response to the observable market illiquidity condition, his portfolio beta would be a function of the market condition. If we assume the function is in a simple linear form, the function could be written as equation 3.3:

$$\beta_{mkt} = \beta_{0,mkt} + \gamma_{Illiq}(Illiq_{Mkt,observable}) \quad (3.3)$$

, where β_{mkt} is the market exposure of the portfolio, which can be separated into two parts: the constant part $\beta_{0,mkt}$, and the part that depends on the observable market illiquidity: $\gamma_{Illiq}(Illiq_{Mkt,observable})$. The γ_{Illiq} captures the sensitivity of market exposure to the market illiquidity. Plug equation 3.3 into equation 3.2, we have the following relationship:

$$R_{pt} = \alpha_p + \sum_{j=1}^4 [\beta_j R_{jt} + \gamma_{Illiq}(Illiq_{Mkt,t-1} \cdot R_{Mkt,t})] + \epsilon_t \quad (3.4)$$

, which is a Carhart (1997) model with an interaction term between the market excess return at time $R_{Mkt,t}$ and the observable market illiquidity $Illiq_{Mkt,t-1}$ at time $t - 1$.

Empirically, I estimate the γ_{Illiq} coefficient in equation 3.4 with slightly modification as our illiquidity reaction measure. First of all, to account for the effects of nonsynchronous trading that occurs in the high-frequency daily data estimation, I put the lag terms of the four factors into equation 3.4. Then I estimate $\hat{\gamma}_{IlliqHold}$ in equation 3.4 as our first measure of managers' illiquidity reaction. Secondly, instead of using actual fund returns as the dependent variable, I compute hypothetical fund returns for the past 1-year at every quarter end q using fund holdings and individual stock returns as the LHS variable. The equation 3.4 can be re-written as:

$$R_{Hold,t} = \alpha_p + \sum_{j=1}^4 [\beta_j R_{jt} + \beta_{lj} R_{j,t-1}] + \hat{\gamma}_{IlliqHold} (Illiq_{Mkt,t-1} \cdot R_{Mkt,t}) + \epsilon_t \quad (3.5)$$

, where $R_{Hold,t}$ are the hypothetical fund returns. Specifically, at every quarter end q , I compute the hypothetical fund return $R_{Hold,t}$ for quarter $[q-3 \text{ to } q]$ by using the holdings that reported in quarter q and the individual stock returns for $[q-3 \text{ to } q]$. Then I run a regression as equation 3.5 using daily data to estimate the coefficient $\hat{\gamma}_{IlliqHold,q}$ as our measure of illiquidity reaction at quarter q . Here I assume that managers use the past-1-year stock returns as his expectation of the stock performance for the next holding period, based on which he adjust his portfolio to match his intended asset allocation. Therefore, the reaction measure $\hat{\gamma}_{IlliqHold,q}$ contains the forward-looking information (since the holdings at quarter end q reflect his allocation for quarter $q+1$). Therefore, we label the illiquidity reaction measure $\hat{\gamma}_{IlliqHold,q}$ as managers' "intended" illiquidity reaction.

However, there are some potential issues that could weaken the validity of measuring managers' reactions using the intended reaction measure. First of all, the reaction level of a fund reflect the aggregate of a manager's historical adjustment based on his information from period to period. If the adjustment cost is too high to stop a manager from making a full adjustment in a short term, the current reaction level will not be able to reflect the manager's optimal reaction to the contemporaneous information. Instead, it would mostly reflect the past portfolio adjustments. Secondly, a portfolio's reaction to market illiquidity might not be driven by information-based motivation. For example, the underlying asset returns could have a mechanical response to market illiquidity. In this case, the time-varying market exposure does not reflect any skill since the manager did nothing in response to market illiquidity condition. Hence, I compute our second measure, the shift

of illiquidity reaction, as a more informative way to capture managers' intention-driven reaction to market illiquidity. Specifically, I first run the same multi-factor regression as equation 3.4, except that we use funds' realized daily returns for [q-3 to q] as the dependent variable:

$$R_{Report,t} = \alpha_p + \sum_{j=1}^3 [\beta_j R_{jt} + \beta_{lj} R_{j,t-1}] + \hat{\gamma}_{IlliqReport} (Illiq_{Mkt,t-1} \cdot R_{Mkt,t}) + \epsilon_t \quad (3.6)$$

to estimate the actual illiquidity reaction $\gamma_{IlliqReport}$ for [q-3 to q]. Then as a way to control for mechanical reasons of illiquidity reaction in $\hat{\gamma}_{IlliqHold}$, our second measure of illiquidity reaction is the difference between the intended reaction and the actual reaction level:

$$\hat{\gamma}_{IlliqShift} = \hat{\gamma}_{IlliqHold} - \hat{\gamma}_{IlliqReport} \quad (3.7)$$

The measure $\hat{\gamma}_{IlliqShift}$ captures manager's change of illiquidity reaction at every quarter end q relative to funds' realized reaction level, and, therefore, more clearly reflect managers' response to the contemporaneous market illiquidity. Following the same procedure, I can also compute mutual fund managers' intended volatility reaction level as well as volatility reaction shift measure:

$$R_{Hold,t} = \alpha_p + \sum_{j=1}^3 [\beta_j R_{jt} + \beta_{lj} R_{j,t-1}] + \gamma_{VolHold} (Vol_{m,t-1} \cdot R_{Mkt,t}) + \epsilon_t \quad (3.8)$$

$$\hat{\gamma}_{VolShift} = \hat{\gamma}_{VolHold,t} - \hat{\gamma}_{VolReport}$$

With managers' holding data, our reaction measures utilize the daily data of individual stocks held by a fund, which brings us superior information advantage over the past return-based measures that use only a lower monthly frequency fund return data, such as in Cao et al. (2013a). Daily data also allows us to have more precise estimators and higher statistic powers.

Instead of the differences between two sequential actual reaction level, our reaction shift measure is the difference between the intended reaction and the actual reaction measured in the identical period. Therefore, our reaction shift measure is not affected by exogenous changes in market conditions across time periods. Such changes are especially significant during market turmoil when managers' portfolio adjustment shows their skills the most and, therefore, bias the results the most. The nice property of our reaction-shift measure allows us to better explore managers' reaction and the corresponding return performances.

3.2.2 Market Illiquidity Measure

To take the information advantage of daily data to explore managers' illiquidity reaction, I slightly modify the Amihud(2002) illiquidity measure as our daily market illiquidity measure. For each trading day d , I first calculate the absolute stock return divided by dollar volume (in millions) for each stock. Then I make the Acharya-Pedersen adjustment following Acharya and Pedersen (2005). Specifically, I compute:

$$Illiq_{i,t} = \min\left\{0.25 + 0.3 \cdot \frac{|R_{i,t}|}{V_{i,t}} \cdot \frac{m_{m-1}}{m_1}, 30\right\} \quad (3.9)$$

, where $Illiq_d^i$ denotes the illiquidity measure of stock i on day d , the scaling factor m_{m-1}/m_1 is the total market value at the end of last month divided by the total market value at the end of July 1980. Acharya and Pedersen put an upper bound of 30 to the illiquid measure for a better property. In our measure, if a stock has 0 trading volume on day t , which could be considered extremely illiquid, I set the $Illiq_{i,t}$ to 30 for the stock i on that trading day t . Finally, we calculate our daily market illiquidity measure as the cross-section average of $Illiq_{i,t}$:

$$Illiq_{mkt,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} Illiq_{i,t} \quad (3.10)$$

, where N_t is the number of stocks on day t .

3.2.3 Market Volatility Measures

I choose EGARCH(1,1) model with a leverage term and t-distribution errors to capture the daily conditional market volatility following Busse (1999). The conditional variance σ_{mt}^2 is specified as follows:

$$\ln \sigma_{mt}^2 = a + a_1 \cdot \frac{|\epsilon_{m,t-1}| + \gamma_1 \epsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1 \ln \sigma_{m,t-1}^2 \quad (3.11)$$

, where $\epsilon_{mt} | \epsilon_{m,t-1}, \epsilon_{m,t-2} \dots \sim t(0, \sigma_{mt}^2)$.

The time-series plot of the liquidity and volatility measure are presented in figure 3.1. To make the two series comparable, I scale the market volatility up for 5000 times. The Gray line is the time series of the market illiquidity, and the black line is the market volatility. Both volatility and illiquidity capture important dimension of market states. I see that the two series show similar patterns. The surge of illiquidity around the year 2001 is due to the burst of dot-com bubble. The market volatility is also high during that period. The other peak happens in the 2008 financial crisis, during when the market lost a lot of liquidity and, investors are experiencing a very high level of uncertainty. These ups and downs of market condition affects fund returns through not only the returns returns of the underlying assets, but also the funding of these funds. For instance, the redemption of investors when facing high uncertainty and the fire sale of assets both hurt fund performance. Therefore, managers' reactions to the market condition is very important, and the study of which helps us better understand managers' skills.

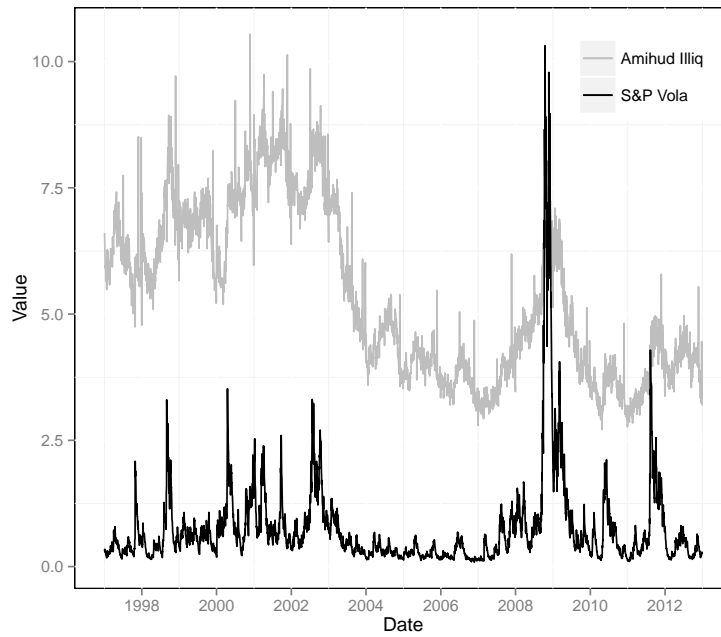


FIGURE 3.1. Time-series Pattern of Volatility and Illiquidity Measures

In this figure, I show the time-series patterns of S&P 500 volatility and our daily version of Amihud Illiquidity measure. The S&P 500 volatility is estimated using EGARCH(1.1) model following Busse (1999) and the Illiquidity measure is computed following Amihud (2002) and Acharya and Pedersen (2005). I use stock data from the CRSP database. To make the two series comparable, I scale the S&P 500 volatility up for 5000 times. The Gray line in the figure is the time series of the market illiquidity, and the black line is time series of the market volatility.

3.3 Motivation of Managers' Reaction and Reaction Shift

With managers' Illiquidity and volatility reactions, I could further investigate managers' portfolio performance, based on which I can distinguish the motives behind these reaction behaviors.

To further investigate the motivation behind managers' reaction behaviors, I incorporate several fund characteristics that are related to the agency problem in the literature to see how these characteristics interact with fund managers' reactions. Specifically, I first sort our mutual fund sample into quintile portfolios by our reaction measures at the end every quarter. Then I further sort funds into 5 subgroups under each reaction quintile by the proxy for the agency problem, including fund expense ratio, fund age, and past performance. Finally, I compute the Carhart alphas for the 25 reaction-characteristic portfolios.

Mutual funds managers charge fees to cover their financial service, operation cost, and advertising costs. However, literature did not find a positive relationship between the fee and the fund performance. For example, Gil-bazo and Ruiz-Verdu (2009) find that even before expense, high-expense funds do not show superior skills. Their explanation of this result is an agency problem. High-expense funds attract non-experienced investors and put their investments in risky assets. In this case, the abnormal returns of positive illiquidity/volatility reactors could be especially lower for funds with higher agency problem.

The asymmetry relationship between fund performance and fund flows addressed in Chevalier and Ellison (1997) gives managers an incentive to take risks. Chevalier and Ellison find that investors tend to move into a fund quickly when it performs well, but they are less sensitive when moving out of a low performance fund. Chevalier and Ellison also find that this asymmetry is stronger for younger firms.

Therefore, using fund age as a proxy for agency problems, I expect that younger firms could perform worse when their reactions are not driven by information.

Through comparing the performance of funds with the same reaction but different level of agency problem proxied by expense ratio and fund age, I can further understand whether managers' reactions are associated with the agency problem, through which I can further understand what kind of reactions reflect skilled managers' discipline and superior risk management ability.

3.4 Trading Costs and Liquidity Concerns

In this section, I further look into how fund managers' trading costs and liquidity concerns interact with managers' illiquidity/volatility reaction and, therefore, provide us a complete picture of managers' behavior.

Turnover rate measures how actively a portfolio is managed. To see if the portfolio difference between different reactors are driven by the cost generated by the strategy, I double sort funds based on the turnover and the reactions. If the return difference between different reactions are not significantly different, then I am more confident to say that the performance difference reflects the incentives behind managers' reactions. I further check manager' cash holdings. Funds with higher cash position suffer less from outflows because they have more cushion for investors' redemptions. I expected those with low cash holdings suffer the most when their behavior is driven by ill incentives.

3.5 Conclusion

Mutual fund managers, probably the most sophisticated investors in the market, adjust their portfolio in response to the conditional market information. The cross-sectional heterogeneity of managers' reactions reflects fund managers' skills and private motivations. However, literature concerning fund managers' skills mainly put emphasis on how managers predict future information while overlook how they

react to the observable information. Even for the very few studies that looked into managers' reactions, there is no evidence that mutual fund managers' reactions are related to their future performance.

This study contribute to the literature by constructing two new reaction measures by using the mutual holdings data. Using managers' holdings data has several advantages. First of all, it allows us to directly observe mutual fund managers' asset allocation and provide us more information about fund managers' decisions. Secondly, using holdings data allows as to utilize individual stocks information in a daily frequency, which brings in the information advantage relative to studies that use only fund returns data. This study evaluates managers' skills from a relatively overlooked angle form the literature and distinguish the economic motives between different reaction behaviors.

Chapter 4

Equity Duration and Stock Market Volatility

4.1 Introduction

Campbell et al. (2001) documented a significant positive slope idiosyncratic volatility trend from 1962 to 1997, whereas the aggregate market volatility seems to be constant during this period. This puzzling result initiates a stream of active asset pricing studies trying to explain the upward trend. Some of the studies explore the phenomena from the perspective of investor composition. For example, Bennett et al. (2003) proposes that institutional investors have change their preference toward smaller and riskier securities and therefore increase the firm-specific risks. Morck et al. (2000a) states that a higher firm specific return variation could be resulted from better shareholder protection. Brandt et al. (2009) argues that the increase of idiosyncratic volatility are most significant firms with low prices and high retail ownership. Other studies put their emphasis on the angle of fundamental changes. For instance, Wei and Zhang (2006) states that firm fundamentals have become more volatile. Irvine and Pontiff (2009) propose that product market have become more competitive. Cao et al. (2008) argues that managers choose more risky project to increase growth option values. While these studies provide different angles to explore the dynamic of market idiosyncratic volatility, most of them fail to explain the downward idiosyncratic volatility trend after year 2000.

In this study, I propose a new explanation based on the cash flow horizon of stocks for to the idiosyncratic volatility puzzle. I show that stock duration plays a role as a multiple, whose change amplifies the shock of discount rate. I propose the dynamic of stock duration as an alternative explanation for the upward trend

through late 1990s. Moreover, I show that the market equity duration explains the ups and downs of market idiosyncratic volatility after year 2000.

Given the positive relationship between equity duration and market volatility, I investigate whether market equity duration is associated with positive market returns. Literature focused on the cross-sectional relationship between the cash flow horizon and risk premium have documented a negative relationship. For example, studies about value premium argues that the premium is associate with the shorter implied stock duration. (see Lettau and Wachter (2007) and Croce et al. (2014). In our study, I complement the literature by showing a time-series relationship between the aggregate market duration and the market risk premium.

4.2 Methodology

In this section, I exhibit the duration model from the fixed income literature. I show how the model is applied to the equity market. Finally, I derive the relationship between the implied equity duration and the expected returns.

4.2.1 Equity Duration and Idiosyncratic Volatility

Following the traditional fixed income literature, the duration of a bond can be expressed as:

$$D = \frac{\sum_1^T t \times \frac{CF_t}{(1+r)^t}}{P} \quad (4.1)$$

, where CF_t is the cash flow of period t (generally expressed as bond dividend D), P is the current price of the bond, and r denotes the discount rate. The idea of duration is basically the weighted average time of receiving the future cash flow, weighted by the proportion of the present value of the cash flow to the present value of the bond. Similarly , the same idea could be applied to stock market as the following equation:

$$\begin{aligned}
D_t &= -\frac{\partial \ln P_t}{\partial \ln(1+q_t)} \\
&= \frac{1}{P_t} \left[\sum_{k=1}^T k \frac{CF_{t+k}}{(1+q_t)^k} + \sum_{k=T+1}^{\infty} k \frac{CF_{t+T+1}}{(1+q_t)^k} \right] \\
&= \frac{1}{P_t} \left[\sum_{k=1}^T k \frac{CF_{t+k}}{(1+q_t)^k} + CF_{t+T+1} \frac{q_t(T+1)+1}{q_t^2(1+q_t)^T} \right]
\end{aligned} \tag{4.2}$$

, where D_t is the equity duration, P_t is the stock price at time t , and CF_t denotes the cash flow at time t . Here I assume the the future cash flow of an equity can be separate into two parts, a finite growing period and an infinite stable period. The first term of the third raw captures the cash flow of the finite growing period, and the second term captures cash flows for the periods where the growth of the cash flow has converged to a economic-wide growth rate.

Shifting the denominator to the right-hand side, the relationship between equity returns and the discount rate shock can be expressed as $d(\ln P_t) = -D_t d(\ln(1+q_t))$. From this equation, I can derive the relationship between the volatility of stock returns and the volatility of the discount rate shock news as:

$$\sigma_t(d(\ln P_t)) = D_t \sigma_t(d(\ln(1+q_t))) \tag{4.3}$$

, which give us a prediction for the following regression:

$$\sigma_t(d(\ln P_t)) = k_0 + k_1 D_t + e_t \tag{4.4}$$

, where $k_1 > 0$.

Further, we see that $d(\ln P_t) = -D_t d(\ln(1+q_t)) = -\frac{D_t}{1+q_t} dq_t$, which means $\sigma_t(d(\ln P_t)) = \frac{D_t}{1+q_t} \sigma_t(dq_t)$. As discount rate q_t is inversely related to duration D_t , $\frac{1}{1+q_t}$ should be positively related to D_t . Therefore, we may use a linear form to approximate $\frac{1}{1+q_t} \approx a + bD_t$, with a $b > 0$.

Given the result, we can rewrite $\sigma_t(d(\ln P_t)) = D_t(a + bD_t)\sigma_t(dq_t) = (aD_t + bD_t^2)\sigma_t(dq_t)$, which gives us the regression relationship as following:

$$\sigma_t(d(\ln P_t)) = k_0 + k_1 D_t + k_2 D_t^2 + e_t \quad (4.5)$$

, with $k_2 = b > 0$.

4.2.2 Equity Duration and Systemic Risks

To show how duration is linked to systematic risk of market portfolio and hence risk premium, I decompose the discount rate shock of firm i into diversifiable and undiversifiable parts from $d(\ln P_t) = -D_t d(\ln(1 + q_t))$. i.e.

$$d(\ln(1 + q_t^i)) = b_i shock_{t+dt}^{undiversifiable} + shock_{i,t+dt}^{diversifiable} \quad (4.6)$$

, where b_i is the beta of firm i 's discount rate shock with respect to undiversifiable shock. Here the subscript $t + dt$ denotes that the shock is from time t to time $t + dt$. To justify this equation, examples of undiversifiable shock can be shock to volatility of aggregate consumption growth (which can be justified in Bansal and Yaron (2004)), shock to representative agents risk aversion due to shock to their habit (which can be justified in Campbell and Cochrane (1999)), or shock to investors aggregate sentiment (Lettau and Wachter (2007)). Examples of diversifiable shock can be shock to firms liquidity or shock to firms information environment due to, e.g., change in firms accounting disclosure activity or publicity activity.

Then

$$\begin{aligned} d(\ln P_t^i) &= -D_t^i d(\ln(1 + q_t^i)) = -D_t^i (b_i shock_{t+dt}^{undiversifiable} + shock_{i,t+dt}^{diversifiable}) \\ &= D_t^i b_i (-shock_{t+dt}^{undiversifiable}) + D_t^i (-shock_{i,t+dt}^{diversifiable}) \\ &= \hat{D}_t^i (-shock_{t+dt}^{undiversifiable}) + D_t^i (-shock_{i,t+dt}^{diversifiable}) \end{aligned} \quad (4.7)$$

, where \hat{D}_t^i is the adjusted duration for firm i at time t .

We now can see that \hat{D}_t^i captures the stock i 's return sensitivity to the systematic discount rate shock. If we label firm i as the market portfolio, we get the prediction that lengthening market duration or positive duration shock is linked to higher market risk premium, hence higher subsequent market ex post risk premium.

Regarding the total volatility, we can also see from the analysis above that

$$\begin{aligned}\sigma_t^{total}(d(\ln P_t^i)) &= D_t^i \sigma_t^{total}(d(\ln(1 + q_t^i))) \\ &= \hat{D}_t^i \sigma_t^{total}(-shock_{t+dt}^{undiversifiable}) + D_t^i \sigma_t^{total}(-shock_{i,t+dt}^{diversifiable})\end{aligned}\tag{4.8}$$

Therefore, total volatility of market can be positively related to duration \hat{D}_t^i and D_t^i .

4.3 Empirical Evidences

In this section, I compute the implied market equity duration for the S&P 500 stocks to empirically test if it affects market volatility and market returns as the model predicts.

4.3.1 Data and Descriptive Statistics

The sample covers the period from January 1977 to December 2010. Monthly analysts earning forecasts are from the I/B/E/S database. The sample firms for idiosyncratic volatility are stocks traded on the NYSE, AMEX, or NASDAQ. The trading information and accounting data are from the CRSP and Compustat database.

To test the informativeness of equity duration for future ex-post risk premiums, I introduce returns predictors that have been proposed in the literature as our control variables. Those variables are term spread (TS), default spread (DEF), trailing dividend-to-price ratio of the S&P 500 (DP), trailing earning-to-price ratio of the S&P 500 (EP), Book to market ratio(BM), long-term rate of bond return

(LTR), and stock variance (SVAR). DP is the 12-month moving sum of dividends paid on the S&P 500 index divided by the S&P 500 index. EP is the 12-month moving sum of earnings on the S&P 500 index divided by the S&P 500 index. Monthly data are available from Professor Robert Shillers website. The B/M ratio is the ratio of book value to market value for the Dow Jones Industrial Average. I leave a gap of at least 3 months before the accounting data could be used. LTR is the return on long-term government bonds. SVAR is the sum of the squared daily returns on the S&P 500 index with a month. BM, LTR, and SVAR data could be find form Professor Amit Goyals website.

First of all, I construct the firm-level duration based on monthly data. I use analysts' forecast to estimate stock future cash flow and calculate the log version of equity duration. Focusing on S&P 500 firms, I construct the value weighted average duration $\log(Dur_{sp500})$ as our proxy for market duration. Secondly, to work with stationary time series as well as discuss the relationship between the change of market duration and the change of realized market risk premium, I compute the monthly log growth rate of market duration $g_{dur,t}$ as well as the monthly shock on the growth rate $Shock_{dur,t}$ by following the procedure similar to Hsu (2009). The two measures are constructed as follows:

$$g_{dur,t} = \log(Dur_{sp500,t}) - \frac{1}{12} \sum_{i=1}^{12} \log(Dur_{sp500,t-i}) \quad (4.9)$$

$$Shock_{dur,t} = g_{dur,t} - \frac{1}{12} \sum_{i=1}^{12} g_{dur,t-i} \quad (4.10)$$

, where the choose of moving average could potentially remove the noise and measurement errors due to seasonality in the data. I choose a moving window of 12 for our using monthly data. I plot the series of $\log(Dur_{sp500})$ as well as the two mea-

asures $g_{dur,t}$ and $Shock_{dur,t}$ in Figure 1 and Figure 2. We can find a positive trend of $\log(Dur_{sp500})$ before year 2000. After peaking in 2000, the market duration starts to decrease in the last decade. For the two measures $g_{dur,t}$ and $Shock_{dur,t}$, the series seems to be stationary with a mean of zero.

Table 4.1 provides the correlation coefficient of our sample. From Table 4.1, we see that the implied market equity duration is positively related to all the three levels of market volatility. The correlation with the industry volatility is the highest among all, with a value of 0.445. It might not be surprising since the equity duration is computed based on analysts' forecasts, which might heavily rely on industry-level information.

TABLE 4.1. Correlation Coefficients

| | σ_{firm} | σ_{ind} | σ_{mkt} | $VwDur$ |
|-----------------|-----------------|----------------|----------------|---------|
| σ_{firm} | 1.000 | 0.934 | 0.762 | 0.325 |
| σ_{ind} | | 1.000 | 0.782 | 0.445 |
| σ_{mkt} | | | 1.000 | 0.171 |
| $VwDur$ | | | | 1.000 |

This table provides the correlation coefficients among the three-levels of market volatility and our value-weighted implied market duration.

Table 4.2 shows the summary statistics of market excess return (MktRf), market duration, its growth rate, and the shock on that growth rate. In addition, I also report traditional predictors (DP, EP, bm, TS, DEF, ltr, svar) literature has proposed to predict future market excess return. The (first-order) autocorrelations of two new predictors that I propose is much lower (around 0.8) than traditional predictors proposed in the literature. It means that, different from traditional predictors, they vary in a much higher frequency and can predict future market return at a shorter horizon, if predictability exists.

Figure 4.1 shows the time-series pattern of the implied market equity duration. The shaded area denote the NBER identified economic recessions. Aggregate mar-

TABLE 4.2. Summery Statistics

| | Mean | Std | Max | Min | AC(1) | AC(12) |
|-----------------|---------|--------|--------|---------|--------|---------|
| MktRf | 0.0053 | 0.0459 | 0.1243 | -0.2314 | 0.1109 | 0.0033 |
| $Dur_{sp500,t}$ | 2.9989 | 0.2115 | 3.4064 | 2.4368 | 0.9861 | 0.8357 |
| $g_{dur,t}$ | 0.0065 | 0.0574 | 0.1689 | -0.1476 | 0.8308 | -0.1274 |
| $Shock_{dur,t}$ | -0.0012 | 0.0566 | 0.1788 | -0.1664 | 0.8074 | -0.4410 |
| DP | 0.0270 | 0.0118 | 0.0637 | 0.0108 | 0.9898 | 0.8393 |
| EP | 0.0571 | 0.0249 | 0.1326 | 0.0079 | 0.9846 | 0.6513 |
| BM | 0.3995 | 0.2380 | 1.2065 | 0.1205 | 0.9878 | 0.8050 |
| TS | 0.0303 | 0.0144 | 0.0593 | -0.0221 | 0.9546 | 0.4089 |
| DEF | 0.0111 | 0.0050 | 0.0338 | 0.0055 | 0.9606 | 0.4520 |
| LTR | 0.0086 | 0.0320 | 0.1443 | -0.1124 | 0.0131 | -0.0416 |
| SVAR | 0.0025 | 0.0051 | 0.0558 | 0.0002 | 0.5412 | 0.0542 |

This table provides the summery statistics as well as the autoregression coefficients of market excess returns(MktRf) and several return predictors, including term spread (TS), default spread (DEF), trailing dividend-to-price ratio of the S&P 500 (DP), trailing earning-to-price ratio of the S&P 500 (EP), Book to market ratio(BM), long-term rate of bond return (LTR), and stock variance (SVAR). TS, EDF, DP, and EP data could be found on Professor Robert Shiller's website; BM, LTR, and SVAR could be found on Professor Amit Goyal's website. AC(1) and AC(12) denotes the autocorrelation coefficient at lags of 1 and 12.

ket duration exhibit an upward trend before late 1990s and reverses after then. One thing worth mentioning is that the market equity duration seems to be a lead indicator of economic condition. For example, the market duration decreases before the 2008 financial crisis and reversed before the recover of the recession. This empirical results shows the forward-looking information advantage of the equity duration measure that utilizing analysis' forecast report data.

Figure 4.2 exhibits the growth and the shock of the market duration measure calculating as equation (4.9) and (4.10). They appear to be stationary and correlated with each other.

4.3.2 Idiosyncratic Volatility and Equity Duration

In this section, I investigate the relationship between the idiosyncratic volatility of individual stocks and its equity duration. I apply a Fama-Macbeth analysis controlling for common firm characteristics. The dependent variable is the idiosyncratic volatility for each firm, and the independent variable are the implied equity

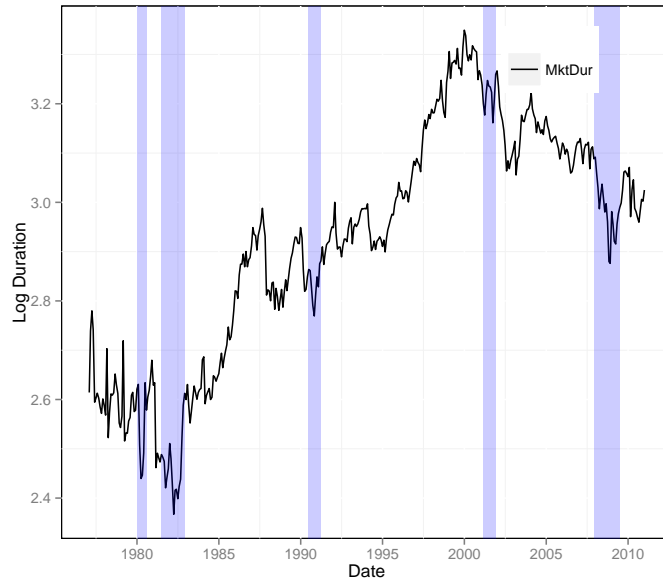


FIGURE 4.1. Market Duration

This figure is the time-series plot of the S&P 500 equity duration from 1978 to 2012. The shaded area are the period of economic depression identified by the NBER.

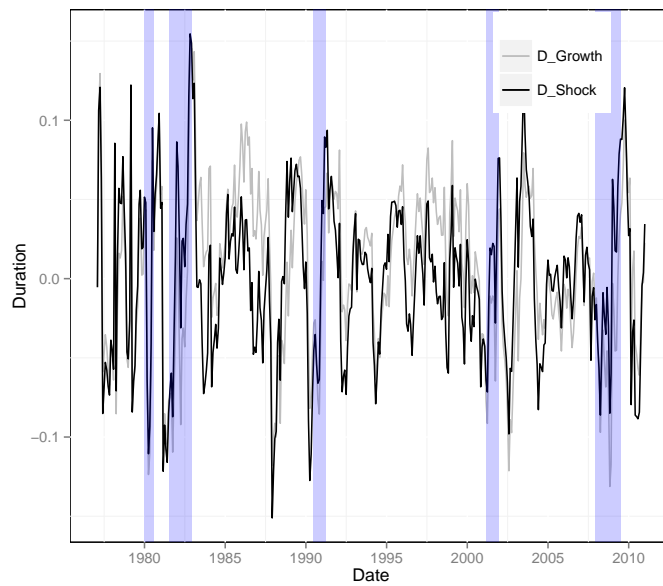


FIGURE 4.2. Growth and Shocks of Market Duration

This figure is the time-series plot of the growth and shocks of value-weighted S&P 500 equity duration from 1978 to 2012. The shaded area are the period of economic depression identified by the NBER.

duration and control variables, including stock price, total assets, institutional ownership, age, book-to-market ratio, leverage (computed as liability divided by total assets). The results are reported in Table 4.3 .

Consistent with the model, the coefficient of the equity duration in Column (2) is positively significant with a p-value less than 0.05, showing that higher equity duration is associated with higher firm idiosyncratic volatility. After adding the interaction term between the equity duration and the indicator of low price firms defined following Brandt et. al. (2009), I find that the predict power of equity duration are especially strong for the low price stocks.

We have seen that the a high implied equity duration is associate with higher idiosyncratic volatility on individual stock level. Now I try to the answer a question of whether this positive relationship can be extended to the market level as I derived in the model section. I calculate the value weighted idiosyncratic volatility of the market based on the CRSP stock data following Campbell et al. (2001). For each month, I first compute the firm-level stock idiosyncratic volatility for each firm based on the Fama and French three-factor model and compute the value-weighted market idiosyncratic volatility by their market share. I plot the log of aggregate idiosyncratic volatility and our market duration measure $\log(Dur_{sp500})$ as in Figure 4.3.

The upper panel shows that time-series of the implied market duration, and the bottom panel is the market idiosyncratic volatility. The two plot seems to co-move pretty well between 1982 and 2007. They both peak at 1987, 1990, and around 2000. During this period, there are positive trends for both series. The result is consistent with our conjecture during this period. However, there are also some conflicts. For example, during 2008 to 2010, the two series seems to move in opposite directions. The potential explanation is that the volatility could still

TABLE 4.3. Determinates of Idiosyncratic Volatility

| | (1) | (2) | (3) |
|----------------|------------------------|------------------------|------------------------|
| price | -0.0000*** (0.0000) | -0.0000*** (0.0000) | -0.0000*** (0.0000) |
| leverage | -0.0021* (0.0008) | -0.0017* (0.0008) | -0.0016* (0.0008) |
| d_{io} | -0.0040*** (0.0011) | -0.0040*** (0.0011) | -0.0032** (0.0010) |
| age | -0.0001*** (0.0000) | -0.0001*** (0.0000) | -0.0001*** (0.0000) |
| b/m | -0.0009*** (0.0002) | -0.0008*** (0.0002) | -0.0008*** (0.0002) |
| size | -0.0031*** (0.0001) | -0.0031*** (0.0001) | -0.0028*** (0.0001) |
| $lag(idio)$ | 0.4496*** (0.0293) | 0.4447*** (0.0286) | 0.4357*** (0.0283) |
| IO | -0.0031*** (0.0007) | -0.0031*** (0.0006) | 0.0023*** (0.0005) |
| $log(dur)$ | | 0.0018** (0.0006) | -0.0001 (0.0006) |
| $Dur*log(prc)$ | | | 0.0027*** (0.0002) |
| $IO*log(prc)$ | | | -0.0105*** (0.0015) |

This table reports Fama MacBeth regression results. The dependent variable is firm-idiosyncratic volatility, which is calculated following Campbell et al. (2001). The dependent variables are: *prc* denotes stock price. *TLTA* is total liability divided by total assets. *IO* denotes the percentage of institutional ownership of the stock. d_{IO} is the change of IO from time $t-1$ to time t . *Age* is the firm age, which is defined as 1 as a firm first showed on the Compustat Database. *BM* denotes Book-to-market ratio and *size* is proxied by market equity. lag_{idio} is the idiosyncratic volatility of a firm on month $t-1$. $LogDur$ is the our equity duration measure. Following Brandt et al. (2009), I incorporate an interaction term between low stock price and other dependent variables. "Low price" is defined as the stocks that have the 30% lowest price based on NYSE break point.

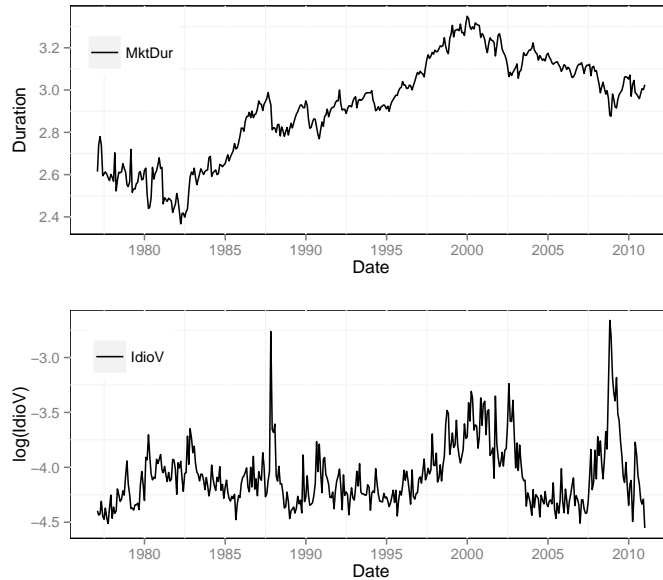


FIGURE 4.3. Market Duration and Idiosyncratic Volatility

This figure exhibits the time-series plot of the value-weighted S&P 500 equity duration and the value weighted idiosyncratic volatility from 1978 to 2012.

comes from shocks to cash flow. Focusing on large/high price stocks, I empirically confirm the prediction of equation (2) and (3) with the associated R^2 equal to 37% and 77%. This means that the relationship between stock volatility and equity duration could be nonlinear. The results also leave us at least 23% unexplained variations in the stock volatility. Note that the connection between stock volatility and duration could also change over time. I leave this potentially time-varying relationship for future research.

4.3.3 Predictability Test

Equity duration plays as a multiple of the discount rate shock. Therefore, during periods when the market equity duration is high, the shock of discount rate would have higher impact to market returns volatility. In other words, investors should ask for a higher premium for bearing the discount rate risk, which leads to a positive relationship between equity duration and the market risk premium. In this section, I explore the market return predictability of equity duration.

Before I conduct a formal test to show the the relationship between market excess return and the two duration predictors, I plot the time-series to justify the idea as in Figure 4.4 and 4.5. The dark line in the figure denotes stands for the excess market return over the 1-month T-bill rate across my sample period, and the light line is the growth of market equity duration in Figure 4.4 and duration shock in 4.5. Market returns appears to comove closely with both the duration growth and shocks.

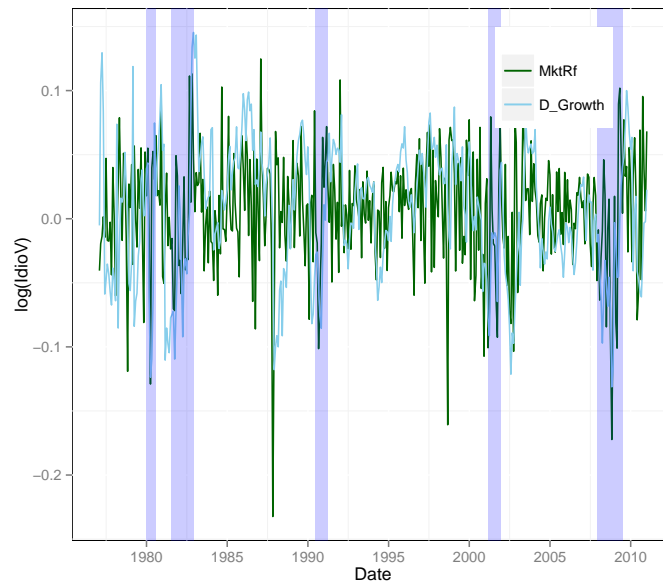


FIGURE 4.4. Market Excess Return and Duration Growth

This figure exhibits the time-series plot of market excess returns (dark green) and market duration growth (dark green). The shaded area are the period of economic depression identified by the NBER.

Following Fama and French (1989) and Li et al. (2011), I conduct the multi-period forecasting regression as the equation (3.11).

$$\sum_{i=1}^K \frac{r_{mkt,t+i}}{K} = a + b'X_t + e_{t+k} \quad (4.11)$$

, where $r_{mkt,t+i}$ is the ex post market excess return at time $t + i$, X_t is a vector of predictor variables, b is a vector of slope coefficients, e_{t+k} denotes the regression residual, and K is the prediction horizon. To adjust for the serial correlation for

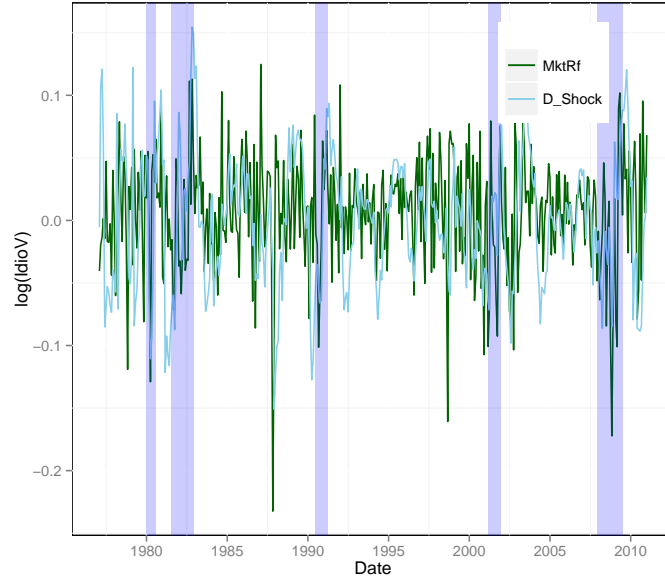


FIGURE 4.5. Market Excess Returns and Duration Shocks

This figure exhibits the time-series plot of market excess returns (dark green) and market duration shocks (dark green). The shaded area are the period of economic depression identified by the NBER.

the residual due to the use of overlapping observation, I use the standard errors computed using GMM with the Newey-West correction and then compute the t-statistics. I conduct the regression for 8 different horizons (1, 3, 6, 12, 24, 36, 48, and 60 months).

Literature has uncovered that the predictive power of this regression is suffered from finite-sample biases (see. Stambaugh (1986), Richardson and Stock (1989), and Richardson and Smith (1991)). To account for these biases, I use the bootstrapping method to simulate the finite sample distribution of the t-statistics of the regression slope under the null of no predictability as a bench mark of significance.

Due to the use of overlapping data, the statistics of the regressions are correlated across horizons. Therefore, I conduct the joint test across horizon by computing the sum of the squared slope coefficients across all horizons as the statistic to test the null hypothesis that the slopes are joint zero. The regression results are reported in table 4.4 and 4.5.

TABLE 4.4. In-sample Predictability using $g_{dur,t}$ as predictor

| Horizon | Without Control | | | | With control | | | |
|------------|-----------------|--------|-------|------------|--------------|--------|-------|------------|
| | b | $t(b)$ | p | $R2_{adj}$ | b | $t(b)$ | p | $R2_{adj}$ |
| 1 | 0.096 | 2.112 | 0.011 | 0.012 | 0.075 | 1.863 | 0.040 | 0.033 |
| 3 | 0.093 | 2.380 | 0.004 | 0.033 | 0.090 | 2.587 | 0.012 | 0.048 |
| 6 | 0.076 | 2.503 | 0.007 | 0.043 | 0.082 | 2.629 | 0.015 | 0.089 |
| 12 | 0.026 | 1.081 | 0.166 | 0.008 | 0.033 | 1.421 | 0.124 | 0.130 |
| 24 | -0002 | -0144 | 0.455 | -0003 | 0.002 | 0.190 | 0.384 | 0.288 |
| 36 | -0002 | -0184 | 0.424 | -0003 | -0004 | -0400 | 0.527 | 0.506 |
| 48 | -0003 | -0283 | 0.439 | -0003 | -0006 | -0761 | 0.592 | 0.561 |
| 60 | -0018 | -2515 | 0.901 | 0.042 | -0023 | -3554 | 0.974 | 0.619 |
| $\sum b^2$ | 0.025 | | 0.038 | | 0.022 | | 0.089 | |

This table provides the results of the risk premium predictability using growth of market equity duration as a predictor over different time horizons(1, 3, 6, 12, 24, 36, 48, and 60 months. In the right panel (without control), I use the growth of market equity duration as a single predictor. In the left panel(with control), I include DP, EP, BM, TS, DEF, LTR, and SVAR as our control variables. $\sum b^2$ computes the sum of squared slope coefficients at different horizons to test the null hypothesis that the slopes at different horizons are jointly zero.

TABLE 4.5. In-sample Predictability using $Shock_{dur,t}$ as predictor

| Horizon | Without Control | | | | With control | | | |
|------------|-----------------|--------|-------|------------|--------------|--------|-------|------------|
| | b | $t(b)$ | p | $R2_{adj}$ | b | $t(b)$ | p | $R2_{adj}$ |
| 1 | 0.097 | 2.306 | 0.015 | 0.011 | 0.060 | 1.513 | 0.067 | 0.030 |
| 3 | 0.105 | 3.099 | 0.005 | 0.042 | 0.099 | 3.011 | 0.009 | 0.053 |
| 6 | 0.103 | 3.826 | 0.002 | 0.079 | 0.104 | 3.552 | 0.005 | 0.115 |
| 12 | 0.063 | 2.988 | 0.009 | 0.057 | 0.063 | 2.887 | 0.019 | 0.167 |
| 24 | 0.009 | 0.680 | 0.236 | 0.000 | 0.010 | 0.860 | 0.238 | 0.291 |
| 36 | 0.008 | 0.957 | 0.190 | 0.001 | 0.001 | 0.098 | 0.434 | 0.505 |
| 48 | 0.013 | 1.714 | 0.075 | 0.012 | 0.007 | 0.966 | 0.232 | 0.561 |
| 60 | 0.005 | 0.750 | 0.171 | 0.000 | 0.000 | 0.065 | 0.438 | 0.554 |
| $\sum b^2$ | 0.035 | | 0.007 | | 0.028 | | 0.035 | |

This table provides the results of the risk premium predictability using shocks of market equity duration as a predictor over different time horizons(1, 3, 6, 12, 24, 36, 48, and 60 months. In the right panel (without control) I use the shocks of market equity duration as a single predictor. In the left panel(with control) I include DP, EP, BM, TS, DEF, LTR, and SVAR as our control variables. $\sum b^2$ computes the sum of squared slope coefficients at different horizons to test the null hypothesis that the slopes at different horizons are jointly zero.

Table 4.4 and 4.5 shows our results of predicting the ex post market risk premiums using the implied equity duration factor. There are two versions of the model. In the left panel, I use only the growth (shock) of the duration measure. In the right panel, I further control for factors that are widely used in the return-predictability literature (DP, EP, BM, TS, DEF, LTR, and SVAR). I see very strong predictive power of the duration shocks to market premium over the horizon of 1, 3, 6, and 12 months. For example, the slope coefficient of the left panel in Table 3.4 is 0.96 with a p-value of 0.11 for the 1-month horizon. The predictability lasts until the 12-month horizon. The results is robust after controlling for other factors as in the right panel.

4.4 Summary

To explore the issue of the increased idiosyncratic volatility documented in Campbell et al. (2001), I propose the implied market duration as an new explanation. I show that stock volatility is positively related to the implied equity duration, since equity duration plays a role of multiplier for the discount rate shock. In the empirical study, I find that the time-series of market equity duration and aggregate idiosyncratic volatility co-move closely during the sample period as in Campbell et al. (2001).

Since the interaction of equity duration and discount rate shock affect equity returns, I explore the time-series predictability of the market duration to the ex-post excess market risk premium. I find strong evidence that shocks to the implied equity duration are informative in predicting ex post positive market excess returns.

However, there are still many unanswered questions that need more work. First of all, in the model I decompose the discount rate shock into diversifiable and undiversifiable terms. I still need more empirical work to see how each component would affect stock volatility and asset pricing. Secondly, the although the trend of

idiosyncratic volatility and the aggregate duration of S&P 500 co-move well before 2005, they move differently in the later period, especially around 2008. Possible explanation is that the cash flow shocks accounts more for idiosyncratic volatility and therefore weaken the connection between volatility and cash flow. How the shock of cash flow and the shock of discount rate would affect stock volatility affect stock market could be conditional, which could be an interesting future research. Third, Brandt et al. (2010) argues that the upward idiosyncratic volatility is due to stocks with low price and high retail ownership. However, in my study, I focused on high price and big firms. I need more work to reconcile the conflict.

Chapter 5

Conclusion

In this dissertation, I wrote three essays on empirical asset pricing. In the first essay, I propose a holdings-based approach to re-examine the evidence on mutual fund managers' illiquidity and volatility timing ability, which is unbiased from the artificial timing issue of the return-based timing measure. The holding-based method uses only ex ante holding information on portfolio formation and, therefore, does not suffer from the artificial timing bias. This holdings-based approach can not only help us re-examine managers' illiquidity and volatility skills, it also allows us to know how important the artificial biases play a role in evaluating managers' skill.

The second essay focuses on how managers' illiquidity and volatility reactions reflect their private incentives and how the reactions predict future fund performance. I propose to construct new reaction measures by using the mutual fund holdings data, which provides us direct information about managers' optimal asset allocation. The new measure contains forward-looking information, which better captures managers' investment decision. The new reaction measure allows us to re-examine managers' illiquidity and volatility reactions, through which I can distinguish the economic motives behind those reaction behaviors.

The third essay tries to solve the idiosyncratically puzzle in Campbell et al. (2001). I propose a new explanation for the idiosyncratic volatility puzzle based on the cash flow horizon of stocks. I show that stock duration plays a role of a multiplier, whose change amplifies the shock of discount rate. I consider the dynamic of stock duration as an alternative explanation for the upward trend through late 1990s.

Moreover, market equity duration explains the ups and downs of market idiosyncratic volatility after year 2000, which makes the explanation more persuasive than those in the literature.

Bibliography

- Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2):375–410.
- Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1):31–56.
- Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics*, 17(2):223–249.
- Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance*, 59(4):1481–1509.
- Becker, C., Ferson, W., Myers, D. H., and Schill, M. J. (1999). Conditional market timing with benchmark investors. *Journal of Financial Economics*, 52(1):119–148.
- Bennett, J. A., Sias, R. W., and Starks, L. T. (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies*, 16(4):1203–1238.
- Bollen, N. P. and Busse, J. A. (2001). On the timing ability of mutual fund managers. *The Journal of Finance*, 56(3):1075–1094.
- Brandt, M. W., Brav, A., Graham, J. R., and Kumar, A. (2009). The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies*, page hhp087.
- Busse, J. A. (1999). Volatility timing in mutual funds: Evidence from daily returns. *Review of Financial Studies*, 12(5):1009–1041.
- Campbell, J. Y. (1993). Understanding risk and return. Technical report, National Bureau of Economic Research.
- Campbell, J. Y. and Cochrane, J. H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *The Journal of Political Economy*, 107(2):205–251.
- Campbell, J. Y. and Cochrane, J. H. (2000). Explaining the poor performance of consumption-based asset pricing models. *The Journal of Finance*, 55(6):2863–2878.
- Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance*, 56(1):1–43.

- Cao, C., Chen, Y., Liang, B., and Lo, A. W. (2013a). Can hedge funds time market liquidity? *Journal of Financial Economics*, 109(2):493–516.
- Cao, C., Simin, T., and Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk? *Review of financial studies*, 21(6):2599–2633.
- Cao, C., Simin, T. T., and Wang, Y. (2013b). Do mutual fund managers time market liquidity? *Journal of Financial Markets*, 16(2):279–307.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82.
- Carlson, R. S. (1970). Aggregate performance of mutual funds, 1948–1967. *Journal of Financial and Quantitative Analysis*, 5(01):1–32.
- Chalmers, J., Edelen, R. M., and Kadlec, G. B. (1999). An analysis of mutual fund trading costs. Available at SSRN 195849.
- Chen, H. J. (2011). Firm life expectancy and the heterogeneity of the book-to-market effect. *Journal of Financial Economics*, 100(2):402–423.
- Chen, H. J. (2014). Do Cash Flows of Growth Stocks Really Grow Faster? Available at SSRN 1903904.
- Chen, J., Hanson, S., Hong, H., and Stein, J. C. (2008). Do hedge funds profit from mutual-fund distress? Technical report, National Bureau of Economic Research.
- Chevalier, J. and Ellison, G. (1998). Career concerns of mutual fund managers. Technical report, National Bureau of Economic Research.
- Chevalier, J. and Ellison, G. (1999). CAREER CONCERNS OF MUTUAL FUND MANAGERS. *Quarterly Journal of Economics*, 114(2).
- Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.
- Croce, M. M., Lettau, M., and Ludvigson, S. C. (2014). Investor information, long-run risk, and the term structure of equity. *Review of Financial Studies*, page hhu084.
- Cutler, D. M. and Gruber, J. (1996). The effect of Medicaid expansions on public insurance, private insurance, and redistribution. *The American Economic Review*, pages 378–383.
- Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance*, 52(3):1035–1058.
- Datar, V. T., Naik, N. Y., and Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2):203–219.

- Dechow, P. M., Sloan, R. G., and Soliman, M. T. (2004). Implied equity duration: A new measure of equity risk. *Review of Accounting Studies*, 9(2-3):197–228.
- Droms, W. G. and Walker, D. A. (1994). Investment performance of international mutual funds. *Journal of Financial Research*, 17(1):1–14.
- Fama, E. F. (1972). Components of investment performance. *The Journal of finance*, 27(3):551–568.
- Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, 25(1):23–49.
- Ferson, S. and Tucker, W. T. (2006). Sensitivity analysis using probability bounding. *Reliability Engineering & System Safety*, 91(10):1435–1442.
- Ferson, W., Henry, T. R., and Kisgen, D. J. (2006). Evaluating government bond fund performance with stochastic discount factors. *Review of Financial Studies*, 19(2):423–455.
- Ferson, W. and Khang, K. (2002). Conditional performance measurement using portfolio weights: Evidence for pension funds. *Journal of Financial Economics*, 65(2):249–282.
- Ferson, W. E. and Schadt, R. W. (1996). Measuring fund strategy and performance in changing economic conditions. *Journal of Finance*, pages 425–461.
- Fink, J., Fink, K. E., Grullon, G., and Weston, J. P. (2010). What drove the increase in idiosyncratic volatility during the internet boom?
- Fortin, R. and Michelson, S. (1995). Are Load Mutual Funds Worth the Price? *Journal of Investing*, 4:89–94.
- Fortin, R. and Michelson, S. E. (1998). Mutual fund trading costs. *The Journal of Investing*, 7(1):66–70.
- French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, 19(1):3–29.
- Gil-bazo, J. and Ruiz-Verdu, P. (2009). The relation between price and performance in the mutual fund industry. *The Journal of Finance*, 64(5):2153–2183.
- Goetzmann, W. N., Ingersoll Jr, J., and Ivkovi, Z. (2000). Monthly measurement of daily timers. *Journal of Financial and Quantitative Analysis*, pages 257–290.
- Grinblatt, M. and Titman, S. (1994). A study of monthly mutual fund returns and performance evaluation techniques. *Journal of financial and quantitative analysis*, 29(03):419–444.
- Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The journal of finance*, 51(3):783–810.

- Henriksson, R. D. and Merton, R. C. (1981). On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills. *Journal of business*, pages 513–533.
- Hicks, J. R. (1946). *Value and capital*, volume 2. Clarendon press Oxford.
- Hsu, P.-H. (2009). Technological innovations and aggregate risk premiums. *Journal of Financial Economics*, 94(2):264–279.
- Huang, J., Sialm, C., and Zhang, H. (2011). Risk shifting and mutual fund performance. *Review of Financial Studies*, page hhr001.
- Ippolito, R. A. (1989). Efficiency with costly information: A study of mutual fund performance, 1965-1984. *The Quarterly Journal of Economics*, pages 1–23.
- Irvine, P. J. and Pontiff, J. (2009). Idiosyncratic return volatility, cash flows, and product market competition. *Review of Financial Studies*, 22(3):1149–1177.
- Jagannathan, R. and Korajczyk, R. A. (1986). Assessing the market timing performance of managed portfolios. *Journal of Business*, 59(2):217–235.
- Jiang, G. J., Yao, T., and Yu, T. (2007). Do mutual funds time the market? Evidence from portfolio holdings. *Journal of Financial Economics*, 86(3):724–758.
- Jiang, H., Verbeek, M., and Wang, Y. (2014). Information content when mutual funds deviate from benchmarks. *Management Science*, 60(8):2038–2053.
- Jiang, W. (2003). A nonparametric test of market timing. *Journal of Empirical Finance*, 10(4):399–425.
- Lettau, M. and Wachter, J. A. (2007). Why is long-horizon equity less risky? a duration-based explanation of the value premium. *The Journal of Finance*, 62(1):55–92.
- Lettau, M. and Wachter, J. A. (2011). The term structures of equity and interest rates. *Journal of Financial Economics*, 101(1):90–113.
- Li, Y., Ng, D. T., and Swaminathan, B. (2011). Implied Cost of Capital and the Predictability of Market Returns.
- Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of financial Economics*, 82(3):631–671.
- Macauley, F. R. (1938). Some theoretical problems suggested by the movements of interest rates, bond yields and stock prices in the United States since 1856. *NBER Books*.
- Mo, H. (2014). Implied Economic Risk Premiums. *Available at SSRN 2302872*.

- Morck, R., Yeung, B., and Yu, W. (2000a). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of financial economics*, 58(1):215–260.
- Morck, R., Yeung, B., and Yu, W. (2000b). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of financial economics*, 58(1):215–260.
- Pastor, L. and Stambaugh, R. F., R. F. (2003). Liquidity risk and expected stock returns. *Journal of political economy*, 111(3):642–685.
- Richardson, M. and Smith, T. (1991). Tests of financial models in the presence of overlapping observations. *Review of Financial Studies*, 4(2):227–254.
- Richardson, M. and Stock, J. H. (1989). Drawing inferences from statistics based on multiyear asset returns. *Journal of Financial Economics*, 25(2):323–348.
- Simutin, M. (2013). Cash Holdings and Mutual Fund Performance*. *Review of Finance*, page rft035.
- Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *Journal of finance*, pages 1589–1622.
- Stambaugh, R. F. (1986). *Bias in regressions with lagged stochastic regressors*. Center for Research in Security Prices, Graduate School of Business, University of Chicago.
- Treynor, J. and Mazuy, K. (1966). Can mutual funds outguess the market. *Harvard business review*, 44(4):131–136.
- Wei, S. X. and Zhang, C. (2006). Why Did Individual Stocks Become More Volatile?*. *The Journal of Business*, 79(1):259–292.

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