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Essays on Hedge Fund Performance

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ESSAYS ON HEDGE FUND PERFORMANCE

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ABSTRACT

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This dissertation consists of two essays on hedge fund performance. The first essay models exposure of hedge fund to risk factors and examines time-varying performance of hedge funds. From existing models such as ABS-factor model, SAC-factor model, and four-factor model, we extract the best six factors for each hedge fund portfolio by investment strategy. Then, we find combinations of risk factors that most explain variance in performance of each hedge fund portfolio by investment strategy. The results show instability of coefficients in the performance attribution regression. Incorporating time-varying factor exposure feature would be the best way to appropriately measure hedge fund performance. Furthermore, the optimal models with fewer factors exhibit greater explanatory power than existing models. Time-varying model customized by investment strategy of hedge funds would clearly show how sensitive to risk factors managements of hedge funds are according to market conditions.

In the second essay, we first conduct multinomial logistic regression analysis to see how hedge fund attributes affect hedge fund managers‟ decision of whether to offer a hurdle rate and/or high-watermark. Hedge funds taking more risky position and collecting high performance fee are more likely to offer hurdle rate and/or high-watermark. Second, we conduct cross-sectional regression analysis to see how hedge fund attributes affect hedge fund performance. Our results indicate that hurdle rate and high-watermark are restrictions for hedge fund managers

on collecting fee and that hurdle rate and high-watermark cannot be considered to be incentives. We also find that hedge funds collecting high performance fee and having large amount of funds are more likely to outperform those collecting low performance fee and having small amount of funds.

While conducting cross-sectional regression analysis, we use three different measures of hedge fund performance: alpha, palpha and Sharpe ratio. Alpha and palpha are obtained from the optimal model by investment strategy controlling for hedge fund risk associated with risk factors different by its investment strategy. In addition, we control for survivorship and instant history biases. So, our results from alpha and palpha are more credible than those of Soydemir et al. (2012) which employs only Sharpe ratio.

DEDICATION

I dedicate this dissertation to my lovely wife, Ummi, and daughter, Erin. Thank you for always being next to me, for supporting me, and for helping me. This dissertation has been done not by me but by ourselves. As I have said, you are my energy that makes me move forward.

I thank my parents Hyunmook Shin and Pyeongja Kim, and parents-in-law, Deoki Kang and the late Jongho Jo for the supports and patience they have shown to my long and tiresome study. I would also like to thank all my brothers, brothers-in-law, sisters-in-law, nephews and niece.

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CHAPTER I

DYNAMIC EXPOSURE OF HEDGE FUNDS TO THE CHANGES IN THE RISK FACTORS

1.1 Introduction

It is well known that hedge funds are less regulated relative to traditional mutual funds so that they can take long/short positions in any financial instruments and extremely high level of leverage. Hedge fund managers are given almost full discretion as to determining investment strategies, composition of portfolio, level of leverage, etc. Highly skilled hedge fund managers can actively respond to the changes in market condition and quickly adjust their portfolio and exposure to risk factors. Therefore, it is natural that hedge fund exposure to risk factors is also dynamic and time-varying. Lo (2001) argues that hedge funds with dynamic investment strategies are exposed to dynamic risks, so that it is hard to capture the dynamic exposure of hedge fund investment to market risk using constant-beta models.

Ackermann, McEnally, and Ravenscraft (1999), Kosowski, Naik, and Teo (2007), and Fung and Hsieh (2004b) find persistence of hedge fund performance at annual horizon whereas they do not shed light on hedge fund exposure to risk factors. Fung and Hsieh (1997a) find returns of trend-following funds exhibit option-like patterns, making it hard for linear style-factor model of Sharpe (1992) to capture systematic risk of hedge fund returns. Fung and Hsieh (1997, 2001, and 2004a) suggest standard asset classes (SAC)-factor model and asset-based style

(ABS)-factor model, both of which do not consider any time-varying features of hedge funds.[1] Fung and Hsieh (2004a), Fung, Hsieh, Naik, and Ramadorai (2008) and Bollen and Whaley (2009) take into account the time-varying exposure of hedge funds to risk factors. However, they limit the number of breakpoints reflecting regime changes to one or two, which are too few to capture relevant shifts relative to their sample period of 12 years.

Hedge funds adopt diverse investment strategies and provide investors with options to select hedge funds that best fit to their risk preference. Since hedge funds can go both long and short and/or can invest in most types of financial instruments, risk in hedge funds can vary from neutral to extremely high. Hedge fund managers usually announce risk characteristics or investment strategies of their funds to investors. Hedge funds likely exhibit different exposures to the changes in risk factors by their investment strategies. For instance, performance and exposure of fixed-income funds tend to be stable and less sensitive to stock market movement, while those of equity hedge funds are relatively more volatile and sensitive to the same stock market movement. Fung and Hsieh (1997a) also find that hedge funds with different investment strategies achieve different level of performance even in the same market environment.

Therefore, it seems to be somewhat contradictory that a set of risk factors is used to estimate performance of overall hedge funds pursuing many different investment strategies, or that an aggregate hedge fund portfolio represents those hedge funds offsetting unique feature of fund in each category. Using ABS-factor model, Fung and Hsieh (2004a) well explains common characteristics of overall hedge funds with high adjusted r-squared values. However, it is

[1] Eight asset classes include the U.S. and non-U.S. equities; emerging market equities; the U.S. and non-U.S. government bonds; One-month Eurodollar deposit return; spot gold; and the U.S. dollar index. Seven risk factors include equity market factor; the size spread factor; bond market factor; credit spread factor; bond-trend-following factor; currency trend-following factor; and commodity trend-following factor.

possible that performance and exposure observed in aggregate hedge fund index be distorted because of diverging return characteristics from hedge funds with different investment strategies.

In this study, using a survivorship-bias-free dataset of hedge funds, we conduct clustering analysis based on the Pearson correlation-coefficients to group risk factors. Then, we run time-varying single-factor regression analysis using risk factors employed in the existing models such as ABS-factor model, SAC-factor model, and four-factor model, and find top six factors for each hedge fund portfolio by investment strategy. Analyzing recursive residuals from constant-beta models, we examine the stability of coefficients over time to prove that constant-beta models are not a proper measure to capture dynamic exposure of hedge funds to the risk factors, and that time-varying model has to be employed to find the combinations of risk factors that most explain performance of hedge funds. Finally, we select an optimal model by investment strategy of hedge fund portfolio that appropriately estimate dynamic performance and exposure of hedge funds to risk factors.

We find that the two types of biases upwardly bias returns on hedge funds, and that they are released by handling data. Our findings also reveal that SAC-factor model is more likely to suffer from multicollinearity problem because risk factors are highly correlated with each other. We select one factor from each group of factors to eliminate this potential problem. By applying time-varying coefficients concepts into the single-factor regression analysis, coefficients of risk factors are instable over time periods. It would be attributed to the active and dynamic hedge fund management of risk exposure responding to the changes in market condition. It is also statistically proven, so that the existing constant-beta models implicitly assuming static or buy-and-hold investment strategy cannot appropriately estimate hedge fund performance and exposure to risk factors. The multi-factor time-varying models by investment strategy of hedge funds proposed in this study provide more explanatory power than the existing constant-beta models. Our models are also more parsimonious than the constant-beta models.

Therefore, this study contributes to the existing literature on hedge funds in the following distinct ways. First, we show that funds of hedge funds portfolio does have survivorship bias and instant history bias, contradicting the argument by Fung and Hsieh (2002a) that fund of hedge funds portfolio can be free from those biases. It is more supportive to the idea that like individual hedge funds, funds of hedge funds are also exposed to the potential risk of those biases, so that they may not be a proper method to handle biases.

Second, we prove that coefficients of time-varying models are instable. Thus, it is inappropriate to estimate hedge fund performance and exposure to risk factors with constant-beta models assuming static or buy-and-hold investment strategy. Management of hedge funds can quickly respond to the changes in market condition. Therefore, employing time-varying model would be the best way to reflect dynamic feature of hedge funds in the model measuring hedge fund performance and exposures.

Third, we find the optimal models that most explain hedge fund performance and exposure to risk factors by investment strategy. The optimal models with fewer factors exhibit greater explanatory power than existing models, and time-varying analysis would make the models more credible in estimating active and dynamic management of hedge funds. In addition, by different combination of factors tailored for investment strategies, we can make the models more elaborate and provide better insight into management of hedge funds. Time-varying model customized by investment strategy of hedge funds would clearly show how sensitive to risk factor managements of hedge funds are according to market conditions.

The remainder of this chapter is structured as follows. In section 2, we review the literature and risk factors. Section 3 explains data, biases and investment strategies. Section 4 elaborates the econometric methodology. Section 5 reports the empirical results. Section 6 concludes.

1.2 Literature Review and Risk Factors

1.2.1 Fama and French (1993)'s Three Factors

Fama and French (1993) add to Capital Asset Pricing Model (CAPM) with two more common risk factors, i.e., firm size factor and the book-to-market factor. Combined with the overall market factor, Fama-French-three-factor model has been widely utilized to explain average returns on stock markets. *Size premium*, defined as the difference in return between small firm and large firm, captures risk premium that investors take for bearing risk from investing in relatively small firm. *Value premium*, defined as the difference in return between firms with high book-to-market value (value stocks) and firms with low book-to-market value (growth stocks), is designed to measure premium for taking risk of value stocks. An example that practically applies three-factor model is Morningstar investing style box utilizing feature of the three-factor model that is able to categorize mutual funds based on the size and value risk of portfolio components. It classifies mutual funds from the lowest risk, one investing in large and growth firms, to the highest risk, one investing in small and value firms. Carhart (1997) develops four-factor model that adds Jegadeesh and Titman (1993)'s one-year *momentum* to Fama-French-three-factor model to explain Hendricks, Patel, and Zeckhauser (1993)'s hot hands effect in mutual fund performance. Under momentum strategy, investors buy (sell) stocks that have performed well (poorly) in the past to obtain significant positive return. In contrast, DeBondt and

Thaler (1985) report that *contrarian strategy* – buying losers and selling winners over the past 3-5 years – provides positive abnormal returns over 3-5 year holding period.

Many studies have used the three-factor model, Jegadeesh and Titman's momentum, and DeBondt and Thaler's contrarian to examine performance traditional mutual funds or ability of fund managers. Unlike mutual funds, however, hedge fund performance, characterized by dynamic and flexible investment strategies in response to the changes in market conditions, is hardly captured by those factors. Hedge funds are generally classified according to investment strategies, even though there is no one standard. If we analyze hedge fund performance by investment strategies, some sort of hedge funds can be well explained by one or more of the above factors. Bollen and Whaley (2009) use the three-factor in their model to estimate alphas by fund types: hedge fund, fund of fund, commodity trading advisor, and commodity pool operator. They find that these factors play an important role in explaining performance of hedge fund and fund of funds. Measuring performance of hedge funds by investment strategies, Do, Faff, and Wickramanayake (2005) find significant influence of size and value premium factors. Hübner, Lambert, and Papageorgiou (2010) employ the four-factor of Carhart (1997) as a directional risk factor to explain hedge fund returns, and consider investing in a momentum strategy to be the most risky and rewarding. Fung and Hsieh (2004b) also apply the four-factor model to investigation of common risk factor of equity hedge funds. Significant contributions of excess return on market and size premium are reported, while value premium and momentum factors are not significant.

1.2.2 Standard Asset Class (SAC) Factors

Sharpe (1992)'s asset class factor model successfully works to estimate mutual fund performance and exposure to market because of investment restrictions placed on managers.

They have limited pool of assets available to invest, limited level of leverage, and benchmarks (returns on asset classes) to exceed. These enable some sort of asset class returns to explain performance of mutual funds well. However, it does not apply to explaining performance of hedge funds that are featured by flexibility to choose among many asset classes and dynamic investment strategies.

Fung and Hsieh (1997a) argue that hedge fund returns are less correlated with those of standard asset classes used in the Sharpe's model, and suggest the extended version of Sharpe's model to explain hedge fund performance. Fung and Hsieh (1997a) extract five style factors, which are mutually orthogonal principal components, "Systems/Opportunistic," "Global/Macro," "Value," "Systems/Trend Following," and "Distressed." To explain the five style factors, they employ standard asset class factors: three equity classes (MSCI U.S. equities; MSCI non-U.S. equities; and IFC emerging market equities), two bond classes (JPMorgan U.S. government bond and JPMorgan non-U.S. government bonds), cash (one-month Eurodollar deposit), commodities (price of gold), and currencies (Federal Reserve's Trade Weighted Dollar Index) plus high yield corporate bonds. They find that the "Value" and "Distressed" styles are sensitive to the changes in the U.S. equity market and high yield corporate bonds. The other three styles are sensitive to asset classes only when markets are in extreme.

Schneeweis and Spurgin (1998) and Brown, Goetzmann, and Ibbotson (1999) also find low return correlation between standard asset classes and individual hedge funds, while Fung and Hsieh (2002a) report high return correlation between the indexes of hedge funds and some of standard asset classes, which appears to be caused by the difference in the return characteristics in hedge fund indexes and individual hedge funds.

1.2.3 Asset-based Style (ABS) Factors

Fung and Hsieh (2004a) suggest seven asset-based style (ABS) factors as a benchmark of hedge fund returns. As Sharpe’s asset class factors, ABS factors capture the common source of risk using conventional asset prices. Benchmarking asset returns reduces biases. Fung and Hsieh (2004a) classify hedge funds according to four groups of risk factors: trend-following funds, merger arbitrage funds, fixed income funds, and equity long/short funds.

Fung and Hsieh (1997b) extract principal components of trend-following funds, whose returns are not correlated to those of standard asset classes, but exhibit option-like pattern. Fung and Hsieh (2001) utilize look-back straddle options to capture returns of trend-following strategies. By providing empirical evidence that returns of look-back straddles resemble those of trend-following funds, returns of standard assets can also be involved with trend-following funds. Fung and Hsieh (2004a) use bond, currency, and commodity trend-following risk factors.

The equity market factor and size spread factor are very analogous to the excess market return and size premium of the three-factor model. These are very useful in explaining merger arbitrage funds and equity long/short funds. The bond market factor and credit spread factor are the fixed-income ABS factors. Fung and Hsieh (2004a) report that their ABS-factor model explains significantly large portion of performance of major hedge fund indexes with about 80% of adjusted r-squared values.

Many studies utilize seven ABS factors to estimate hedge fund performance, and apply their findings to subsequent analyses. Jagannathan, Malakhov, and Novikov (2010) identify hedge fund managers with skills based on the measure of performance from the modified version of the ABS factor model. They find significant persistence in superior funds but not in inferior funds. Kosowski et al. (2007) also find performance persistence at annual horizon using a robust bootstrap procedure to handle non-normality of hedge fund returns. Fung et al. (2008) group funds of hedge funds into have-alpha and beta-only according to whether or not to generate significant alpha. They find that have-alpha funds are more likely to be alive and to have steady capital inflows.

1.3 Data, Biases and Investment Strategies

1.3.1 Data and Descriptive Statistics

In this study, we use monthly time series returns on hedge funds, funds of hedge funds, Fung and Hsieh's ABS-factor and SAC-factor, Carhart (1997)'s four factors, DeBondt and Thaler (1985)'s contrarian strategy, and volatility index (VIX). Returns on hedge funds and funds of hedge funds are collected from Global Hedge Fund Database provided by BarclayHedge. It provides 2,689 (2,072) of active and 4,200 (1,845) inactive hedge funds (funds of hedge funds). We exclude funds with observations less than 12 months; funds that report returns not in net-of-all fee; and funds that are not involved with the four broad investment strategies suggested by Agarwal et al. (2009).

As a result, we have 2,556 (1,970) of active and 3,786 (1,705) inactive hedge funds (funds of hedge funds), and then, we create six equally-weighted portfolios for aggregate hedge funds and funds of hedge funds as well as for four broad investment strategies. The data cover period from January 1994 to December 2008 (180 months). We select the sample period because since 1994, we have at least forty of hedge funds on every month to make up portfolio for investment strategies. In addition, majority of recent studies also choose sample period from 1994 because major database vendors have started providing information about funds that stop reporting, which controls for survivorship bias.

Data associated with Fung and Hsieh's studies are available at the Professor Hsieh's homepage. He provides returns on bond, currency and commodity trend-following factors, and sources of other factors used in his studies.[2] Following Fung and Hsieh (2004a)'s ABS-factor, we use the monthly total return of S&P 500 index as an "Equity market factor"; the monthly total return of Russell 2000 index less S&P 500 index as a "Size spread factor"; the monthly change in the 10-year treasury constant maturity yield as a "Bond market factor"; and the monthly change in Moody's Baa yield less 10-year treasury constant maturity yield as a "Credit spread factor." We also utilize SAC-factor from Fung and Hsieh (1997a): MSCI North American equities as an "U.S. equities"; MSCI non-U.S. equities as a "non-U.S. equities"; JPMorgan U.S. Government bonds as an "U.S. Government bonds"; JPMorgan non-U.S. Government bonds as a "Non-U.S. Government bonds"; one-month Eurodollar deposit rate of the previous month as an "Eurodollar deposit return"; gold bullion in London bullion marketas a "Spot Gold"; and Federal Reserve Traded Weighted Index of the U.S. dollar against major currencies as an "U.S. dollar index." The 10-year treasury constant maturity yield, Moody's Baa yield, and traded-weight index of the U.S. dollar against major currencies are obtained from the Board of Governors of the Federal Reserve System.[3] The rests are collected from DataStream.

Carhart's four factors (the excess return on the market, the performance of small stocks relative to large stocks, the performance of value stocks relative to growth stocks, and momentum) and DeBondt and Thaler's Contrarian strategy are provided at the Professor French's home page.[4]

[2] http://faculty.fucua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

[3] http://www.federalreserve.gov/econresdata/releases/statisticsdata.htm

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

In addition, we employ the Chicago Board Options Exchange Market Volatility Index (VIX) as a proxy for investor sentiment. The VIX is obtained from DataStream, and the value measured at the beginning of every month will be used.

Panel A in Table 1 reports summary statistics of monthly returns on equally-weighted hedge fund portfolios including mean, standard deviation, median, minimum, maximum, skewness, kurtosis, and Jarque-Berastatistics as well as Sharpe ratio. Panel A also reports the number of funds active and inactive along with percentage of each strategy as of December 2008. All statistics in this table are obtained after controlling for the survivorship and instant history biases. Sharpe ratio is measured by dividing average excess return by standard deviation on return of each variable. Mean monthly returns on hedge fund portfolios are ranged from 0.55% to 1.00% with standard deviations from 1.15% to 3.01%. Among the four broad investment strategies, portfolios of Directional Traders (DT) and Security Selection (SS) exhibit the highest mean monthly returns compared to two other portfolios of Relative Value (RV) and Multi-process (MP) while they also show the highest standard deviation. This is consistent with the idea that the higher the risk, the greater the return. In fact, the investments of DT and SS are conducted based on their prediction of market movements or on their estimation of asset values, leading to a relatively greater risk. In contrast, RV takes positions maintaining certain level of spread to minimize risk or market exposure, and therefore, leads to lower risk. Funds of Hedge Funds (FoF) provides with the lowest mean return and Shape ratio. It can be partially attributed to the fact that investors pay fees to FoF as well as hedge funds included in the portfolio of the FoFs. In addition, the fact that the fees paid to hedge funds are substantially high compared to traditional mutual funds well supports low mean return and Sharpe ratio of FoF.

Highly significant Jarque-Bera statistics indicate the nonnormal distribution of returns on hedge fund portfolios which is consistent with the literature (Fung and Hsieh, 1999; Mitchell and Pulvino, 2001; Brooks and Kat, 2002; and Amin and Kat, 2003). Then, mean-variance analysis is insufficient way to describe the distribution of hedge fund returns.

Panel B in Table 1 also reports the same summary statistics as Panel A for returns on the risk factors, all of which, excluding Non-US Government Bonds and US Dollar Index, are nonnormally distributed. Scott and Horvath (1980) claim that investors with positive marginal utility and risk averse for all wealth levels prefer high first and third moments (mean and skewness) and low second and fourth moments (standard deviation and kurtosis). By comparing descriptive statistics of hedge fund portfolios with those of equity market indexes (S&P 500, US equity, Non-US equity, Emerging market, and market risk premium), hedge funds seem to be outperforming equity market indexes based only on mean and standard deviation. Taking skewness and kurtosis into an account due to the nonnormal distribution of returns on hedge fund portfolios and risk factors, we may not reach the same conclusion. Higher mean returns and lower standard deviation, or higher Sharpe ratios must be given at some costs.

1.3.2 Types of Biases

Since they are voluntarily reported, hedge fund data suffer from the following biases: survivorship and instant history (backfilled) biases. Survivorship bias is caused by excluding information about funds that are liquidated or delisted from database. Majority of funds are excluded from database because they are liquidated with poor performance. In this case, survivorship bias upwardly affects returns. On the other hand, some funds are unwilling to provide information to the public because they are very successful and no longer have to collect more funds. Since hedge fund managers are not legally required to report performance, it is possible to stop reporting whenever it is considered to be no more beneficial. In this case, survivorship bias downwardly affects returns. Fortunately, our database provides “graveyard” where includes those funds that cease reporting. By combining information of active and inactive funds, we can minimize the survivorship bias caused by liquidated or delisted hedge funds. However, we are still unable to discern whether those that stop reporting still exist or not.

Instant history bias (or backfilled bias) is caused by the backfilled-period information. When hedge funds enter certain database, they provide the previous period information. However, those hedge funds entering database are more likely to have superior historical performance. The reason is very simple. Hedge funds are prohibited from advertising to attract investors, so they disclose their performance through database as an indirect way of attracting investors. Therefore, if hedge funds have shown poor historical performance, they have no incentives to enter database. General method of handling instant history bias is to drop the returns of the first year. Aggarwal and Jorion (2009) argue that the way of dropping the first year returns is insufficient and recommend selecting a sample of funds with inception date very close to a fund’s inclusion date into the database. However, Exhibit 1 in Aggarwal and Jorion (2009) displays alpha values in which bias is highly questionable. Therefore, we choose dropping first year (12 months) return observations as a way of controlling for the instant history bias.

Fung and Hsieh (2002a) introduce the use of funds of hedge funds in mitigating both types of biases. Funds of hedge funds invest in portfolios of other hedge funds, and their returns consist of value-weighted returns on individual hedge funds in their portfolio. Although the individual hedge funds may stop reporting to database, or may be liquidated, returns on funds of hedge funds reflect performance of all hedge funds as long as funds of hedge funds invest in those hedge funds or till the time when they are liquidated or excluded from the portfolio.

Furthermore, funds of hedge funds do not include prior performance of individual hedge funds to the inclusion of portfolio. For these reasons, Fung and Hsieh (2002a) show that funds of hedge funds can minimize the biases in hedge fund data. However, funds of hedge funds also need to attract investors and they will stop reporting to vendors unless they benefit from doing so. They can also be liquidated. Further, funds of hedge funds may stop investing in a certain hedge funds, which results in the same effect as being delisted or liquidated. Therefore, funds of hedge funds are also exposed to the risk of survivorship and instant history biases, so that we apply the same methods to release the biases.

Table 2 reports monthly mean returns on hedge fund portfolios for various investment strategies and results of comparison before and after controlling for either or both of instant history bias or/and survivorship bias. The three columns under (B) are controlled for instant history bias, columns under "Alive (or Dead)" denote mean returns of active (or inactive) hedge fund portfolios, and columns under "All" (both 3 and 6) denote hedge fund returns that are controlled for survivorship bias. Therefore, the column under (B) and "Alive" denotes hedge fund returns controlled for only instant history bias; the column under (A) and "All" denotes hedge fund returns controlled for only survivorship bias; the column under (B) and "All" denotes hedge fund returns controlled for both instant history and survivorship bias; and the column under (A) and "Alive" denotes hedge fund returns controlled for no bias. Columns (C), (D), and (E) include differences in mean returns between portfolios controlled and not controlled for instant history bias, for survivorship bias, and for both biases.

The column (C), which is the mean difference between mean returns of hedge fund portfolios controlled and not controlled for instant history bias, exhibits positive figures from about 0.24% to 2.3% on annual basis over all investment strategies of hedge fund portfolios significant at 5% level. This indicates that hedge fund returns tend to be inflated by backfilled information, and can be at least partially eliminated by removing returns reported for a certain period from their inceptions.

The column (D) is the mean difference between mean returns of hedge fund portfolios controlled and not controlled for survivorship bias. All figures for hedge fund portfolios are positive, but only three of six portfolios – Aggregate (AG), DT, and FoF – exhibit significant difference at 5% level. Column (E) shows the results that control for both of instant history and survivorship biases. The difference between hedge fund portfolio returns controlled for both and none of the biases all appear to be positive with only one exception insignificant. Especially, funds of hedge funds show significant differences in all results of controlling each bias and both biases. Our results are inconsistent with the claim in Fung and Hsieh (2002a) and indicate that funds of hedge funds are also exposed to the risk of both biases.

To control for biases, we remove returns of the first year since inception of each hedge fund, and combine returns on active and inactive hedge funds. The comparisons of those returns not only confirm the existence of instant history bias and survivorship bias, but also show that the ways we utilize to release biases appear to be quite effective.

1.3.3 Investment Strategies of Hedge Funds

Large vendors, such as the TASS Research, Hedge FundResearch (HFR), and BarclayHedge, of hedge fund database manage aggregate hedge fund indexes as well as sub-indexes categorized into many different investment strategies. Each vendor has its own system to categorize hedge funds into many different investment strategies. But the standards do not exactly correspond with each other. Fung and Hsieh (2002b) and Malkiel and Saha (2005) utilize sub-indexes of hedge funds provided by HFR and TASS, respectively. Others attempt to classify hedge funds by investment strategies. Agarwal, Daniel, and Naik (2009) suggest the four broad investment strategies – Directional Traders (DT), Relative Value (RV), Security Selection (SS), and Multiprocess (MP) – involving strategies provided by different vendors. Since "simplicity" is one of the virtues that a good model should pursue, we categorize hedge funds into the four broad investment strategies as in Agarwal et al. (2009).

1.4 Econometric Methodology

Brown and Goetzmann (2001) claim that "*there are at least eight distinct styles or philosophies of asset management currently employed by hedge funds, and risk exposure depends very much on style affiliation.*" In addition, it is very well known fact that hedge fund managers are able to quickly adjust their exposure to risk factors in response to the changes in market conditions. These lead to the idea that hedge fund performance and exposure to risk factors may vary by investment strategies and market conditions. Therefore, static models may not be adequate to examine hedge fund performance and risk exposure. We modify and combine Jensen (1967)'s model and Sharpe (1992)'s model with time-varying concepts to estimate hedge fund performance and exposure to risk factors.

To estimate performance and exposure of hedge funds with different investment strategies to risk factors, we first create four equally-weighted portfolios for hedge funds based on investment strategies (DT, RV, SS and MP), one for aggregate hedge funds (AG) and one for funds of hedge funds (FoF). These six portfolios include all monthly time-series returns of hedge funds with corresponding investment strategy after controlling for instant history and survivorship biases.

As a second step, we estimate hedge fund exposure to each of the following known risk factors: Fung and Hsieh's ABS-factor and SAC-factor, Carhart's four-factor, contrarian strategy, and volatility index (VIX). We employ the single-factor time-series model of Jensen (1967) and Black, Jensen, and Scholes (1972):

$$R_{it} - R_{ft} = \alpha_i + (R_{mt} - R_{ft})\beta_i + \varepsilon_{it}\,, \qquad (1)$$

where i = AG, DT, RV, SS, MP, and FoF. R_{it}, R_{mt}, and R_{ft} denote returns on hedge fund index i, risk factors, and risk-free asset at time t, respectively. β_i indicates the factor loadings or exposures of returns on hedge fund indexes to the changes in risk factors. We conduct a time-varying OLS regression analysis of the model with a fixed window of 24 (36) month observations, and then take an expected value of adjusted r-squared values for relation between hedge fund indexes and risk factors. The top six factors that provide highest adjusted r-squared values are selected for the multi-factor model to estimate hedge fund exposure to risk factors. In this way, we obtain information of unique relationships between each of risk factors and specific investment strategies of hedge funds based on the adjusted r-squared values.

Among the variables to be considered, some variables are proxy for the same or similar risk factors. For example, equity market factor (S&P 500) among ABS factors, the U.S. equities (MSCI North America Equities) and emerging market equities among SAC factors and market premium among the four factors all are used as a proxy for the U.S. stock market. We select one among the variables that works as a proxy for the same or similar factor. Table 3 reports the Pearson correlation-coefficients between risk factors and groups of those risk factors from clustering based on the Pearson correlation-coefficients. The twenty one risk factors are clustered into fifteen groups. Risk factors clustered in the same group, especially, those that proxy for equity markets, are highly correlated with each other, whose correlation-coefficients are ranged from 0.69 to 0.98. Employing variables highly correlated with each other as independent variables in the same model results in the increased possibility of mulitcollinearity, and leads to biased conclusion. Therefore, we choose only one risk factor from those factors clustered into the same group based on correlation-coefficients. Other than equity markets proxies, Fama and French (1993)'s size premium and Fung and Hsieh (2004)'s size spread factor, as well as returns on the U.S. Government Bonds and non-U.S. Government Bonds are clustered into the same group, respectively.

As a last step, in order to simultaneously estimate hedge fund performance and exposure to specific risk factors, we extend single-factor model into Sharpe (1992)'s multi-factor model to consider all factors in one regression analysis.

$$R_{it} - R_{ft} = \alpha_i + \sum_{t=1}^{n} (X_t - R_{ft}) B_i + \varepsilon_{it} \qquad (2)$$

where X_t denotes vector of risk factors at time t; α_i denotes abnormal returns of hedge fund index i and fund managers' investment skill; and B_i denotes vector of exposure of hedge fund index i to risk factors. α_i and B_i are estimated by a time-varying OLS regression analysis with a fixed window of 24 (36) month observations. From the obtained time-varying B_i we can see how different hedge funds are in exposure to risk factors depending on the changes in market conditions.

1.5 Empirical Results

1.5.1 Correlation Analysis between Returns on Hedge Fund Portfolios and Risk Factors

Correlation analysis may be the most basic analysis to see how dependent and independent variables are related. Prior to estimating hedge fund portfolios' performance and exposure to risk factors, we conduct correlation analysis and report the results in Table 4. Equity market-related risk factors generally exhibit high correlations with returns of hedge fund portfolios with coefficients ranging from 0.56 to 0.88. Especially, market risk premium and emerging market returns appear most highly correlated with returns on six hedge fund portfolios.

VIX also has relatively high correlation with performance of the six hedge fund portfolios. High correlation-coefficients associated with equity market-related returns and VIX indicate that investment decisions of hedge funds are basically made based on equity market conditions or movements. As a bond-oriented risk factor, the credit spread factor exhibits correlation-coefficient around -0.5 over the six hedge fund portfolios, and -0.65 for returns on RV. The highly correlated relationship between the credit spread factor and returns on RV can be attributed to investment strategy of RV that maintains a certain level of return and minimizes exposure to risk.

Other than equity market- and bond-related risk factors, size premium factors show somewhat high correlation, especially with SS portfolio returns. Based on the results of correlation analysis, we may have a rough idea of what sort of risk factors hedge funds are exposed to. For example, equity market-related risk factors are readily expected to account for significant part of hedge fund exposure with high correlation-coefficients, which would be proven by high adjusted r-squared statistics. However, it is possible that contribution of each risk factor to the exposures of six different hedge fund portfolios may vary due to the different investment strategies of hedge funds.

1.5.2 Time-varying OLS Regression Analysis of a Single-factor Model

The goal of this study is to find appropriate risk factors underlying the performance of hedge funds with different investment strategies and to show that traditional capital asset pricing model assuming static or buy-and-hold investment strategy is not a good method for such a task. In order to select those risk factors, we run single-factor regression analysis for all available factors. Furthermore, we apply time-varying concept to the regression analysis to reflect dynamic property of hedge funds in the model. Since determination of window size in time-varying analysis has been under debate, we utilize two different window sizes, 24 and 36 months.

Table 5 reports average coefficients of risk factors and average adjusted r-squared statistics over the time frames, as well as number of time frames during which the coefficient of each variable is significant at 5% significance level from time-varying OLS regression analysis of a single-factor model. Comparing the results from models of 24- and 36-month windows, selection of appropriate risk factors would not significantly differ, so that interpretation of Table 5 would be focused on the results from analysis of 24-month window. Most of all, equity market-related factors, which take account for majority of hedge fund exposure, exhibit almost identical results in the average coefficients, adjusted r-squared statistics, and number of time frames significant from both window sizes. AG, DT and FoF portfolios are most exposed to emerging market movements. Emerging market index significantly explains variance in performance of these hedge funds over all time frames, and shows substantially high adjusted r-squared statistics. Similarly, RV, SS and MP portfolios are most exposed to Fama and French's market risk premium factor compared to other risk factors. Compared to other investment strategies, however, RV more likely pursuing stable income shows the lowest sensitivity to the change in market risk premium factor along with relatively low adjusted r-squared statistics. As the first factor to which hedge funds are primarily exposed, therefore, we select emerging market index for AG, DT and FoF portfolios, and Fama and French's market risk premium for RV, SS and MP portfolios among equity market-related risk factors.

VIX is the second most powerful risk factor to explain performance and exposure of hedge fund portfolios. Since VIX increases as market uncertainty increases. As investors turn into a pessimistic view about market, it is inversely related with hedge fund performance. While all hedge fund portfolios are significantly exposed to VIX over the majority of time frames, only RV is relatively less sensitive to the change in VIX. Instead, RV is most significantly exposed to credit spread factor with the highest adjusted r-squared statistics, 0.21. What we need to be cautious is that due to the property of VIX measuring investor sentiment about equity markets and relatively high correlation (from -0.52 to -0.65) with equity market related factors, use of VIX and equity market-related factor simultaneously in the same model may lead to a biased result and multicollinearity. Based on the average adjusted r-squared statistics and the number of time frames when hedge funds are significantly exposed to each risk factor, we select six risk factors. All hedge fund portfolios are exposed to very similar set of risk factors, but degree of those factors to which each portfolio is exposed may somewhat differ by investment strategy of hedge funds.

1.5.3 Stability Test for Hedge Fund Exposure to the Selected Risk Factors

We utilize time-varying analysis to point out the weakness of traditional capital asset pricing model with implicit assumption of static investment strategy. We expect that the coefficients estimated by time-varying model must be unstable because of active management of hedge funds, so that coefficients estimated from the traditional capital asset pricing model should be biased.

Figure 1 and 2 plot time-varying coefficients of equity market-related risk factors for six different hedge fund portfolios from a time-varying single-factor regression analysis with 24- and 36-month windows, respectively. For both sizes of window, we observe instability of coefficients that appear to have been fluctuating a lot over sample period. In case of coefficients for emerging market index, coefficients are more fluctuating around the periods of Asian

Financial Crisis in 1997 and Dot-com Bubble Burst, and both of market risk premium and emerging market index are critically affected by the U.S. Financial Crisis in 2008.

To formally test time-varying coefficients, we employ two different methods. First, we run a regression of time-varying coefficients against their corresponding time periods. We have 157 (145) of β_i from time-varying regression analysis with 24 (36)-month window of equation (1). Then, we can define first 24-month as T=1, second 24-month as T=2, and so on. The regression model to test stability of coefficients would be:

$$\beta_{iT} = C + T + T^2 + \varphi$$

T is sequence of window from 1 to 157 for 24-month window and from 1 to 145 for 36-month window. β_{iT} is coefficient at each sequence. If β_{iT} is stable over time, T and T^2 must be insignificant and be zero. However, if T and/or $T^2$are significant, β_{iT} is regarded as having a certain pattern on the change in time. Then, we can reach a conclusion that time-varying coefficients of corresponding risk factor are unstable, so that traditional capital asset pricing model is inappropriate to estimate dynamic hedge fund performance.

Table 6 reports the results of the regression analysis of time-varying coefficients of equity market-related risk factor against time, T. With a single exception of coefficients for DT, all time-varying coefficients of both 24- and 36-month windows for hedge fund portfolios exhibit linear and quadratic relationships with time, T. Even DT, the only exception, also shows a linear relationship. Even though coefficients of T and T^2 are very low, they are significantly different from zero so that β_{iT}s in every sequence are also significantly different from each other. It indicates that those coefficients have a significant pattern on time, and therefore, we may consider the time-varying coefficients to be instable over time.

As a second approach to prove instability of time-varying coefficients for a single-factor regression analysis, we utilize the method of recursive residuals. Recall our single-factor regression model of equation (1): $R_{it} - R_{ft} = \alpha_i + (R_{mt} - R_{ft})\beta_i + \varepsilon_{it}$, and substitute $R_{it} - R_{ft}$ with y_t and $R_{mt} - R_{ft}$ with x_t. Then, we have a standard simple linear regression model: $y_t = \beta \cdot x_t + \varepsilon_t$, where $\varepsilon_t \sim iid\ N(0, \sigma^2)$ and t=1, …, T. Unlike traditional capital asset pricing model that estimates the model using all sample period at a time, we estimate with the first k observations, $k+1$ observations, and so on. Because we estimate a single-factor regression analysis, $k=1$. Then, this procedure end up with recursive coefficients, $\hat{\beta}_t$. At each time period t, $t=k, \ldots, T-1$, we can forecast the next time period $t+1$, and can express as: $\hat{y}_{t+1,t} = \hat{\beta}_t \cdot x_{t+1}$. The forecasting errors or recursive residuals are also expressed as: $\hat{e}_{t+1,t} = y_{t+1} - \hat{y}_{t+1,t}$. The variance of the recursive residuals changes as the number of observations increase from k through T, because the model is estimated more precisely as the sample size increases. The recursive residuals are reported in the form of graph with two standard error bands. The recursive residuals out of the bands indicate instability of coefficients.

Other than the recursive residuals, we can consider the standardized recursive residuals as: $w_{t+1,t} \equiv \frac{\hat{e}_{t+1,t}}{\sigma\sqrt{r_t}}$, where $t=k, \ldots, T-1$. The cumulative sum (CUSUM) of the standardized recursive residuals is one of the methods to test parameter stability using the standardized recursive residuals. Because $w_{t+1,t} \sim iid\ N(0,1)$, CUSUM is just a sum of $iid\ N(0,1)$ random variables, and express as $CUSUM_t \equiv \sum_{\tau=k}^{t} w_{\tau+1,\tau}$, $t=k, \ldots, T-1$. CUSUM is reported with its 95% probability bounds in the graph. CUSUM out of the bounds indicates evidence of parameter instability.

Figure 3 displays results of stability tests of coefficients for equity market-related risk factors using recursive residuals. Each row of figures includes figures of recursive residuals, the CUSUM of the standardized residuals and CUSUM of squares from a single-factor regression analysis, respectively. Looking at the figures in the first row for aggregate hedge fund portfolio, recursive residual, CUSUM and CUSUM of squares mostly stay within the 95% critical bounds. However, we can observe some time periods where those statistics goes out of the boundaries. Those periods include Asian Financial Crisis in 1997-1998, Dot com bubble around 2000, and U.S. Financial Crisis in 2008 triggered by Lehman Brothers. In the figure of CUSUM, we can also observe CUSUM that starts sharply declining since 2000 and that finally get out of lower bound in 2008. It may be a partial evidence enough to say that regression coefficients are instable over the time periods.

Specifically, figures of DT portfolio are very similar to those of aggregate hedge fund portfolio with movements of recursive residuals, CUSUM and CUSUM of squares. However, the rest of figures show different shape of movements in those statistics. Recursive residual in RV portfolio maintains relatively narrow 95% critical bounds, and shows greater jumps out of bounds around 1998 and 2008. CUSUM of squares stays out of bound all the way from 1997 to 2008. These indicate that regression coefficients for RV portfolio are instable over the majority of sample periods. Figures of SS portfolio commonly exhibit violations of bounds around periods of Dot com bubble burst between 2000 and 2003. It shows that during that period SS portfolio has substantially changed its exposure to equity market-related risk factors. In the figures of MP and FoF portfolios, we can observe violations of bounds during critical financial events that substantially affect global economy. All these figures commonly indicate that hedge fund portfolios with different strategies more actively respond and change their risk exposure to events by which global economies are severely affected. With globalization of the world economy, those events will occur more frequently in the future. Thus, the tendency of hedge funds actively responding to such events becomes more remarkable, and so does instability of regression coefficients.

With results of the two methods examining stability of regression coefficients from traditional capital asset pricing model, we can conclude that the coefficients are instable, especially when an event that affects global economy happens. In addition, with a recent pattern in global economy, highly developed investment techniques and hedge funds' active management of exposure to risk factors, the stability of regression coefficients from the model is more likely to be deteriorated in the future. Therefore, time-varying regression model is more efficient to capture dynamic management style of hedge funds and to measure hedge fund exposure to risk factors.

1.5.4 Selection of Optimal Multi-factor Time-varying Model

In the section 5.2, six risk factors by investment strategy of hedge funds are selected based on the average adjusted r-squared statistics and the number of time frames when hedge funds are significantly exposed to each risk factor from the single-factor time-varying regression analysis. In this section, we need to find the best combination of those risk factors that most optimally explains performance of hedge fund portfolio with different investment strategy. Thus, we conduct multi-factor time-varying regression analysis with combination of the selected risk factors in section 5.2. The combinations of risk factors consist in the way of adding a factor to the most powerful factor(s).

Table 7 reports coefficients (mean, median, minimum and maximum) of the selected risk factors and adjusted r-squared statistics from the multi-factor (two to six) time-varying regression analysis. We select best combination of risk factors based on the number of factors in the model, the average adjusted r-squared statistics and the number of time frames with above 70% adjusted r-squared statistics. Thus, the best combination would most explain performance and risk exposure of hedge fund portfolio in the most stable manner.

In Table 7(A) summarizing the results of the regression analysis of aggregate (AG) hedge fund portfolio, we first observe coefficients of VIX and size spread factor (SCLC) that are ranged from positive to negative, indicating hedge funds' exposure to those risk factors varies by market condition. Approximately 75% of variation in the performance of aggregate hedge fund portfolio is explained by two-factor model and approximately 80% by six-factor model. As the number of factors to be considered increases, the average adjusted r-squared statistics and number of time frames with adjusted r-squared statistics greater than 70% also increase. Adding three more risk factors to the two-factor model, the explanatory power of the model improves almost to 80% with 135 time frames out of 157 where r-squared statistics are greater than 70%. Even though the six-factor model has slightly greater r-squared statistics, it doesn't seem to be as big as to add additional risk factor. For AG portfolio, therefore, we have an optimal combination of five risk factors: emerging market equities, VIX, SCLC, credit spread factor, and HML.

In Table 7(B) summarizing the results of the regression of DT portfolio, r-squared statistics appear to be higher than those of aggregate hedge fund portfolio. Even two-factor model explains 80% of variation in the performance of DT portfolio, and by adding additional factors the explanatory power improves up to approximately 84%. Similarly, results of the regression analysis of SS portfolio in Table 7(D) exhibit that approximately 83% of variation in the portfolio's performance is explained by two-factor model and 87% of variation by six-factor model. Especially, five-factor model of SS portfolio explains at least 70% of variation over all of

157 time frames, representing that the model has a great stability in explanatory power. It can be attributed to investment strategies of DT and SS portfolios that mostly rely on the equity market movements. On the contrary, results in Table 7(C) display relatively low r-squared statistics ranging from about 47% for two-factor model to about 54% for six-factor model. The number of time frames with r-squared statistics greater than 70% also very low. Because RV portfolio takes positions maintaining certain level of spread to minimize risk or market exposure, RV portfolio puts relatively greater weight on credit-related financial assets. In fact, RV portfolio exhibits lower coefficients for equity market variable, indicating less exposure to equity market movements than hedge fund portfolios with other investment strategies, whereas RV portfolio exhibits substantially high sensitivity to credit spread factor relying on the movements of credit-related financial assets. For MP and FoF portfolios, the multi-factor models in Table 7(E) and 7(F) account for approximately 70% of variation. The optimal combinations of risk factors for each investment strategy of hedge fund portfolio are summarized in Table 8.

Table 9 reports paired t-test results to compare explanatory power of the selected model with ABS-factor model, SAC-factor model and Four-factor model. Mean deference of most pairs are positive and significant, indicating that explanatory power of the selected model is greater than those of the existing models. Considering smaller number of factors in the selected model than ABS- and SAC-factor models, it appears that customized model by investment strategy of hedge funds is very effective in improving explanatory power and stability of the model. In some parts, we can observe negative difference, but none of them is significant at 5% significance level. Moreover, mean difference between the optimal model and SAC-factor model appears to be relatively small, so that SAC-factor model can be considered to be almost as good as the selected model, or better than other two models. However, we must not miss that fact that SAC-factor model simultaneously includes U.S. equity, Non-U.S. equity, and emerging market equity leading to multicollinearity problem. The selected model provides much more reliable measure of dynamic hedge fund performance and stable, improved explanatory power.

1.6 Conclusion

In this study, we make several attempts to find the best customized models to optimally estimate dynamic performance and exposures of hedge funds by their investments strategies. First, we handle two types of biases: survivorship bias and instant history bias. We simply combine active and inactive hedge fund data to handle survivorship bias, and exclude first 12-month return data for hedge funds that started reporting since 1993 to handle instant history bias. Comparing returns on hedge funds before and after handling biases, we find significant upward bias from both.

Second, we conduct time-varying single-factor regression analysis using the risk factors in the previous models, and select six factors that most explain variance in hedge fund performance by investment strategy. Then using the selected risk factors from time-varying single-factor regression analysis, we conduct multi-factor time-varying regression with combinations of the factors. We find the best combinations, by investment strategy of hedge fund portfolio, with consideration of the adjusted r-squared statistics and number of time frames where adjusted r-squared statistics are greater than 70%. The optimal models consisting of the best combination exhibit greater and more stable explanatory power than the existing models, which is proven by the mean comparisons of time-varying adjusted r-squared statistics over time periods.

With the empirical results, we make the following contribution to the existing literature. First, we provide evidence that FoF portfolio itself cannot be a method to handle biases caused in data collection process, which is inconsistent with Fung and Hsieh (2002a). Our findings reveal that like individual hedge funds, funds of hedge funds are also exposed to the potential risk of those biases. We can apply the same methods for FoF portfolio to handle biases: combining active and inactive data, and excluding first 12-month data.

Second, we prove that hedge funds are managed in an active and dynamic manner responding to the changes in market conditions, so that it is inappropriate to estimate hedge fund performance and exposure to risk factors with existing models assuming static or buy-and-hold investment strategy. Employing time-varying concepts would be the best way to reflect dynamic feature of hedge funds in the model measuring hedge fund performance and exposures.

Third, we find the optimal models that most explain hedge fund performance and exposure to risk factors by investment strategy. The optimal models with fewer factors exhibit greater explanatory power than existing models, and time-varying analysis would make the models more stable and credible in estimating active and dynamic management of hedge funds. In addition, by differing combination of factors in each model by investment strategy of hedge fund, we can make the models more elaborate and have better insight into management of hedge funds, which exhibit extremely different pattern of performance depending on market condition. We believe that our model customized to the specific investment strategy would be very useful for both academic and practical views.

Table 1.1 Descriptive Statistics for the Returns on Hedge Fund Portfolios and Risk Factors

This table reports summary statistics including mean, standard deviation, skewness, kurtosis, and Jarque-Bera statistics as well as Sharpe ratios for the monthly returns on hedge fund portfolios and on risk factors. Sharpe ratio is a change in an average excess return against a unit change in risk (standard deviation). Jarque-Bera normality test is asymptotically distributed as a central χ^2 with two degrees of freedom under the null hypothesis with 5% critical value 5.99. '*' denotes significance at the 5% level.

For Panel A, each portfolio is an equally weighted average of individual hedge fund returns with corresponding investment strategy with exceptions of the aggregate hedge fund return consisting of all hedge fund returns and fund of hedge funds return. The four hedge fund investment strategies follow suggestion of Agarwal et al. (2009). Directional Traders mostly predict the direction of market price movements of currencies, commodities, equities, and bonds in the futures and cash market, and based on their analyses, perform investment. Emerging markets, Macro, Market timing, Foreign exchange, Sector, and Short Bias/Selling are included in Directional Trading. Relative Value focuses on spread relationships between prices of assets to minimize exposure to risk factors. It does include Arbitrages (Convertible/Merger Arbitrages), Market neutral, Fixed income, and Long-short credit. Security Selection mainly focuses on reducing the systematic risk in the process by taking long and short positions in undervalued and overvalued securities, respectively. It does include Equity hedge/non-hedge, Long/short equity hedge, Global, No bias, and Variable bias. Multi-process involves multiple strategies performed by the hedge funds. Those hedge funds usually invest in the opportunities created by significant transaction events, such as mergers & acquisitions, spin-offs, bankruptcy reorganizations, recapitalizations, and share buybacks. Multi-process does includes Event driven, Distressed securities, and Multi-strategy.

For Panel B, table includes seven Asset-based style (ABS) factors suggested by Fung and Hsieh (2004a), and eight Standard asset class factors suggested by Fung and Hsieh (1997a). In addition, additionally included are Fama and French (1993)'s three factors along with Carhart (1997)'s momentum, DeBondt and Thaler (1985)'s contrarian strategy, and volatility index for investor sentiment.

Panel A: Returns on hedge fund portfolios

Fund Type	Active(%) /Inactive(%)	Return					Sharpe Ratio	Skewness	Kurtosis	Jarque-Bera
		Mean	Std. Dev	Median	Max	Min				
AG	2,556/3,786	0.87*	2.19	1.05	7.80	-8.58	0.26	-0.90	6.75	129.68*
DT	868(34)/771(20)	0.92*	3.01	1.32	9.90	-13.44	0.20	-0.96	6.57	122.95*
RV	341(13)/713(19)	0.61*	1.15	0.76	2.18	-7.91	0.26	-3.24	21.81	2969.31*
SS	1,030(40)/1,275(34)	1.00*	2.72	1.18	10.63	-9.42	0.25	-0.21	4.81	25.93*
MP	317(12)/1,027(27)	0.84*	1.70	0.99	6.41	-6.90	0.31	-0.97	7.96	212.60*
FoF	1,970/1705	0.55*	1.74	0.66	6.19	-7.03	0.14	-0.96	7.35	169.14*

Panel B: Returns on risk factors

Asset Class	Return					Sharpe Ratio	Skewness	Kurtosis	Jarque-Bera
	Mean	Std. Dev	Median	Max	Min				
PTFSBD	-0.80	14.89	-3.70	68.86	-25.36	-0.07	1.42	5.87	122.33*
***PTFSCOM**	0.20	14.03	-2.51	64.75	-23.04	0.04	1.26	5.48	93.40*
PTFSFX	0.85*	19.91	-2.82	90.27	-30.13	-0.01	1.34	5.62	105.58*
S_P	0.52	4.46	1.18	12.05	-18.20	0.05	-0.90	5.16	59.01*
SC_LC	-0.04*	3.65	0.04	17.61	-21.88	-0.10	-0.57	11.65	571.09*
D_10Y	-0.02*	0.28	-0.02	0.95	-1.08	-1.19	-0.04	4.23	11.40*
D_CREDSPR	0.02*	0.20	0.01	1.53	-0.44	-1.43	2.72	19.95	2376.99*
USEQ	0.53*	4.58	1.20	10.68	-18.53	0.05	-1.02	5.25	69.19*
NONUSEQ	0.34	4.74	0.92	10.26	-22.93	0.01	-1.19	6.11	115.12*
EMF	0.23*	7.19	0.93	12.63	-34.13	-0.01	-1.28	6.37	133.92*

USGB	0.54*	1.38	0.65	6.26	-4.59	0.17	-0.04	4.86	26.10*
NONUSGB	0.54	2.44	0.55	7.99	-5.62	0.09	0.20	3.46	2.75
EURODOLLAR	0.35*	0.15	0.42	0.59	0.08	0.29	-0.56	1.92	18.07*
GOLD	0.44	4.39	-0.17	18.84	-18.76	0.03	0.05	5.94	65.00*
USDOLLAR	-0.07*	1.69	0.13	6.49	-4.79	-0.23	-0.04	3.85	5.42
MKT_RF	0.31*	4.48	1.01	8.18	-18.54	0.07	-0.99	4.77	52.97*
SMB	-0.08*	3.79	-0.19	13.81	-22.19	-0.10	-1.16	10.75	490.70*
HML	0.47	3.42	0.34	13.84	-9.95	0.05	0.56	5.69	63.64*
MOM	0.87	5.06	0.77	18.39	-25.03	0.11	-0.56	7.73	176.96*
CONTRARIAN	0.37	4.13	0.19	16.27	-14.51	0.01	0.17	7.12	128.38*
VIX	0.98*	17.39	-0.29	64.58	-39.55	0.04	0.60	3.82	15.68*

Table 1.2 Control for Biases: Instant History and Survivorship Biases

This table reports mean returns on hedge fund portfolios for various investment strategies and comparison results before and after controlling for either or both of instant history bias or/and survivorship bias. The three columns under (B) are controlled for instant history bias, columns under "Alive (or Dead)" denote mean returns of active (or inactive) hedge fund portfolios, and columns under "All" (both 3 and 6) denote hedge fund returns that are controlled for survivorship bias. Therefore, the column under (B) and "Alive" denotes hedge fund returns controlling for only instant history bias; the column under (A) and "All" denotes hedge fund returns controlling for only survivorship bias; the column under (B) and "All" denotes hedge fund returns controlling for both instant history and survivorship bias; and the column under (A) and "Alive" denotes hedge fund returns controlling for no bias. Columns (C), (D), and (E) include differences in mean returns between portfolios controlling and not controlling for instant history bias, for survivorship bias, and for both biases. The figures in the parentheses are t-statistics, and '*' denotes significance at the 5% level.

	(A) Instant history bias			(B) No Instant history bias			(C) Controlling for instant history bias only	(D) Controlling for survivorship bias only	(E) Controlling for both biases
	(1) Alive	(2)Dead	(3)All	(4)Alive	(5)Dead	(6)All	(1)-(4)	(1)-(3)	(1)-(6)
AG	1.0472	0.8212	0.9639	0.9397	0.7379	0.8706	0.1075*	0.0832*	0.1766*
							(9.1483)	(3.8543)	(8.5297)
DT	1.2247	0.8574	1.0713	1.0323	0.7347	0.9189	0.1924*	0.1533*	0.3058*
							(5.2066)	(3.6557)	(6.6755)
RV	0.6906	0.5963	0.6802	0.6225	0.5304	0.6128	0.0681*	0.0104	0.0778*
							(5.7452)	(0.4531)	(3.2007)
SS	1.1337	0.9725	1.0975	1.0370	0.8794	0.9975	0.0968*	0.0362	0.1362*
							(5.9609)	(1.0865)	(3.8048)
MP	0.9119	0.8102	0.9062	0.8598	0.7513	0.8401	0.0522*	0.0058	0.0719
							(3.1714)	(0.1169)	(1.4318)
FOF	0.6044	0.5028	0.5709	0.5837	0.4800	0.5506	0.0207*	0.0335*	0.0539*
							(2.4922)	(3.2378)	(3.9553)

Table 1.3 Clustering and Correlation-coefficients between Monthly Returns on Risk Factors

This table reports the Pearson correlation-coefficients between risk factors and groups of those risk factors from clustering based on the Pearson correlation-coefficients.

The twenty one risk factors are clustered into fifteen groups. Risk factors clustered in the same group, especially, those that proxy for equity markets, are highly correlated with each other, the correlation coefficients that are ranged from 0.69 to 0.98. Employing variables highly correlated with each other as independent variables in the same model tends to increase the possibility of mulitcollinearity, and lead to biased conclusion. Therefore, we choose only one risk factor from those factors clustered into the same group based on correlation-coefficients. Other than equity markets proxies, Fama and French (1993)'s size premium and Fung and Hsieh (2004)'s size spread factor, as well as returns on the U.S. Government Bonds and non-U.S. Government Bonds are clustered into the same group, respectively. '**' and '*' denotes significance at the 1% and 5% level, respectively.

Group	Risk Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
1	MKT_RF																				
1	S_P	0.91**																			
1	USEQ	0.93**	0.98**																		
1	NONUSEQ	0.83**	0.82**	0.81**																	
1	EMF	0.78**	0.69**	0.72**	0.79**																
2	SMB	0.18*	0.09	0.10	0.18*	0.28**															
2	SC_LC	0.18*	0.05	0.06	0.21**	0.27**	0.54**														
3	HML	-0.41**	-0.33**	-0.36**	-0.26**	-0.31**	-0.45**	0.00													
4	MOM	-0.23**	-0.32**	-0.29**	-0.19*	-0.20**	-0.08	0.08	0.04												
5	CONTRARIAN	0.29**	0.36**	0.34**	0.23**	0.25**	0.25**	-0.02	-0.16*	-0.35**											
6	PTFSBD	-0.17*	-0.11	-0.13	-0.15*	-0.20**	0.00	-0.08	-0.08	-0.05	0.05										
7	PTFSCOM	-0.15*	*-0.15*	-0.14*	-0.10	-0.14	-0.03	-0.02	-0.01	0.19*	-0.09	0.18*									
8	PTFSFX	-0.19*	-0.14	-0.17*	-0.18*	-0.21**	0.00	0.02	0.05	0.10	-0.11	0.19*	0.36**								
9	D_10Y	0.14	0.10	0.09	0.15*	0.19**	0.23**	0.18*	-0.12	-0.18*	0.03	-0.15*	-0.09	-0.13							
10	D_CREDSPR	-0.50**	-0.49**	-0.48**	-0.56**	-0.53**	-0.32**	-0.25**	0.15*	0.28**	-0.24**	0.16*	0.22**	0.30**	-0.49**						
11	USGB	-0.16*	-0.13	-0.12	-0.18*	-0.20**	-0.20**	-0.21**	0.08	0.10	0.01	0.13	0.03	0.11	-0.94**	0.47**					
11	NONUSGB	-0.01	0.00	0.00	0.20**	0.00	0.00	-0.01	-0.05	0.01	0.06	0.14	0.07	0.20**	-0.48**	0.18*	0.48**				
12	EURODOLLAR	0.07	0.11	0.11	0.00	-0.09	-0.17*	-0.13	0.00	0.08	-0.08	-0.04	-0.03	-0.03	-0.03	0.11	0.07	-0.09			
13	GOLD	0.08	0.02	0.03	0.23**	0.25**	0.13	0.21**	0.00	0.13	-0.01	0.00	0.22**	0.02	-0.16*	-0.08	0.12	0.36**	-0.13		
14	USDOLLAR	-0.22**	-0.20**	-0.22**	-0.33**	-0.28**	-0.15*	-0.08	0.13	0.08	-0.18*	0.01	0.08	-0.06	0.10	0.17*	-0.08	-0.53**	0.16*	-0.23**	
15	VIX	-0.65**	-0.56**	-0.57**	-0.52**	-0.54**	-0.11	-0.14	0.22**	0.12	-0.21**	0.26**	0.09	0.22**	-0.12	0.34**	0.14	0.15*	0.04	-0.02	0.04

Table 1.4 Correlation-coefficients between Monthly Returns on Hedge Fund Portfolios and Risk Factors

This table reports correlation-coefficients between monthly returns on hedge fund portfolios by investment strategies and risk factors for the period from January 1994 to December 2008. Groups are determined by clustering based on the Pearson correlation-coefficients. Risk factors in the same groups are likely to be highly correlated each other so that only one among those in the same groups is to be included into the model. Investment strategies for hedge fund portfolios are categorized by the four broad investment strategies (Directional Traders, Relative Value, Security Selection, and Multi-Process), the suggestion of Aggarwal et al. (2009), as well as by general big categories, hedge funds and fund of hedge funds. ‘**’ and ‘*’ denotes significance at the 1% and 5% level, respectively.

Group		Agg. Hedge Funds	Directional Traders	Relative Value	Security Selection	Multi-process	Fund of Funds
1	MKT_RF	0.84**	0.80**	0.66**	0.86**	0.76**	0.69**
1	S_P	0.71**	0.68**	0.60**	0.72**	0.63**	0.56**
1	USEQ	0.73**	0.70**	0.61**	0.74**	0.65**	0.58**
1	NONUSEQ	0.76**	0.74**	0.63**	0.75**	0.69**	0.65**
1	EMF	0.81**	0.88**	0.60**	0.76**	0.72**	0.72**
2	SMB	0.24**	0.23**	0.14	0.28**	0.22**	0.19*
2	SC_LC	0.34**	0.29**	0.20**	0.39**	0.33**	0.28**
3	HML	-0.30**	-0.31**	-0.08	-0.36**	-0.23**	-0.19*
4	MOM	-0.02	-0.04	-0.06	-0.01	0.02	0.11
5	CONTRARIAN	0.16*	0.16*	0.23**	0.14	0.16*	0.08
6	PTFSBD	-0.20**	-0.22**	-0.24**	-0.16*	-0.23**	-0.24**
7	PTFSCOM	-0.13	-0.13	-0.20**	-0.10	-0.13	-0.08
8	PTFSFX	-0.16*	-0.16*	-0.24**	-0.11	-0.14	-0.12
9	D_10Y	0.14	0.14	0.08	0.14	0.13	0.11
10	D_CREDSPR	-0.52**	-0.50**	-0.65**	-0.45**	-0.51**	-0.50**
11	USGB	-0.14	-0.13	-0.08	-0.15*	-0.13	-0.11
11	NONUSGB	-0.03	-0.06	-0.04	-0.03	-0.02	-0.09
12	EURODOLLAR	0.15*	0.08	0.22**	0.16*	0.17*	0.18*
13	GOLD	0.18*	0.21**	0.16*	0.14	0.14	0.19*
14	USDOLLAR	-0.18*	-0.17*	-0.21**	-0.15*	-0.19	-0.14
15	VIX	-0.51**	-0.51**	-0.40**	-0.52**	-0.44**	-0.42**

Table 1.5 Results from the Single-factor Time-varying Regression Model by Investment Strategies and Size of Window

This Table reports (1) average coefficients, (2) average adjusted R-squared statistics, and (3) number of time frames during which the coefficient of each variable is significant at 5% significance level, from single-factor time-varying regression model. Full sample periods are ranged from January 1994 to December 2008. The time-varying regression analyses are performed with 24 months and 36 months of window sizes. We select variables that are to be applied for multi-factor time-varying regression model based on the number of time frames during which variable is significant and average adjusted R-squared values. Risk factors clustered in the same group cannot be chosen into the model as independent variables to avoid multicollinearity problem and redundancy. The number of time frame with significant coefficient at 5% significance level is given more weight than the adjusted R-squared statistics. **Figures in bold** indicate the selected risk factors based on (2) and (3).

		(A) 24M						**(B) 36M**					
		AG	DT	RV	SS	MP	FoF	AG	DT	RV	SS	MP	FoF
USEQ	(1)	0.3552	0.4791	0.1092	0.4747	0.2282	0.2176	0.3525	0.4812	0.1064	0.4696	0.2269	0.2159
	(2)	0.5014	0.4653	0.2860	0.5205	0.3722	0.3140	0.5138	0.4832	0.2879	0.5338	0.3807	0.3215
	(3)	157	155	142	157	154	145	145	145	145	145	145	145
NonUSEQ	(1)	0.3599	0.4846	0.1085	0.4730	0.2418	0.2430	0.3630	0.4919	0.1097	0.4761	0.2451	0.2394
	(2)	0.5945	0.5494	0.3323	0.6056	0.4812	0.4543	0.6093	0.5669	0.3462	0.6187	0.4956	0.4569
	(3)	157	152	144	157	156	148	145	144	142	145	145	144
EMF	(1)	**0.2459**	**0.3683**	0.0712	0.3048	0.1590	**0.1740**	**0.2455**	**0.3674**	0.0721	0.3047	0.1591	**0.1674**
	(2)	**0.7037**	**0.7943**	0.3733	0.6403	0.5340	**0.5955**	**0.7160**	**0.8041**	0.3887	0.6544	0.5443	**0.5839**
	(3)	**157**	**157**	155	157	157	**157**	**145**	**145**	145	145	145	**145**
sp	(1)	0.3540	0.4766	0.1105	0.4728	0.2265	0.2165	0.3530	0.4827	0.1073	0.4700	0.2264	0.2149
	(2)	0.4723	0.4399	0.2751	0.4912	0.3456	0.2940	0.4877	0.4607	0.2752	0.5062	0.3566	0.3007
	(3)	157	150	142	157	153	144	145	145	145	145	145	145
mktf	(1)	0.4046	0.5319	**0.1248**	**0.5430**	**0.2682**	0.2603	0.3987	0.5305	**0.1216**	**0.5335**	**0.2649**	0.2547
	(2)	0.6973	0.6113	**0.3956**	**0.7363**	**0.5549**	0.4626	0.7014	0.6266	**0.3950**	**0.7399**	**0.5542**	0.4671
	(3)	157	157	**156**	**157**	**157**	154	145	145	**145**	**145**	**145**	145
sclc	(1)	**0.2691**	**0.3059**	**0.0734**	**0.3896**	**0.1829**	**0.1649**	**0.2644**	**0.3006**	**0.0739**	**0.3787**	**0.1805**	**0.1673**
	(2)	**0.2273**	**0.1533**	**0.1005**	**0.2734**	**0.1916**	**0.1713**	**0.2166**	**0.1469**	**0.1015**	**0.2611**	**0.1804**	**0.1660**
	(3)	**125**	**93**	**71**	**138**	**134**	**114**	**138**	**102**	**110**	**141**	**139**	**117**
smb	(1)	0.2641	0.2990	0.0768	0.3782	0.1856	0.1639	0.2514	0.2887	0.0755	0.3555	0.1736	0.1580
	(2)	0.2213	0.1452	0.1012	0.2631	0.2023	0.1537	0.2010	0.1335	0.1008	0.2408	0.1797	0.1386
	(3)	111	91	69	121	115	88	103	91	81	108	103	85
USGB	(1)	-0.2443	-0.3186	-0.0883	-0.3114	-0.1513	-0.1535	-0.2627	-0.3539	-0.0876	-0.3347	-0.1633	-0.1554
	(2)	0.0341	0.0265	0.0500	0.0465	0.0203	0.0177	0.0246	0.0155	0.0319	0.0382	0.0103	0.0063
	(3)	38	30	41	45	32	30	32	30	28	52	22	21
NonUSEGB	(1)	-0.0482	-0.1064	-0.0347	-0.0360	-0.0171	-0.0727	-0.0512	-0.1143	-0.0354	-0.0357	-0.0206	-0.0742
	(2)	-0.0033	0.0156	0.0245	-0.0107	0.0180	0.0367	-0.0049	0.0127	0.0351	-0.0143	0.0213	0.0362
	(3)	7	23	43	8	25	44	6	34	57	7	39	43
Eurodollar	(1)	10.3657	10.8810	1.4608	16.8335	5.9389	6.5588	9.3804	9.5663	0.6940	15.7770	5.4535	6.2145
	(2)	0.0174	0.0154	0.0102	0.0224	0.0175	0.0270	0.0313	0.0241	0.0200	0.0377	0.0332	0.0400
	(3)	26	27	16	31	24	39	39	36	27	47	42	49
Gold	(1)	0.0943	0.1275	0.0279	0.1161	0.0703	0.0852	0.0903	0.1203	0.0252	0.1146	0.0659	0.0728
	(2)	0.0501	0.0755	0.0160	0.0370	0.0361	0.0574	0.0507	0.0747	0.0155	0.0376	0.0365	0.0555
	(3)	37	46	30	37	36	47	47	50	34	36	49	52
Usdollar	(1)	-0.1344	-0.1255	-0.0481	-0.1961	-0.1256	-0.0548	-0.1487	-0.1413	-0.0512	-0.2205	-0.1351	-0.0588
	(2)	0.0128	0.0043	0.0460	0.0099	0.0472	0.0264	0.0086	-0.0014	0.0453	0.0082	0.0460	0.0226
	(3)	27	26	31	33	36	31	16	14	40	26	43	29
10y	(1)	1.3513	1.9808	**0.5277**	1.5739	0.8486	0.8611	1.4143	2.0923	0.5164	1.6687	0.8880	0.8464
	(2)	0.0525	0.0504	**0.0696**	0.0601	0.0336	0.0326	0.0350	0.0322	0.0453	0.0451	0.0161	0.0114
	(3)	46	40	**63**	41	38	36	39	49	42	53	20	21
credspr	(1)	**-3.8081**	**-5.3474**	**-1.7007**	**-4.2895**	**-2.9915**	**-3.0709**	**-4.2905**	**-6.0481**	**-1.9484**	**-4.8566**	**-3.3332**	**-3.3337**
	(2)	**0.1650**	**0.1395**	**0.2103**	**0.1574**	**0.1699**	**0.1378**	**0.1690**	**0.1480**	**0.2174**	**0.1578**	**0.1701**	**0.1359**

	(3)	**88**	**80**	**106**	**70**	**99**	**93**	**111**	**106**	**130**	**87**	**118**	**111**
ptbd	(1)	-0.0169	-0.0220	-0.0122	-0.0163	-0.0145	-0.0134	-0.0207	-0.0275	**-0.0135**	-0.0205	-0.0179	-0.0164
	(2)	0.0390	0.0360	0.0604	0.0260	0.0441	0.0351	0.0386	0.0415	**0.0741**	0.0204	0.0493	0.0353
	(3)	31	31	41	32	31	36	47	44	**48**	40	47	43
ptcom	(1)	-0.0106	-0.0144	-0.0054	-0.0147	-0.0066	0.0011	-0.0096	-0.0139	-0.0046	-0.0134	-0.0055	0.0017
	(2)	0.0251	0.0350	0.0073	0.0209	0.0153	0.0253	0.0119	0.0226	0.0007	0.0072	0.0031	0.0125
	(3)	33	39	19	31	31	33	19	31	13	16	13	16
ptfx	(1)	-0.0067	-0.0098	-0.0041	-0.0069	-0.0044	-0.0009	-0.0070	-0.0106	-0.0036	-0.0075	-0.0043	-0.0008
	(2)	0.0083	0.0155	0.0164	0.0033	0.0080	0.0173	0.0031	0.0069	0.0095	-0.0015	0.0063	0.0097
	(3)	23	29	27	18	23	25	14	15	17	8	21	18
hml	(1)	**-0.1844**	**-0.2489**	-0.0103	**-0.2861**	**-0.0968**	-0.0781	**-0.1750**	**-0.2345**	**-0.0105**	**-0.2742**	**-0.0931**	-0.0740
	(2)	**0.1223**	**0.1019**	0.0481	**0.1425**	**0.1079**	0.0565	**0.1215**	**0.1032**	**0.0435**	**0.1463**	**0.1007**	0.0576
	(3)	**75**	**74**	46	**79**	**71**	48	**87**	**88**	**63**	**87**	**81**	66
mom	(1)	**0.0530**	**0.0773**	**0.0276**	**0.0613**	**0.0194**	**0.0761**	**0.0321**	0.0433	0.0161	**0.0380**	0.0127	**0.0633**
	(2)	**0.1312**	**0.1299**	**0.0472**	**0.1428**	**0.0649**	**0.0932**	**0.1005**	0.0981	0.0348	**0.1109**	0.0534	**0.0738**
	(3)	**76**	**66**	**48**	**80**	**54**	**74**	**66**	61	45	**66**	50	**80**
cont	(1)	0.1106	0.1148	0.0362	0.1683	0.0907	0.0445	0.1050	0.1194	0.0365	0.1537	0.0827	0.0423
	(2)	0.0403	0.0300	0.0338	0.0451	0.0447	0.0288	0.0286	0.0208	0.0272	0.0327	0.0326	0.0158
	(3)	38	33	28	43	39	35	46	39	32	49	56	26
vix	(1)	**-0.0608**	**-0.0846**	**-0.0166**	**-0.0818**	**-0.0374**	**-0.0349**	**-0.0632**	**-0.0883**	**-0.0172**	**-0.0850**	**-0.0390**	**-0.0352**
	(2)	**0.2600**	**0.2536**	**0.1139**	**0.2779**	**0.1691**	**0.1575**	**0.2714**	**0.2640**	**0.1226**	**0.2907**	**0.1743**	**0.1533**
	(3)	**139**	**129**	**97**	**143**	**112**	**117**	**142**	**136**	**117**	**143**	**129**	**130**

Table 1.6 Stability Tests for Coefficients of Equity Market-related Risk Factors from Time-varying Single-factor Regression Analysis

This table reports the results from stability tests for coefficients of equity market-related risk factors from time-varying single factor regression analysis. The testing models are $\beta_{iT} = C + T + \varphi$ and $\beta_{iT} = C + T + T^2 + \varphi$, where T denotes sequence of window from 1 to 157 for 24-month window and 1 to 145 for 36-month window, as well as the β_{iT} is coefficient at each sequence."*" indicates significance at the 5% level.

	24M			36M		
	C	T	T^2	C	T	T^2
AG	0.2297*	2.05E-04*		0.2274*	2.49E-04*	
	0.2024*	1.24E-03*	-6.53E-06*	0.2066*	1.10E-03*	-5.81E-06*
DT	0.3910*	-2.87E-04*		0.3901*	-3.11E-04*	
	0.3909*	-2.84E-04*	-2.02E-08	0.3966*	-5.78E-04*	1.83E-06
RV	0.1064*	2.33E-04*		0.1022*	2.66E-04*	
	0.1916*	-2.98E-03*	2.04E-05*	0.1826*	-3.02E-03*	2.25E-05*
SS	0.6206*	-9.83E-04*		0.6022*	-9.41E-04*	
	0.7000*	-3.98E-03*	1.90E-05*	0.6810*	-4.16E-03*	2.20E-05*
MP	0.3002*	-4.05E-04*		0.2992*	-4.70E-04*	
	0.3626*	-2.76E-03*	1.49E-05*	0.3680*	-3.28E-03*	1.92E-05*
FoF	0.1593*	1.85E-04*		0.1473*	2.75E-04*	
	0.2189*	-2.06E-03*	1.42E-05*	0.2063*	-2.13E-03*	1.65E-05*

Table 1.7 Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(A) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on aggregate hedge fund portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	AG	EMF	VIX	SCLC	CRED	MOM	HML	C	Rsq
(1)	Mean	0.2402	-0.0056					0.6512	0.7088
	Median	0.2386	-0.0030					0.4732	0.7357
	Min	0.1469	-0.0432					-0.2981	0.3340
	Max	0.3433	0.0366					1.5030	0.9048
	#Sig.	157	34					107	91
***(2)**	Mean	0.2279		0.1217				0.7085	**0.7499**
	Median	0.2172		0.1126				0.4639	**0.7646**
	Min	0.1399		-0.1207				-0.2925	**0.4380**
	Max	0.3340		0.2785				1.6371	**0.9109**
	#Sig.	157		115				111	**113**
(3)	Mean	0.2387			-0.5588			0.6892	0.7145
	Median	0.2302			-0.8433			0.4527	0.7566
	Min	0.1408			-4.4496			-0.0232	0.3400
	Max	0.3913			6.9998			1.4383	0.9017
	#Sig.	157			44			112	106
(4)	Mean	0.2444				0.0274		0.6198	0.7198
	Median	0.2368				0.0166		0.4722	0.7766
	Min	0.1533				-0.0928		-0.4366	0.3544
	Max	0.3556				0.2065		1.4838	0.8871
	#Sig.	157				29		113	109
(5)	Mean	0.2399					-0.0498	0.6579	0.7272
	Median	0.2376					-0.0150	0.5097	0.7394
	Min	0.1485					-0.3100	-0.3607	0.3503
	Max	0.3934					0.1561	1.5356	0.8895
	#Sig.	157					35	110	94
***(6)**	Mean	0.2199	-0.0058	0.1280				0.6913	**0.7571**
	Median	0.2185	-0.0029	0.1236				0.4666	**0.7564**
	Min	0.0978	-0.0508	-0.1042				-0.3043	**0.4240**
	Max	0.3334	0.0335	0.2786				1.6426	**0.9474**
	#Sig.	157	36	115				105	**114**
(7)	Mean	0.2367	-0.0032		-0.6525			0.6763	0.7216
	Median	0.2297	-0.0011		-0.8586			0.4497	0.7648
	Min	0.1401	-0.0432		-4.9936			-0.0623	0.3487
	Max	0.4050	0.0412		6.6586			1.5033	0.9102
	#Sig.	157	42		43			106	100
(8)	Mean	0.2406	-0.0046			0.0271		0.6073	0.7256
	Median	0.2364	-0.0032			0.0148		0.4654	0.7685
	Min	0.1515	-0.0419			-0.0913		-0.3408	0.3221
	Max	0.3449	0.0407			0.2070		1.5334	0.9053
	#Sig.	157	31			29		107	108
(9)	Mean	0.2371	-0.0040				-0.0509	0.6451	0.7306
	Median	0.2319	-0.0033				-0.0209	0.4718	0.7411
	Min	0.1270	-0.0469				-0.3229	-0.3555	0.3200
	Max	0.3886	0.0369				0.1829	1.5659	0.9012

	#Sig.	157	33				32	106	92
***(10)**	Mean	0.2187	-0.0022	0.1318	0.1406			0.7220	**0.7815**
	Median	0.2106	-0.0009	0.1258	-0.5374			0.4382	**0.7901**
	Min	0.1037	-0.0510	-0.2471	-5.2206			-0.0735	**0.5266**
	Max	0.4105	0.0482	0.2882	8.1095			1.6872	**0.9448**
	#Sig.	157	42	126	64			99	**125**
(11)	Mean	0.2196	-0.0050	0.1277		0.0379		0.6481	0.7687
	Median	0.2164	-0.0023	0.1248		0.0322		0.4581	0.7946
	Min	0.1045	-0.0497	-0.0632		-0.0612		-0.3075	0.4007
	Max	0.3434	0.0390	0.3208		0.1629		1.6076	0.9486
	#Sig.	157	36	102		36		106	116
(12)	Mean	0.2167	-0.0044	0.1199			-0.0360	0.6791	0.7658
	Median	0.2105	-0.0010	0.1161			-0.0081	0.4586	0.7566
	Min	0.0706	-0.0495	-0.1023			-0.2701	-0.3618	0.3950
	Max	0.3715	0.0337	0.2985			0.1825	1.6856	0.9463
	#Sig.	157	37	94			34	101	126
(13)	Mean	0.2140	-0.0018	0.1326	0.0702	0.0465		0.6818	0.7928
	Median	0.2059	-0.0012	0.1258	-0.2248	0.0441		0.4517	0.8183
	Min	0.1022	-0.0506	-0.2095	-5.4772	-0.0677		-0.0568	0.5026
	Max	0.3836	0.0625	0.3348	8.0161	0.1761		1.6445	0.9461
	#Sig.	157	42	106	58	41		101	124
*** (14)**	Mean	0.2102	0.0002	0.1241	0.0792		-0.0576	0.7197	**0.7916**
	Median	0.2081	0.0032	0.1274	-0.5674		-0.0274	0.4211	**0.7911**
	Min	0.0805	-0.0491	-0.1839	-5.3774		-0.2694	-0.1193	**0.5003**
	Max	0.4027	0.0604	0.3261	6.8525		0.1059	1.6894	**0.9473**
	#Sig.	157	41	116	68		41	94	**135**
***(15)**	Mean	0.2061	-0.0010	0.1207	-0.1959	0.0369	-0.0269	0.6762	**0.8035**
	Median	0.1929	-0.0012	0.1267	-0.4126	0.0421	0.0076	0.4300	**0.8181**
	Min	0.0869	-0.0495	-0.1817	-5.2795	-0.0835	-0.2434	-0.1089	**0.4800**
	Max	0.3991	0.0605	0.3381	7.0702	0.1735	0.1872	1.6541	**0.9442**
	#Sig.	157	39	103	59	39	37	97	**134**

Table 1.7 (Continued) Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(B) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on DT portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	DT	**Emf**	**vix**	**sclc**	**cred**	**hml**	**mom**	**C**	**Rsq**
***(1)**	Mean	0.3697	-0.0018					0.6930	**0.8084**
	Median	0.3821	0.0043					0.5401	**0.8088**
	Min	0.2181	-0.0644					-0.2504	**0.5573**
	Max	0.4881	0.0393					1.7220	**0.9363**
	#Sig.	157	63					107	**140**
(2)	Mean	0.3574		0.0748				0.7501	0.8032
	Median	0.3534		0.0802				0.5456	0.8253
	Min	0.2811		-0.2666				-0.1995	0.5071
	Max	0.4908		0.2673				1.7032	0.9185
	#Sig.	157		31				109	139
(3)	Mean	0.3652			-0.5948			0.7578	0.7965
	Median	0.3560			-0.5226			0.5938	0.8159
	Min	0.2588			-6.6748			-0.0427	0.4940
	Max	0.5180			5.0950			1.6246	0.9212
	#Sig.	157			27			113	135
(4)	Mean	0.3654				-0.0308		0.7236	0.7987
	Median	0.3606				-0.0248		0.5505	0.8084
	Min	0.2667				-0.2736		-0.3343	0.5605
	Max	0.5386				0.1946		1.6909	0.9177
	#Sig.	157				20		105	142
(5)	Mean	0.3661					0.0380	0.6703	0.8043
	Median	0.3623					0.0267	0.5738	0.8347
	Min	0.2738					-0.0831	-0.4691	0.4930
	Max	0.4752					0.2218	1.6259	0.9152
	#Sig.	157					37	104	136
***(6)**	Mean	0.3534	-0.0028	0.0888				0.7158	**0.8187**
	Median	0.3687	0.0034	0.0874				0.5459	**0.8287**
	Min	0.1668	-0.0715	-0.2585				-0.2981	**0.5459**
	Max	0.4752	0.0338	0.2706				1.7473	**0.9434**
	#Sig.	157	61	47				99	**142**
(7)	Mean	0.3675	-0.0008		-0.8382			0.7267	0.8130
	Median	0.3696	0.0037		-0.8342			0.5660	0.8241
	Min	0.2187	-0.0644		-6.7767			-0.1119	0.5394
	Max	0.5111	0.0408		4.7347			1.7203	0.9349
	#Sig.	157	68		32			108	139
(8)	Mean	0.3698	-0.0009			-0.0347		0.6920	0.8119
	Median	0.3753	0.0064			-0.0257		0.5517	0.8098
	Min	0.1941	-0.0630			-0.2884		-0.3024	0.5844
	Max	0.5154	0.0427			0.1868		1.7513	0.9332

	#Sig.	157	61			18		104	144
(9)	Mean	0.3695	-0.0010				0.0394	0.6382	0.8186
	Median	0.3767	0.0054				0.0258	0.5351	0.8443
	Min	0.2386	-0.0620				-0.0739	-0.4114	0.5380
	Max	0.4835	0.0390				0.2229	1.7201	0.9334
	#Sig.	157	60				36	100	140
(10)	Mean	0.3525	-0.0012	0.0868	-0.4027			0.7545	0.8259
	Median	0.3541	0.0039	0.0938	-0.2925			0.5627	0.8378
	Min	0.1678	-0.0715	-0.3649	-6.7892			-0.1582	0.5221
	Max	0.5250	0.0400	0.2909	7.3906			1.7529	0.9405
	#Sig.	157	64	58	37			100	140
(11)	Mean	0.3524	-0.0020	0.0844		-0.0223		0.7108	0.8196
	Median	0.3629	0.0061	0.0786		-0.0203		0.5398	0.8252
	Min	0.1068	-0.0667	-0.2579		-0.2515		-0.3480	0.5626
	Max	0.5024	0.0374	0.2648		0.1871		1.7608	0.9628
	#Sig.	157	63	41		18		102	143
***(12)**	Mean	0.3532	-0.0021	0.0870			0.0466	0.6644	**0.8261**
	Median	0.3670	0.0048	0.0781			0.0504	0.5334	**0.8458**
	Min	0.1703	-0.0709	-0.1866			-0.0867	-0.3132	**0.5253**
	Max	0.4822	0.0376	0.3061			0.1715	1.7172	**0.9410**
	#Sig.	157	59	43			32	95	**141**
(13)	Mean	0.3464	0.0000	0.0828	-0.5762	-0.0429		0.7582	0.8260
	Median	0.3441	0.0051	0.0871	-0.1453	-0.0297		0.5723	0.8351
	Min	0.1232	-0.0663	-0.3402	-8.0715	-0.2469		-0.2243	0.5384
	Max	0.5309	0.0399	0.2776	5.9050	0.1392		1.7785	0.9621
	#Sig.	157	63	47	37	16		107	141
***(14)**	Mean	0.3465	-0.0008	0.0861	-0.5189	0.0508		0.7107	**0.8326**
	Median	0.3544	0.0062	0.0807	-0.3497	0.0610		0.5945	**0.8566**
	Min	0.1676	-0.0709	-0.2937	-6.8778	-0.0870		-0.1306	**0.4994**
	Max	0.5250	0.0513	0.3341	7.2632	0.1667		1.7221	**0.9377**
	#Sig.	157	63	48	37	35		99	**139**
***(15)**	Mean	0.3434	-0.0017	0.0742	-1.0075	-0.0061	0.0532	0.6975	**0.8372**
	Median	0.3457	0.0037	0.0786	-0.9442	0.0046	0.0658	0.5952	**0.8598**
	Min	0.1316	-0.0659	-0.3090	-7.9971	-0.2589	-0.1075	-0.2075	**0.5116**
	Max	0.5527	0.0391	0.3180	5.8432	0.2869	0.2151	1.7327	**0.9631**
	#Sig.	157	64	44	34	28	40	108	**141**

Table 1.7 (Continued) Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(C) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on RV portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	RV	**mkt**	**cred**	**vix**	**sclc**	**10y**	**mom**	**C**	**Rsq**
***(1)**	Mean	0.0966	-1.5351					0.3876	**0.4672**
	Median	0.1059	-1.0057					0.3646	**0.4517**
	Min	-0.0045	-5.0119					0.0623	**0.0719**
	Max	0.1985	1.1970					0.9079	**0.8890**
	#Sig.	128	70					128	**11**
(2)	Mean	0.1407		0.0051				0.3346	0.3904
	Median	0.1376		0.0030				0.3173	0.3851
	Min	0.0461		-0.0081				-0.1826	0.0518
	Max	0.3997		0.0371				0.9532	0.7831
	#Sig.	137		9				94	5
(3)	Mean	0.1163			0.0295			0.3534	0.4205
	Median	0.1079			0.0362			0.3399	0.4241
	Min	0.0382			-0.1172			-0.1549	0.0512
	Max	0.3590			0.1080			0.9108	0.8110
	#Sig.	143			46			107	5
(4)	Mean	0.1212				0.2989		0.3564	0.4238
	Median	0.1164				0.0995		0.3401	0.4162
	Min	0.0522				-0.9867		-0.2355	0.0344
	Max	0.3633				1.8672		0.9125	0.8029
	#Sig.	155				55		98	4
(5)	Mean	0.1215					0.0268	0.3313	0.3962
	Median	0.1153					0.0159	0.3281	0.3927
	Min	0.0222					-0.0352	-0.2756	0.0487
	Max	0.3680					0.1242	0.8121	0.7826
	#Sig.	139					18	96	4
(6)	Mean	0.1100	-1.5459	0.0045				0.3706	0.4629
	Median	0.1201	-1.0263	0.0034				0.3268	0.4474
	Min	-0.0170	-5.1692	-0.0167				0.0711	0.0373
	Max	0.2281	1.1095	0.0363				0.9486	0.8846
	#Sig.	111	72	23				110	19
(7)	Mean	0.0900	-1.4567		0.0251			0.3909	0.4872
	Median	0.0887	-0.8152		0.0336			0.4070	0.4896
	Min	0.0062	-5.2615		-0.1573			0.0863	0.0296
	Max	0.1955	1.1865		0.1170			0.9100	0.9016
	#Sig.	106	64		49			123	23
***(8)**	Mean	0.0952	-2.3293			-0.5306		0.3745	**0.5099**
	Median	0.0990	-2.1415			-0.4988		0.3411	**0.5016**
	Min	0.0102	-7.1218			-2.1573		0.0237	**0.1078**
	Max	0.1889	1.2984			0.7579		0.9049	**0.8935**
	#Sig.	131	94			46		128	**15**

(9)	Mean	0.0929	-1.5728				0.0323	0.3690	0.4764
	Median	0.1040	-1.0701				0.0223	0.3365	0.4830
	Min	-0.0054	-4.6807				-0.0228	-0.0201	0.0257
	Max	0.1818	2.0994				0.1427	0.8159	0.8874
	#Sig.	113	70				25	119	13
(10)	Mean	0.1017	-1.4813	0.0044	0.0246			0.3723	0.4846
	Median	0.1087	-0.8483	0.0041	0.0353			0.3527	0.4731
	Min	-0.0351	-5.6298	-0.0179	-0.1638			0.0780	-0.0073
	Max	0.2237	1.1072	0.0384	0.1088			0.9423	0.9010
	#Sig.	98	64	24	49			113	25
***(11)**	Mean	0.1048	-2.2750	0.0028		-0.4828		0.3516	**0.5077**
	Median	0.1153	-2.1504	0.0036		-0.5153		0.3021	**0.4859**
	Min	-0.0095	-6.7118	-0.0219		-1.7058		0.0122	**0.0609**
	Max	0.2057	1.2949	0.0314		0.7968		0.9468	**0.8937**
	#Sig.	113	86	21		41		109	**19**
(12)	Mean	0.1078	-1.5830	0.0050			0.0332	0.3520	0.4744
	Median	0.1132	-1.1352	0.0055			0.0255	0.3208	0.4795
	Min	-0.0194	-4.9418	-0.0125			-0.0208	0.0470	-0.0121
	Max	0.2057	1.9277	0.0356			0.1377	0.8561	0.8819
	#Sig.	107	71	29			23	112	16
***(13)**	Mean	0.0968	-2.2018	0.0030	0.0279	-0.4614		0.3604	**0.5316**
	Median	0.1064	-1.9301	0.0038	0.0382	-0.4829		0.3370	**0.5019**
	Min	-0.0375	-6.9707	-0.0260	-0.1466	-2.1563		0.0057	**0.0164**
	Max	0.2004	1.3272	0.0349	0.1222	0.9637		0.9438	**0.9067**
	#Sig.	98	83	20	49	47		110	**27**
(14)	Mean	0.1014	-1.4341	0.0048	0.0264		0.0282	0.3622	0.4964
	Median	0.1100	-0.8313	0.0051	0.0335		0.0163	0.3293	0.4978
	Min	-0.0497	-5.7070	-0.0221	-0.1664		-0.0332	0.0686	-0.0631
	Max	0.1991	1.9812	0.0390	0.1343		0.1455	0.8695	0.8957
	#Sig.	98	69	26	50		29	111	26
***(15)**	Mean	0.1006	-2.1809	0.0037	0.0284	-0.5028	0.0276	0.3515	**0.5417**
	Median	0.1061	-2.1547	0.0054	0.0341	-0.4396	0.0196	0.3298	**0.5064**
	Min	-0.0249	-6.7947	-0.0244	-0.1367	-1.9883	-0.0292	0.0056	**0.1141**
	Max	0.1798	1.7230	0.0344	0.1433	0.6013	0.1329	0.8710	**0.9016**
	#Sig.	102	88	21	40	48	16	107	**26**

Table 1.7 (Continued) Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(D) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on SS portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	SS	mkt	vix	sclc	mom	hml	cred	C	Rsq
(1)	Mean	0.5854	0.0160					0.4825	0.7397
	Median	0.6067	0.0145					0.3833	0.7362
	Min	0.3413	-0.0283					-0.0898	0.5223
	Max	0.8056	0.0883					1.8449	0.8945
	#Sig.	157	26					81	106
***(2)**	Mean	0.4877		0.2239				0.5850	**0.8323**
	Median	0.5018		0.2398				0.4249	**0.8525**
	Min	0.3030		-0.2244				-0.0582	**0.5359**
	Max	0.6733		0.4177				1.6121	**0.9527**
	#Sig.	157		141				119	**142**
(3)	Mean	0.5289			0.0651			0.4792	0.7713
	Median	0.5444			0.0583			0.4170	0.7840
	Min	0.3113			-0.2034			-0.1249	0.5648
	Max	0.7512			0.3444			1.6340	0.8807
	#Sig.	157			72			82	138
(4)	Mean	0.5380				0.0183		0.4897	0.7478
	Median	0.5372				0.0192		0.3896	0.7580
	Min	0.3881				-0.3043		-0.0720	0.4984
	Max	0.7239				0.2903		1.8069	0.8857
	#Sig.	157				46		73	114
(5)	Mean	0.5310					-2.9243	0.5172	0.7518
	Median	0.5636					-2.2382	0.3707	0.7632
	Min	0.2279					-13.5164	0.0647	0.5014
	Max	0.8094					2.1844	1.8730	0.8792
	#Sig.	157					41	76	122
***(6)**	Mean	0.5330	0.0177	0.2260				0.5470	**0.8394**
	Median	0.5391	0.0100	0.2391				0.4128	**0.8667**
	Min	0.2759	-0.0252	-0.2259				-0.0946	**0.5449**
	Max	0.8288	0.0931	0.3919				1.6555	**0.9565**
	#Sig.	157	49	138				107	141
(7)	Mean	0.5851	0.0190		0.0691			0.4394	0.7772
	Median	0.6009	0.0178		0.0578			0.3924	0.7830
	Min	0.2821	-0.0264		-0.2048			-0.1891	0.5447
	Max	0.7857	0.0849		0.3591			1.6869	0.9017
	#Sig.	157	36		73			71	139
(8)	Mean	0.5818	0.0169			0.0187		0.4625	0.7515
	Median	0.5962	0.0120			0.0190		0.3718	0.7530
	Min	0.3634	-0.0298			-0.3161		-0.1197	0.5019
	Max	0.8247	0.0885			0.2916		1.8944	0.8905
	#Sig.	157	25			45		65	112

(9)	Mean	0.5740	0.0153				-2.8988	0.4781	0.7554
	Median	0.6301	0.0148				-2.2403	0.3452	0.7555
	Min	0.1983	-0.0277				-13.5325	-0.0720	0.5048
	Max	0.7972	0.0808				2.2359	1.8967	0.9002
	#Sig.	157	22				45	67	124
***(10)**	Mean	0.5448	0.0196	0.2065	0.0750			0.5025	**0.8588**
	Median	0.5591	0.0162	0.2295	0.0310			0.3886	**0.8629**
	Min	0.2409	-0.0250	-0.1259	-0.0407			-0.1722	**0.6676**
	Max	0.8168	0.0897	0.3980	0.3306			1.6355	**0.9542**
	#Sig.	157	51	119	44			100	**154**
(11)	Mean	0.5426	0.0186	0.2286		0.0478		0.4974	0.8456
	Median	0.5417	0.0134	0.2389		0.0350		0.3251	0.8650
	Min	0.2851	-0.0269	-0.0799		-0.2856		-0.0868	0.5261
	Max	0.8359	0.0952	0.4235		0.2622		1.6930	0.9567
	#Sig.	157	48	133		46		84	141
(12)	Mean	0.5213	0.0176	0.2186			-1.4839	0.5506	0.8452
	Median	0.5485	0.0127	0.2352			-1.4591	0.4175	0.8680
	Min	0.2027	-0.0257	-0.3134			-6.9734	-0.0769	0.5273
	Max	0.8235	0.0969	0.3771			3.9028	1.6532	0.9587
	#Sig.	156	51	140			39	113	143
(13)	Mean	0.5437	0.0199	0.2104	0.0632	0.0490		0.4737	0.8608
	Median	0.5599	0.0158	0.2269	0.0245	0.0435		0.3271	0.8622
	Min	0.2492	-0.0267	-0.0919	-0.0547	-0.2591		-0.1836	0.6534
	Max	0.8218	0.0918	0.4268	0.3136	0.2833		1.6743	0.9543
	#Sig.	157	52	120	36	31		81	154
***(14)**	Mean	0.5314	0.0196	0.1996	0.0732		-1.6080	0.5123	**0.8648**
	Median	0.5289	0.0171	0.2232	0.0289		-1.7341	0.3838	**0.8643**
	Min	0.2309	-0.0257	-0.2129	-0.0497		-7.4954	-0.0764	**0.7095**
	Max	0.8163	0.0909	0.3773	0.3965		3.7343	1.6437	**0.9587**
	#Sig.	157	50	122	39		47	103	**157**
***(15)**	Mean	0.5352	0.0211	0.2069	0.0627	0.0463	-1.8173	0.4788	**0.8685**
	Median	0.5275	0.0172	0.2208	0.0200	0.0348	-2.1035	0.3215	**0.8734**
	Min	0.2368	-0.0269	-0.1743	-0.0639	-0.2634	-9.7522	-0.0527	**0.6924**
	Max	0.8426	0.0996	0.4280	0.4024	0.2388	3.1757	1.6847	**0.9587**
	#Sig.	157	61	123	32	37	43	73	**155**

Table 1.7 (Continued) Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(E) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on MP portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	MP	**mkt**	**sclc**	**vix**	**cred**	**hml**	**mom**	**C**	**Rsq**
***(1)**	Mean	0.2476	0.0971					0.5458	**0.6265**
	Median	0.2694	0.1191					0.5048	**0.6458**
	Min	0.0619	-0.1755					-0.2047	**0.1443**
	Max	0.3858	0.2614					1.1744	**0.8975**
	#Sig.	154	94					134	**57**
(2)	Mean	0.3039		0.0118				0.4870	0.5611
	Median	0.3262		0.0123				0.4468	0.5803
	Min	0.0729		-0.0207				-0.2439	0.1026
	Max	0.4591		0.0633				1.3151	0.8403
	#Sig.	152		24				115	20
(3)	Mean	0.2464			-2.4677			0.5430	0.6062
	Median	0.2790			-2.9058			0.4776	0.6246
	Min	0.0095			-6.5783			-0.1497	0.0807
	Max	0.3812			2.9567			1.3227	0.8941
	#Sig.	148			84			143	48
(4)	Mean	0.2776				0.0619		0.4789	0.5866
	Median	0.2858				0.0650		0.4744	0.6042
	Min	0.1259				-0.2090		-0.3162	0.2888
	Max	0.4215				0.2460		1.2523	0.8352
	#Sig.	157				48		104	34
(5)	Mean	0.2635					0.0141	0.5038	0.5654
	Median	0.2782					0.0111	0.4759	0.5978
	Min	0.0703					-0.1269	-0.3751	0.0753
	Max	0.3804					0.1444	1.1989	0.8628
	#Sig.	154					35	119	27
(6)	Mean	0.2820	0.1017	0.0123				0.5138	0.6374
	Median	0.2984	0.1176	0.0121				0.4679	0.6487
	Min	0.0338	-0.1764	-0.0254				-0.2092	0.1441
	Max	0.4698	0.2547	0.0641				1.2043	0.8962
	#Sig.	145	93	36				118	59
***(7)**	Mean	0.2270	0.0906		-1.8715			0.5723	**0.6660**
	Median	0.2554	0.1031		-1.8262			0.5458	**0.6817**
	Min	0.0202	-0.2320		-5.6762			-0.0358	**0.1071**
	Max	0.3860	0.2691		3.1410			1.1781	**0.9192**
	#Sig.	143	100		76			145	**72**
(8)	Mean	0.2637	0.0938			0.0742		0.4960	0.6531
	Median	0.2827	0.1182			0.0485		0.4792	0.6717
	Min	0.0979	-0.1502			-0.1503		-0.2559	0.2658
	Max	0.4048	0.2697			0.2481		1.1277	0.8962
	#Sig.	157	92			46		114	61

(9)	Mean	0.2479	0.0909				0.0158	0.5338	0.6207
	Median	0.2719	0.1081				0.0113	0.5350	0.6451
	Min	0.0525	-0.1318				-0.0590	-0.3175	0.1040
	Max	0.3923	0.2661				0.1270	1.1586	0.8959
	#Sig.	150	90				12	133	63
***(10)**	Mean	0.2613	0.0950	0.0123	-1.8627			0.5342	**0.6784**
	Median	0.2797	0.0999	0.0116	-2.0149			0.4746	**0.6933**
	Min	-0.0450	-0.2631	-0.0258	-5.9446			-0.0241	**0.1127**
	Max	0.4690	0.2682	0.0653	3.1607			1.1889	**0.9272**
	#Sig.	137	99	41	71			128	**74**
(11)	Mean	0.2988	0.1001	0.0130		0.0779		0.4660	0.6667
	Median	0.3220	0.1178	0.0126		0.0613		0.4428	0.6767
	Min	0.0432	-0.0997	-0.0278		-0.1545		-0.2633	0.2485
	Max	0.5042	0.2659	0.0639		0.2605		1.1845	0.8949
	#Sig.	139	92	35		46		93	64
(12)	Mean	0.2857	0.0930	0.0125			0.0193	0.4995	0.6341
	Median	0.3096	0.1062	0.0134			0.0127	0.4726	0.6645
	Min	0.0013	-0.1253	-0.0254			-0.0663	-0.3338	0.0998
	Max	0.4735	0.2592	0.0629			0.1435	1.1986	0.8946
	#Sig.	140	83	40			15	117	64
***(13)**	Mean	0.2804	0.0947	0.0138	-1.9683	0.0697		0.4907	**0.7069**
	Median	0.3007	0.0995	0.0133	-2.0492	0.0733		0.4488	**0.7267**
	Min	-0.0264	-0.1966	-0.0292	-6.5212	-0.1344		-0.0696	**0.2227**
	Max	0.5360	0.2635	0.0630	2.9746	0.2313		1.1913	**0.9237**
	#Sig.	136	100	45	71	52		104	**83**
(14)	Mean	0.2650	0.0862	0.0128	-1.9735		0.0205	0.5245	0.6786
	Median	0.2879	0.0938	0.0151	-2.0089		0.0146	0.4955	0.7029
	Min	-0.0107	-0.2441	-0.0265	-5.9395		-0.0630	-0.1424	0.0691
	Max	0.4730	0.2591	0.0642	2.6357		0.1893	1.1881	0.9279
	#Sig.	135	83	42	71		20	129	80
***(15)**	Mean	0.2760	0.0905	0.0132	-2.0545	0.0752	0.0098	0.4808	**0.7063**
	Median	0.3001	0.0941	0.0138	-1.8638	0.0751	-0.0013	0.4575	**0.7244**
	Min	-0.0075	-0.1976	-0.0290	-6.9683	-0.1370	-0.0718	-0.1486	**0.1775**
	Max	0.5224	0.2511	0.0603	2.3480	0.3440	0.1729	1.1888	**0.9244**
	#Sig.	127	88	49	72	45	11	103	**85**

Table 1.7 (Continued) Results from the Multi-factor Time-varying Regression with 24 Months Window using Selected Risk Factors

(F) This table reports results from two-factor, three-factor, four-factor, five-factor, and six-factor time-varying regression analyses using as dependent variable the monthly returns on FoF portfolio. The sample periods are ranged from January 1994 to December 2008, and the time-varying regression analyses are performed with 24-month window. Risk factors in this table are selected from the single-factor time varying regression analyses based on the number of time frame during which coefficients are significant at 5% significance level and mean R-squared value. The results include mean, median, minimum, and maximum regression coefficients of each variable; number of time frames during which coefficients of each variable is significant at 5% significance level; and mean, median, minimum, and maximum adjusted R-squared value, as well as number of time frames during which adjusted R-squared value (#Sig.) is greater than 70%.

Figures in bold and '*' indicate the best models in each level that show the most stable and highest R-squared value based on the mean adjusted R-squared value and #Sig.

	FoF	**Emf**	**vix**	**sclc**	**cred**	**mom**	**hml**	**C**	**Rsq**
(1)	Mean	0.1836	0.0056					0.3540	0.5983
	Median	0.1848	0.0069					0.2683	0.5880
	Min	0.0679	-0.0246					-0.4463	0.3195
	Max	0.2922	0.0501					1.1234	0.8692
	#Sig.	157	25					81	29
(2)	Mean	0.1652		0.0602				0.3764	0.6242
	Median	0.1714		0.0696				0.2612	0.6172
	Min	0.0675		-0.2044				-0.4730	0.3140
	Max	0.2640		0.2016				1.2267	0.8566
	#Sig.	157		52				85	42
(3)	Mean	0.1675			-0.9888			0.3945	0.6112
	Median	0.1657			-1.2752			0.2668	0.5990
	Min	0.0637			-5.2728			-0.2767	0.3279
	Max	0.2723			3.9899			1.0993	0.8591
	#Sig.	157			45			83	35
***(4)**	Mean	0.1784				0.0410		0.3058	**0.6386**
	Median	0.1819				0.0278		0.2459	**0.6287**
	Min	0.0951				-0.0773		-0.7178	**0.3170**
	Max	0.2705				0.1926		1.0933	**0.8736**
	#Sig.	157				43		68	**58**
(5)	Mean	0.1755					0.0245	0.3453	0.6017
	Median	0.1717					0.0329	0.2531	0.5897
	Min	0.0787					-0.1884	-0.5797	0.2649
	Max	0.2670					0.1838	1.1376	0.8582
	#Sig.	157					24	76	35
(6)	Mean	0.1727	0.0050	0.0646				0.3680	0.6284
	Median	0.1747	0.0068	0.0741				0.2583	0.6122
	Min	0.0272	-0.0245	-0.1909				-0.4636	0.2927
	Max	0.2910	0.0468	0.2016				1.2278	0.8754
	#Sig.	155	28	49				85	41
(7)	Mean	0.1788	0.0065		-1.0648			0.3846	0.6181
	Median	0.1718	0.0092		-1.1561			0.2608	0.6066
	Min	0.0652	-0.0242		-5.5255			-0.2901	0.3232
	Max	0.2951	0.0485		3.9192			1.1247	0.8684
	#Sig.	157	34		42			80	40
***(8)**	Mean	0.1886	0.0061			0.0407		0.2983	**0.6441**
	Median	0.1838	0.0064			0.0247		0.2380	**0.6431**
	Min	0.0961	-0.0248			-0.0748		-0.6354	**0.2937**
	Max	0.2940	0.0557			0.1974		1.1170	**0.8755**
	#Sig.	157	33			41		70	**59**

(9)	Mean	0.1844	0.0055				0.0226	0.3398	0.6032
	Median	0.1799	0.0061				0.0218	0.2517	0.5892
	Min	0.0588	-0.0237				-0.1964	-0.5098	0.2997
	Max	0.3308	0.0501				0.2086	1.1586	0.8653
	#Sig.	157	20				20	78	32
(10)	Mean	0.1696	0.0066	0.0626	-0.7193			0.4034	0.6570
	Median	0.1641	0.0080	0.0709	-1.0509			0.2559	0.6674
	Min	0.0420	-0.0248	-0.3336	-5.5528			-0.3084	0.3139
	Max	0.3013	0.0550	0.2327	5.2599			1.2301	0.8777
	#Sig.	154	40	65	56			80	59
***(11)**	Mean	0.1783	0.0055	0.0628		0.0458		0.3244	**0.6579**
	Median	0.1790	0.0065	0.0563		0.0284		0.2609	**0.6580**
	Min	0.0590	-0.0233	-0.1196		-0.0713		-0.5724	**0.2616**
	Max	0.2941	0.0536	0.2308		0.2134		1.1830	**0.8751**
	#Sig.	157	34	38		47		77	**67**
(12)	Mean	0.1729	0.0051	0.0673			0.0309	0.3580	0.6320
	Median	0.1699	0.0069	0.0681			0.0288	0.2504	0.6269
	Min	0.0124	-0.0233	-0.2012			-0.1587	-0.5252	0.3151
	Max	0.3293	0.0467	0.2386			0.2076	1.2320	0.8730
	#Sig.	152	24	52			19	81	50
***(13)**	Mean	0.1692	0.0068	0.0609	-0.9452	0.0517		0.3661	**0.6845**
	Median	0.1674	0.0090	0.0566	-1.1636	0.0526		0.2555	**0.7142**
	Min	0.0619	-0.0237	-0.2663	-6.3679	-0.0837		-0.2929	**0.2852**
	Max	0.2731	0.0694	0.2502	5.2699	0.2256		1.1852	**0.8732**
	#Sig.	157	42	52	55	47		75	**84**
(14)	Mean	0.1670	0.0079	0.0669	-0.7791		0.0168	0.3997	0.6626
	Median	0.1611	0.0078	0.0739	-0.9747		0.0178	0.2320	0.6726
	Min	0.0257	-0.0243	-0.2815	-5.5069		-0.1568	-0.3967	0.3368
	Max	0.2945	0.0688	0.2588	5.1267		0.2062	1.2330	0.8711
	#Sig.	155	38	59	58		22	77	67
***(15)**	Mean	0.1681	0.0064	0.0635	-1.0944	0.0518	0.0490	0.3537	**0.6913**
	Median	0.1638	0.0085	0.0624	-1.1048	0.0565	0.0380	0.2283	**0.7133**
	Min	0.0493	-0.0244	-0.2489	-6.0409	-0.0795	-0.0968	-0.3852	**0.3455**
	Max	0.2831	0.0688	0.2532	5.1555	0.2207	0.2917	1.1880	**0.8658**
	#Sig.	153	35	44	49	45	19	72	**83**

Table 1.8 Optimal Combinations of Risk Factors for Measuring Performance of Hedge Funds by Investment Strategy

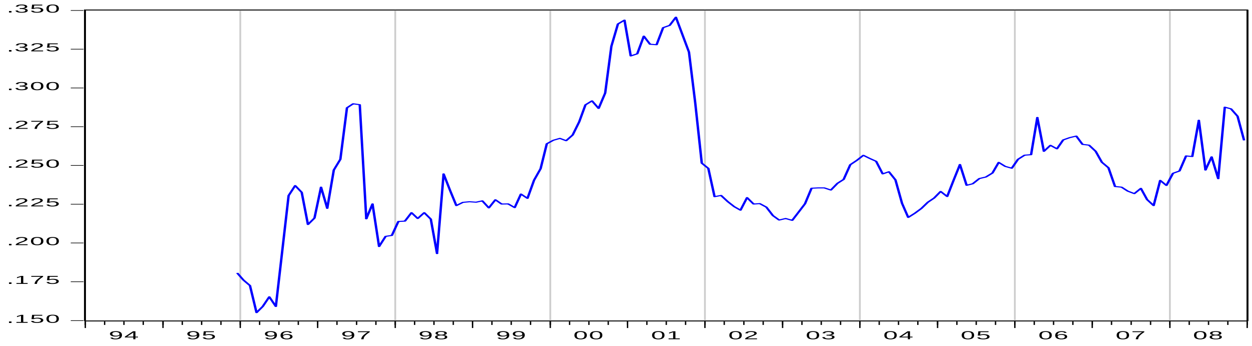
	Combination of Risk factors
AG	EMF, VIX, SCLC, CRED, HML
DT	EMF, VIX, SCLC, MOM
RV	MKT, CRED, VIX, SCLC, 10Y, MOM
SS	MKT, VIX, SCLC, MOM, CRED
MP	MKT, SCLC, VIX, CRED, HML
FoF	EMF, VIX, SCLC, CRED, HML

Table 1.9 Paired t-test of r-squared Statistics between the Selected Model and ABS-, SAC- and Four-factor Models

This table reports results for testing mean difference in explanatory power (adjusted r-squared statistics) between our optimal model by investment strategy and existing model. ‘*’ denotes significance at the 5% level.

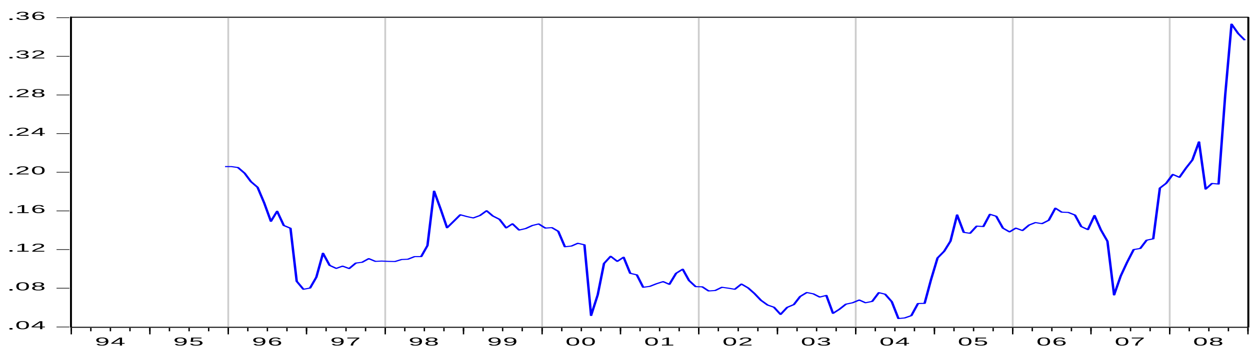
		Opt - ABS	Opt - SAC	Opt - Ffactor
AG	Mean	0.0909*	0.0020	-0.0176
	t-statistics	6.3353	0.3458	-1.9443
DT	Mean	0.2429*	-0.0033	0.1492*
	t-statistics	14.4324	-1.0386	14.5148
RV	Mean	0.0643*	0.0479*	0.0446*
	t-statistics	7.2488	3.0134	4.5406
SS	Mean	0.1129*	0.0980*	-0.0012
	t-statistics	12.1288	8.7566	-0.2937
MP	Mean	0.0940*	0.0447*	0.0254*
	t-statistics	9.7943	3.6611	5.1601
FoF	Mean	0.1772*	-0.0154	0.0882*
	t-statistics	10.4143	-1.2545	7.1976

(A) Time-varying Coefficients of Emerging Market Index for Aggregate HF Portfolio

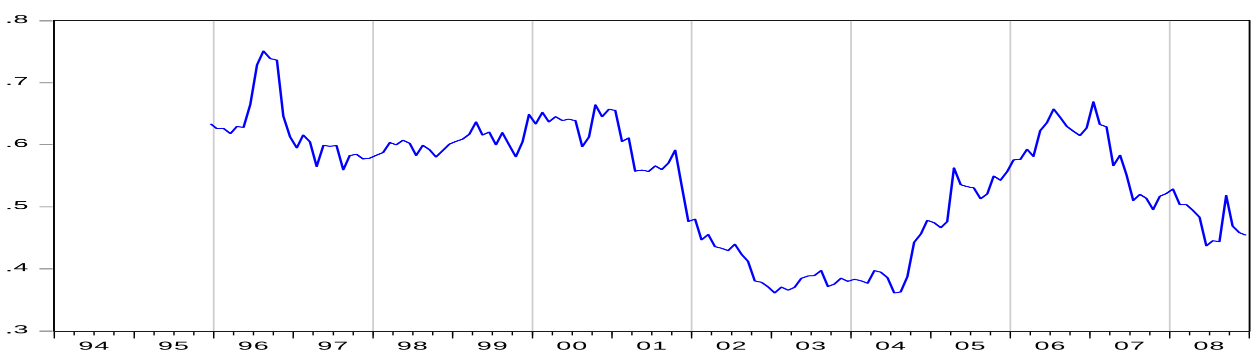


(B) Time-varying Coefficients of Emerging Market Iindex for DT Portfolio

(C) Time-varying Coefficients of Market Risk Premium for RV Portfolio



(D) Time-varying Coefficients of Market Risk Premium for SS Portfolio



(E) Time-varying Coefficients of Market Risk Premium for MP Portfolio

(F) Time-varying Coefficients of Emerging Market Index for FoF Portfolio

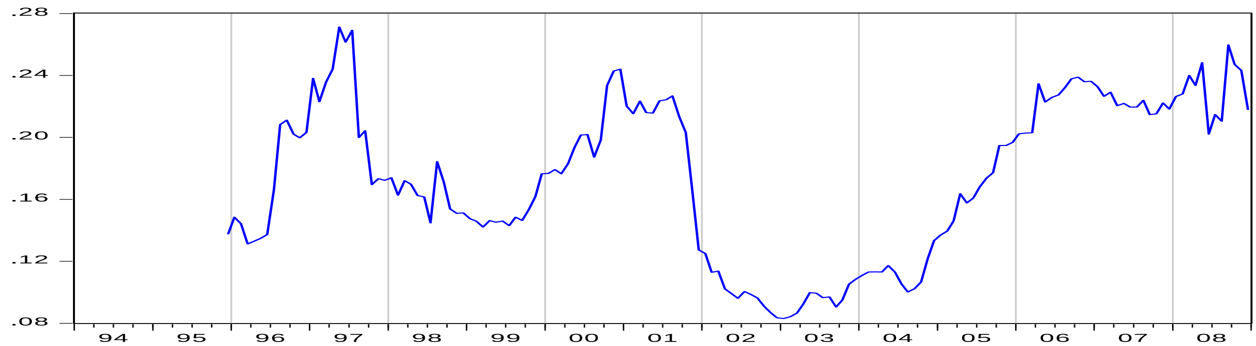
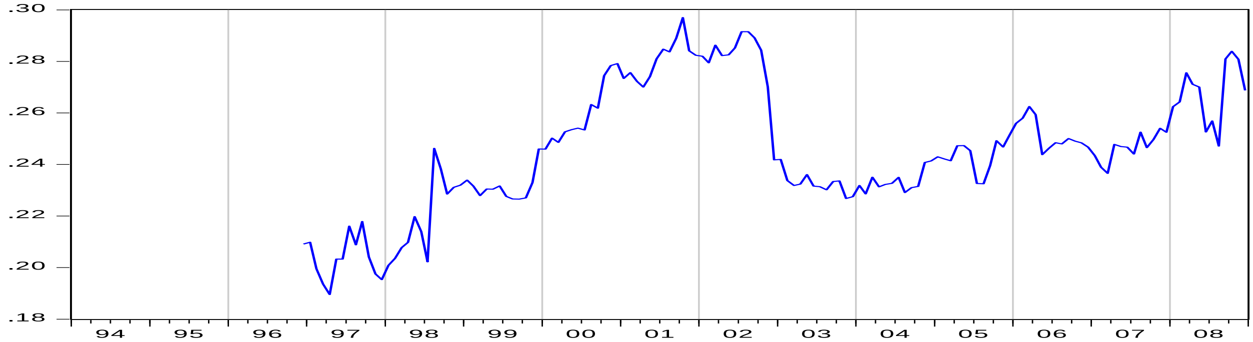


Figure 1.1 Graphs for Time-varying Coefficients of Equity Market-related Risk Factor for a Single-factor Regression Analysis with 24-month Window.

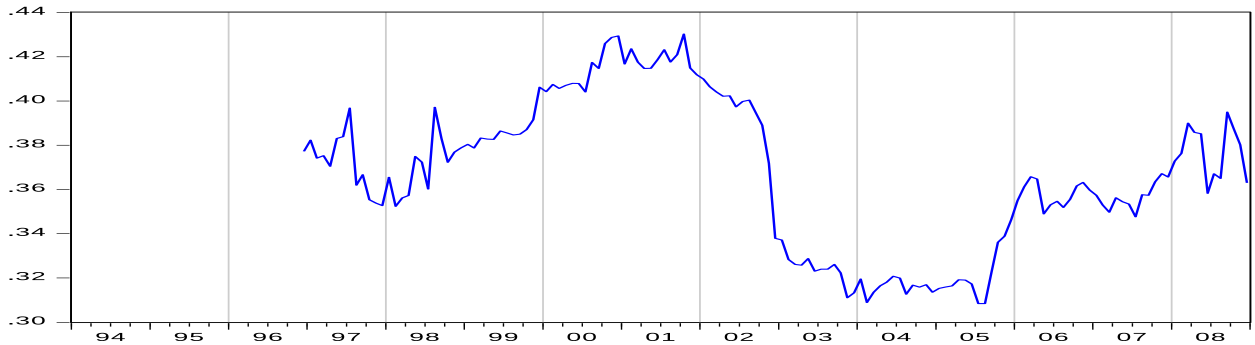
These graphs intend to exhibit how actively changing exposures of hedge funds following different investment strategies are to the same risk factor. With 24-month window for time-varying regression analysis, the first coefficient recorded on December 1995 is for the sample period from January 1994 to December 1995, and then, the coefficients and fixed size of windows moves to right by a month.

We use other risk factors for time-varying regression analysis, and therefore, we need to provide with graphs for those other factors. Since equity market-related risk factor, however, take account for significant part of hedge fund exposure to risk factors, showing instability of equity market-related factor would be sufficient to support time-varying regression analysis for estimating actively managed portfolio such as hedge funds.

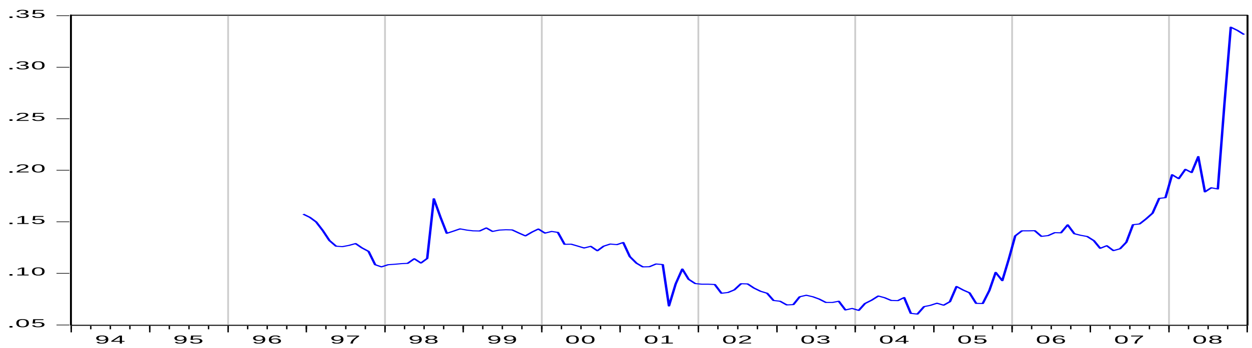
(A) Time-varying Coefficients of Emerging Market Index for Aggregate HF Portfolio



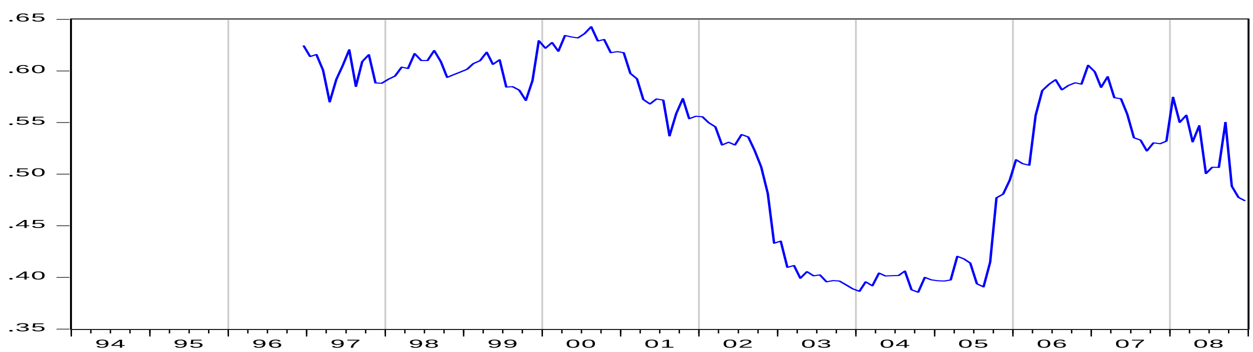
(B) Time-varying Coefficients of Emerging Market Index for DT Portfolio



(C) Time-varying Coefficients of Market Risk Premium for RV Portfolio



(D) Time-varying Coefficients of Market Risk Premium for SS Portfolio



(E) Time-varying Coefficients of Market Risk Premium for MP Portfolio

(F) Time-varying Coefficients of Emerging Market Index for FoF Portfolio

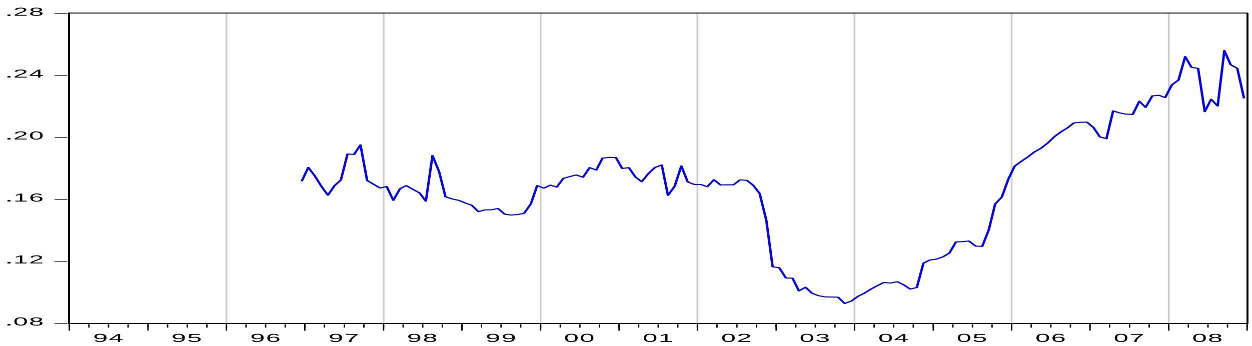
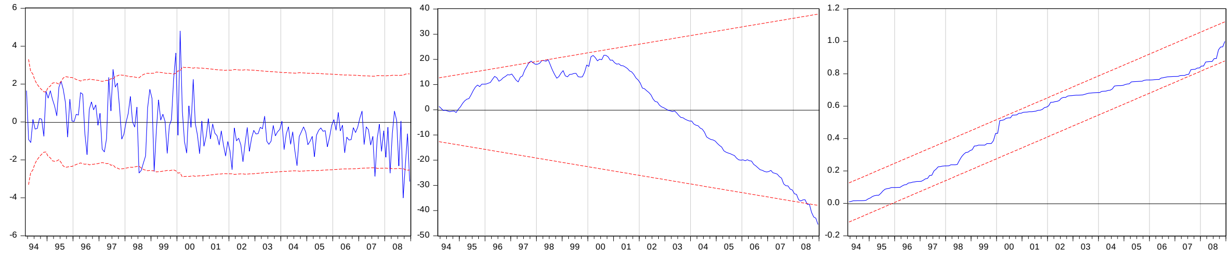


Figure 1.2 Graphs for Time-varying Coefficients of Equity Market-related Risk Factor for a Single-factor Regression Analysis with 36-month Window

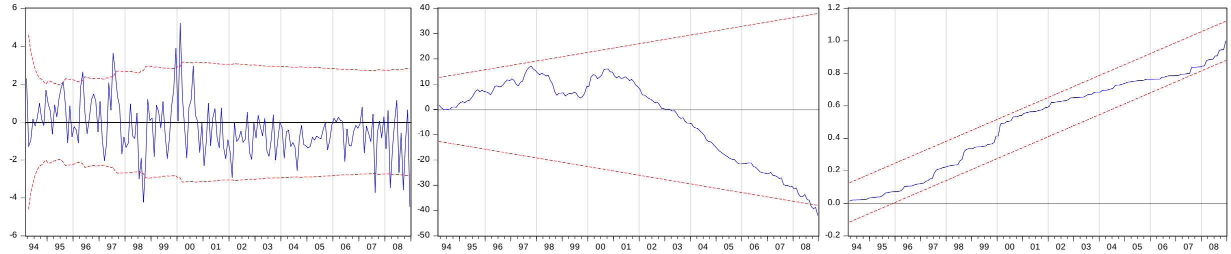
These graphs intend to exhibit how actively changing exposures of hedge funds following different investment strategies are to the same risk factor. With 36-month window for time-varying regression analysis, the first coefficient recorded on December 1996 is for the sample period from January 1994 to December 1996, and then, the coefficients and fixed size of windows moves to right by a month.

We use other risk factors for time-varying regression analysis, and therefore, we need to provide with graphs for those other factors. Since equity market-related risk factor, however, take account for significant part of hedge fund exposure to risk factors, showing instability of equity market-related factor would be sufficient to support time-varying regression analysis for estimating actively managed portfolio such as hedge funds.

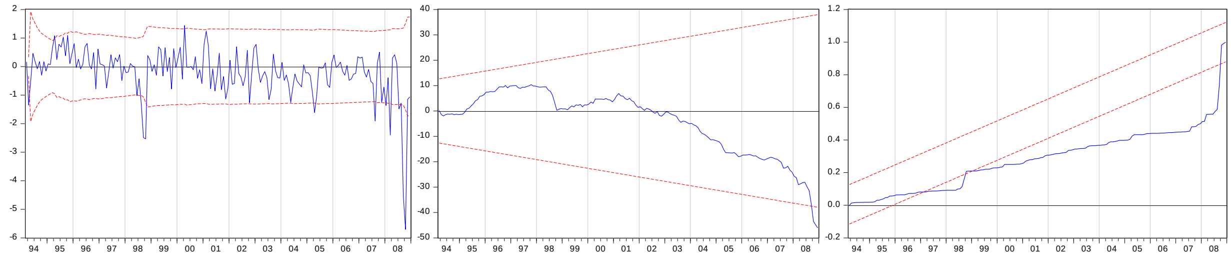
(A) Agg.



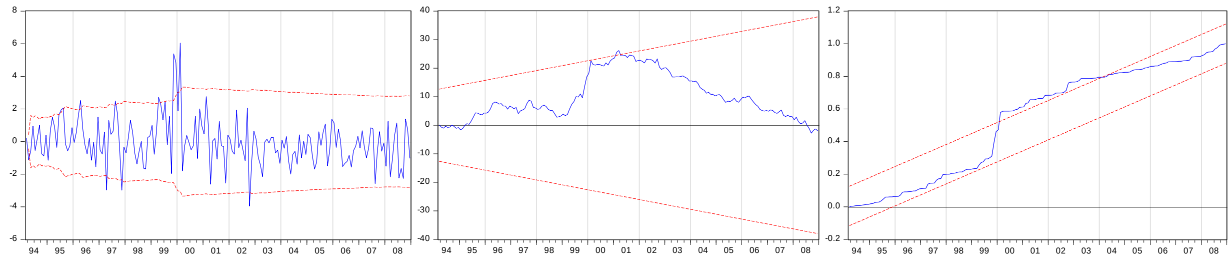
(B) DT



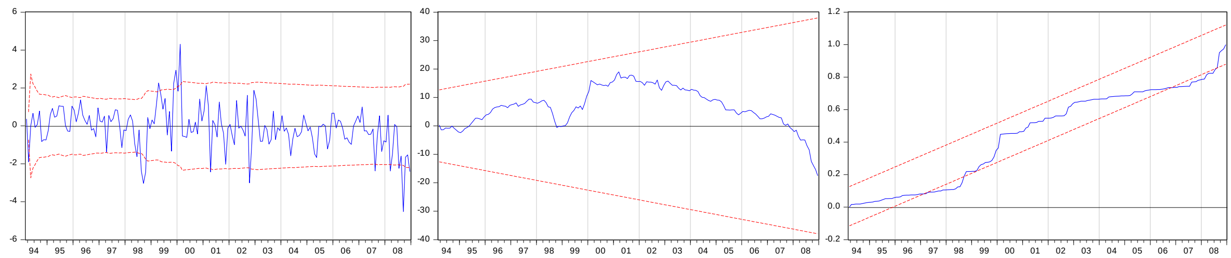
(C) RV



(D) SS



(E) MP



(F) FoF

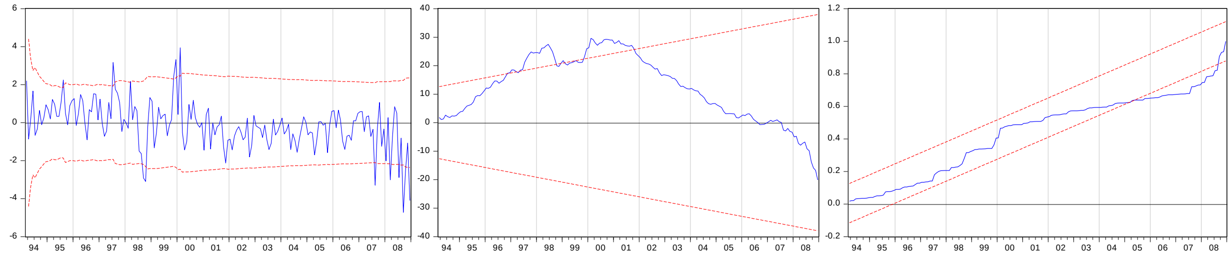


Figure 1.3 Stability Tests of Coefficients for Equity Market-related Risk Factors using Recursive Residuals

These graphs are drawn for stability tests of coefficients for equity market-related risk factors using recursive residuals. Each row includes plots respectively displaying recursive residuals, the cumulative sum (CUSUM) of the standardized residuals, and CUSUM of squares from a single-factor regression analysis. The red (dotted) lines in the graphs of recursive residuals indicate two standard error bands, and those in the graphs of CUSUM and CUSUM of squares indicate 5% critical lines. The blue (solid) lines in graphs indicate the recursive residuals, CUSUM of standardized residuals, and CUSUM of squares, respectively.

CHAPTER II

FOR WHOM HURDLE RATE AND HIGH-WATERMARK EXIST?

2.1 Introduction

Hedge funds are not open to all the investors who want to commit their funds in contrast to other investment vehicles such as traditional mutual funds and ETFs. Most hedge funds require investors a minimum amount of investment, even though there is no stated rule of qualifications that investors have to meet. In general, the level of minimum required investment amount is ranged from as low as $10,000 to as high as $10,000,000 or more. But, a common range is between $250,000 and $500,000, which is hardly an affordable amount for average investors. Therefore, hedge funds investors are regarded as wealthy l and sophisticated, who are well informed about distinct feature of hedge funds. These features include the level of risk or leverage, investment strategies, substantially high management and performance fees relative to mutual funds, and restrictions for withdrawing funds. To attract investors, hedge fund managers suggest not incurring fees to investors unless certain level of required returns is achieved. Hurdle rate and high-watermark are considered to be incentives for managers, too, in the way that if they achieve a certain level of returns, investors pay part of their returns as a reward. Depending on the point of view, the role of a hurdle rate and high-watermark can be favor of or against managers. In principle, hurdle rate and high-watermark are devised in the same purpose: to protect investors' wealth or to promote fund managers for better performance. However, they are somewhat different in definition. Hurdle rate is a minimum rate of return that fund managers must achieve to collect performance fees without consideration of historical performance, while high-watermark requires fund managers to restore any previous loss in order to collect performance fees. It tells that high-watermark is a stricter provision for fund managers in favor of investors.

Majority of studies see those from investors' point of view that funds with better managerial incentives such as a hurdle rate and/or high-watermark should provide better performance (see Arya and Mittendorf, 2005; Panageas and Westerfield 2009; and Agarwal, Daniel and Naik, 2009). On the other hand, Soydemir, Smolarski, and Shin (2012) consider it to be restrictions for managers and argue that providing a hurdle rate and/or high-watermark has no positive effect on hedge fund performance.

In this study, we first extend the study of Soydemir et al. (2012) by taking account of biases associated with database as well as of risk associated with investment strategies into a model that measures performance of individual hedge funds. Then, by utilizing multinomial logistic regression model, we simultaneously examine hedge fund attributes that lead fund manager to offering a hurdle rate and/or high-watermark.

Our results indicates that funds taking risky positions and collecting high performance fee tend to offer hurdle rate and high-watermark, so that it appears that hurdle rate and high-watermark are tools to assure investors that their money is safe from unreasonable fees and restrictions for hedge fund managers from collecting fee. In addition, lockup month, which is a restriction from investors' viewpoint, does significantly affect likelihood of offering hurdle rate, but not of high-watermark.

Furthermore, this study examines how hedge fund performance is affected by a hurdle rate and high-watermark as well as level of leverage, fees, restrictions on redemption, size, etc.

In measuring hedge fund performance, we allow for distinct characteristics of variety of investment strategies using the optimal model by investment strategy developed in the first essay. We find that high-watermark is negatively related to hedge fund performance while hurdle rate has no significant effect on performance. It means that hurdle rate and high-watermark do not work at least as incentives for fund managers against Arya and Mittendorf (2005), Panageas and Westerfield (2009), and Agarwal et al. (2009). We also find that performance fee is the only incentives for fund manager with significant and positive relationship with performance. Lastly, lockup month positively affects hedge fund performance. It indicates that managers' discretion in the use of funds allows investing more in illiquid assets earning illiquidity premium or waiting more until the position becomes in the money.

The remainder of this chapter is structured as follows. Section 2, we review the literature and propose hypotheses. Section 3 explains data and descriptive statistics. Section 4 elaborates the econometric methodology. Section 5 reports the empirical results. Section 6 concludes.

2.2 Literature Review and Hypotheses Development

2.2.1 Hurdle Rate and High-watermark

Soydemir et al. (2012) is, to my knowledge, the only paper examining factors leading hedge fund managers to offering a hurdle rate. They define hurdle rate as a dummy variable and conduct a binomial logistic regression analysis using hedge fund attributes as well as investment strategies. They find that investment strategies significantly affect hedge fund managers' decision whether or not to offer a hurdle rate. In addition, they also find that attributes such as performance and management fees and level of leverage are significantly associated with the decision. However, they use high-watermark as one of independent variables, whose role is, similarly to the role of a hurdle rate, to specify a required level of performance for fund managers to collect performance fee. They elaborate that there is no endogeneity problem, but the potential of the problem still remain. To avoid even the potential problem, we take both of a hurdle rate and high-watermark into account.

We set up four hypotheses regarding to the factors affecting decision of offering a hurdle rate and/or high-watermark.

Hypothesis 1-1. *Risky investment strategies have no effect on the likelihood of offering a hurdle rate and/or high-watermark.*

Depending on the investment strategies that individual hedge funds choose, levels of risk or leverage for funds may vary. Since hedge fund managers announce their investment strategies, levels of risk are well known to investors. Hedge funds with relatively risky investment strategies are more likely to ensure investors that their money is safe. Providing a hurdle rate and/or high-watermark may signal that the hedge funds providing either or both of the provisions are surely able to achieve the stated level of return. In addition, investors may feel that their funds are protected given the fact that fund managers cannot collect fees unless they meet requirement.

Hypothesis 1-2. *Management fee is not related to and performance fee is positively related to offering a hurdle rate and/or high-watermark.*

Since performance fee is paid when managers achieve the stated level of return, it should be positively related with offering a hurdle rate and/or high-watermark. For management fee paid for covering operating costs of the managers irrespective of performance, it likely has no significant impact on offering a hurdle rate and/or high-watermark. But, large funds may misappropriate management fee for a significant part of managers' profits.[5] Therefore, hedge funds charging investors high level of management fee may be prone to collecting lower performance fee and, therefore, less offering a hurdle and/or high-watermark.

Hypothesis 1-3. *Stronger restrictions on the redemption are no more likely to offer a hurdle rate and/or high-watermark than those with relatively weaker restrictions.*

Hedge funds generally attempt to keep the invested funds as long as possible and devise various restrictions, such as lockup period, redemption period and fee that limit investors from withdrawals. Those restrictions give hedge fund managers a substantial discretion that greatly facilitates planning investment and operating funds. But from investors' point of view, it seems that the longer the period during which investors are limited from withdrawals, the greater is the risk that investors should bear. Therefore, investors are reluctant to invest in hedge funds with relatively longer lockup and redemption periods and high redemption fee, and hedge fund managers need to offer incentives or provisions that alleviate investors' anxiety. Aragon and Qian (2010) find that hedge funds with stronger restriction on redemption more likely offer a high-watermark.

2.2.2 Agency Theory, Signaling Effect and Hedge Fund Performance

According to agency theory, higher compensation leads to superior performance. Kambhu, Schuermann, and Stiroh (2007) claim that due to information asymmetry between fund managers and investors, agency problem may exist within hedge funds. Agarwal et al. (2009) create new proxy for managerial incentives, which is an "option delta" based on Black and Scholes (1973)'s option pricing model for European call options, and test hypothesis based on

[5] James Mackintosh, "Hedge fund investors have a great chance to cut fees," Financial Times on February 2009. (http://www.ft.com/cms/s/0/cf7f91e2-f3f0-11dd-9c4b-0000779fd2ac.html#axzz1HLd3KAt3)

agency theory. They find positive relationship between option delta and performance, as well as positive impact of high-watermark on hedge fund performance.

Manager's Option Delta = $N(Z) \times S \times 0.01 \times I$

, *where* $Z = \dfrac{\{\ln(\frac{S}{X}) + T(r + \frac{\sigma^2}{2})\}}{\sigma T^{0.5}}$; S denotes spot price (market value of the investor's assets as of the end of the current year), T denote time to maturity of the option; r denotes ln(1+risk-free interest rate); σ denotes annualized volatility of monthly net returns; I denotes incentive fee rate; and *N(Z)* denotes cumulative distribution function (*cdf*) of standard normal distribution.

This equation is utilized to compute option delta. X is an exercise price and Agarwal et al. (2009) use high-watermark as an exercise price. According to this equation, as X increases Z and option delta decrease. Here, one thing that seems to be wrong is the relationship of option delta and high-watermark with performance both of which are positively related to performance at the same time even though option delta and high-watermark are inversely related with each other. Let's assume that the positive relationship between option delta and performance is true and that high-watermark is offered or increases. Then, option delta should decrease and performance also becomes poor, so that the positive relationship between high-watermark and performance becomes false. Either of the relationships between option delta and performance or high-watermark and performance must be wrong. I would like to put more weight on the one between high-watermark and performance. In other words, because high-watermark is inversely related to option delta, high-watermark and option delta cannot affect performance in the same direction at the same time.

Similarly, Ray (2009) defines compensation system for hedge fund managers as holding call options, and looks at the effects of high-watermark on fund performance and risk. He found that as net asset values of hedge funds become less than requirement of high-watermark, expected Sharpe ratio decreases and standard deviation increases. Increased risk may indicate that managers of hedge funds whose assets go below standard high-watermark likely take greater risk to recoup the loss and collect incentive fees. On the contrary, Aragon and Nanda (2010) find that hedge funds that poorly perform and are less likely liquidated are significantly less prone to increasing risk. The common idea of those studies is that high-watermark is provided as incentives for fund managers.

Soydemir et al. (2012) take an ex-ante approach from different point of view by defining a hurdle rate and high-watermark as kind of marketing tools to attract more funds from investors, while true incentives for fund managers are performance fee only. Furthermore, those provisions impose impediments for fund managers to collect fees. The existence of information asymmetry between fund managers and investors allows release of information to be signaling. Such that providing a hurdle rate and/or high-watermark can be interpreted as a signal, in the sense that fund managers are confident to achieve the stated level of return, by investors with inferior information to managers. They find that offering a hurdle rate has little impact on hedge fund performance while providing a high-watermark is negatively associated with performance.
We set up three hypotheses regarding to relationships between hedge funds attributes and performance.

Hypothesis 2-1. *Hedge funds that offer a hurdle rate and/or high-watermark should perform no differently from those that do not offer.*

According to Soydemir et al. (2012), hurdle rate and high-watermark may work as restrictions for investment decision of fund managers rather than incentives. Those provisions likely make managers reluctant to take risky positions with high potential return, and eventually, more likely lose chances that bring high returns relative to the risk managers need to bear. It is the similar view as Aragon and Nanda (2010) as well as Panageas and Westerfield (2009) that even risk neutral managers do not hold unbounded weights on risky assets in their portfolio. We follow the idea of Soydemir et al. (2012).

Hypothesis 2-2. *Hedge funds collecting higher performance fee do not outperform those collecting lower performance fee.*

Including the studies mentioned above, Do, Faff, and Widkramanayake (2005) and Liang (1999) report that hedge funds with higher performance fee rate achieve greater returns, while Kowenberg and Ziemba (2007) reports mixed results, in which average returns and Sharpe ratio for hedge funds are negatively related with performance fee while those for funds of hedge funds are positively related. We believe performance fee is the only incentive among hedge fund attributes.

Hypothesis 2-3. *Hedge funds with stronger restrictions on the redemption do not outperform those with relatively weaker restrictions.*

It is well known that unlike traditional mutual fund managers, hedge fund managers are given substantial discretion while operating the funds under management by imposing restrictions on fund redemption. This makes it possible for fund managers to conduct dynamic investment strategies involving illiquid assets. Nanda, Narayanan, and Warther (2000) and Johnson (2004) argue that short-term flows incur significant costs to long-term investors. Aragon (2007) and Liang and Park (2007) examine the relationship between share restrictions on those short-term flows and hedge fund performance. They commonly claim that share restrictions such as lockup, notice and redemption periods give managers room to store illiquid assets in their portfolio, which deliver illiquidity premiums.

Since high level of discretion may be considered to be favorable for fund managers, it is certain that investors require sufficient compensation for their patience incurred by the discretion given to managers and that fund managers are expected to provide higher returns. Lockup period and redemption period and fee that limit investors' right for a certain period may work as a proxy for the restrictions on the redemption. As the period and fee get longer and higher, the restriction on investors becomes stronger.

Hypothesis 2-4. *Hedge funds with larger assets do not outperform those with less.*

The issue associated with the relationship between fund performance and size is still in dispute. Xiong, Idzorek, Chen, and Ibbotson (2007) find that fund size is positively correlated with performance and negatively correlated with standard deviation of returns, indicating that larger funds have a superior risk-adjusted return. On the contrary, Chen, Hong, Huang, and Kubik (2004) and Yan (2008) find fund returns that decline with fund size. The relationship between fund size and performance becomes stronger for funds holding illiquid portfolio. We place more weights on positive relationship between fund size and performance because of economies of scale. Hedge fund managers have discretion to close the fund if they believe that current level of assets is most optimal to operate in an efficient way. That is, hedge fund managers collect funds as much as possible to efficiently manage.

2.3 Data

In this study, we use attributes of individual hedge funds to examine what affects fund managers' decision of offering a hurdle rate and/or high-watermark and what affects hedge fund performance. The data being a proxy for various attributes include hurdle rate, high-watermark, investment strategies, management and performance fees, level of leverage, lockup period, amount of assets under management, number of return observations, location of headquarters, etc., and all are collected from Global Hedge Fund Database provided by BarclayHedge. Hurdle rate and high-watermark are combined to represent the degree to which fund managers are limited from collecting performance fee. We express these attributes in terms of nominal numbers. If managers offer none of both, it is “0”; hurdle rate only, it is “1”; high-watermark only, it is “2”; and both of hurdle rate and high-watermark, it is “3”.

Similarly, lockup period is employed as a proxy for restrictions on fund redemptions and is measured in terms of the number of months for which investors must wait until their money is available. Following Agarwal et al. (2009), hedge funds are divided into four different investment strategies: directional traders (DT), relative value (RV), security selection (SS), and multiprocess (MP). Argarwal et al. (2009) define that DT tends to bet on the direction of market prices of currencies, commodities and bonds in the futures and cash markets; that RV takes positions on spread relationships between prices of financial assets or commodities and aims to minimize market exposure; that SS takes long and short positions in undervalued and overvalued securities, respectively, and reduce the systematic market risk in the process; and that MP takes multiple strategies employed by funds, usually involving investment in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. Fund of hedge funds (FoF) is also one of widely known and used investment strategies. FoF holds portfolios of other hedge funds rather than directly investing in shares, bonds and commodities.

Asset under management (AUM) in the U.S. dollar is log-transformed and used as a proxy for hedge fund size. Location of headquarter distinguishes hedge funds headquartered in offshore financial centre (OFC), denoted as “1”, or not, as “0”. IMF provides the list of OFC. [6] Offshore financial centre indicates the location of hedge fund headquarters. Significant number of hedge funds is located in the offshore financial centre where offers financial services to nonresidents on a scale that is incommensurate with size and financing of its domestic economy. Length of funds’ life is measured by counting the number of monthly return observations for individual funds. In the analysis, it can be a proxy for experience of hedge fund managers. Management fee and Performance fee charged by hedge funds are expressed in percentage.

In order to estimate performance of individual hedge funds, we employ the optimal models, estimated by time-varying regression analysis and developed for each investment strategy, are employed along with monthly return data of individual hedge funds.[7] Average alpha values obtained from the time-varying regression analysis without consideration of p-value are denoted by “*alpha*,” and alpha values with consideration of p-value are denoted by “*palpha*.” In other words, “alpha” involves all alpha values as they are regardless of p-value, whereas “palpha” consider all alpha values with p-value greater than 0.1 to be zero. For example, fund A has a alpha of 0.117 with a p-value of 0.836 in the first window. Then, its “alpha” is 0.117 while “palpha” is zero. Similarly, alpha and p-value of the fund A in the fourteenth window are 0.843 and 0.079, respectively. Then, both of “alpha” and “palpha” are 0.843. We collect the 10-year treasury constant maturity yield, Moody’s Baa yield, and Federal Reserve traded weighted index of the U.S. dollar against major currencies from website of Board of Governors of the Federal Reserve System; S&P 500 index, Russell 2000 index, MSCI North American equities, MSCI non-U.S. equities, IFC emerging markets, JPMorgan U.S. and non-U.S. government bonds,

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[6] Offshore financial centers, IMF background paper by Monetary and Exchange Affairs Department. (http://www.imf.org/external/np/mae/oshore/2000/eng/back.htm

[7] Please refer to the models for each investment strategy in Table 8 of the chapter 1.

Eurodollar deposit rate, Gold London Bullion, and volatility index (VIX) from DataStream; and FF's three factors , momentum and contrarian strategy from French's home page.

To ensure sufficient degree of freedom, we exclude hedge funds with less than 36-month of return history before controlling for instant history bias by deleting 12-month observations since inception. In case where inception of funds is far ahead of sample period, we do not delete observations. Therefore, return observations for individual funds consist of at least 24-month. Time series data cover the period from January, 1994 to December, 2008. Further, we also control for survivorship bias by combining the data for active funds with those for inactive funds. After controlling for instant history and survivorship biases, our data consist of 7,102 hedge funds.

2.4 Econometric Methodology

2.4.1 Multinomial Logistic (MNL) Regression Model

In order to consider a hurdle rate and high-watermark at the same time, we employ a multinomial logistic (MNL) regression model. MNL regression model is designed to handle more than two discrete outcomes and to predict the probability of outcomes of those dependent variables. In this study, we utilize the model to examine how hedge fund attributes affect the probability that hedge fund managers offer a hurdle rate and/or high-watermark. We have four possible responses: 0, if none is offered; 1, if a hurdle rate only is offered; 2, if a high-watermark only is offered; and 3, if both are offered. If we base the case where none is offered, then the probabilities (P) of responses are:

$$P_0 = \frac{1}{1+\sum_{j=1}^{3} e^{X\beta_j}} \text{ and } P_i = \frac{e^{X\beta_i}}{1+\sum_{j=1}^{3} e^{X\beta_j}}, \; i = 1, 2, 3.$$

Then, we can write MNL model as:

$$\ln[\frac{P_i}{P_0}] = X \cdot B \text{, } i = 1,2,3.$$

X and B denotes the 1×N vector of independent variables and N×1 vector of unknown parameters, respectively. Independent variables to be used in this model are four different dummy variables for investment strategies; performance and management fees in percentage; level of leverage from one through eight; lockup periods in number of months and minimum investment amount; OFC in dummy variables; and log transformed amount of asset under management. Now, we can estimate the model using maximum likelihood.

We can interpret the coefficients ($\hat{\beta}_i$) in the same way as coefficients from binary logistic model are interpreted. In our study, positive coefficient from MNL model indicates that as independent variable increases, hedge fund manager is more likely to offer a hurdle rate, high-watermark, or both.

2.4.2 Cross-sectional Model

2.4.2.1 Performance Measurements. To measure individual hedge fund performance, we use two different returns. One is Sharpe ratio; the other is the alpha value from Sharpe's multi-factor models using risk factors particularly selected for each of four investment strategies and FoF in the first essay.

$$R_{it}^{str} - R_{ft} = \alpha_i + \sum_{j=1}^{k} (X_{jt}^{str} - R_{ft})\beta_{ij} + \varepsilon_{it} \text{ (} i = 1, 2, \ldots, \text{N)}$$

,where R_{ft} and R_{it}^{str} denote the return on risk-free asset and hedge fund i with investment strategy str at time t, respectively. X_{jt}^{str} and β_{ij} denote the returns on selected risk factors and unknown parameters for hedge funds pursuing investment strategy str, respectively. Applying time-varying regression analysis with 24-month window, we obtain T alpha values, $\alpha_{i,}$ for each hedge fund, where T denotes the number of 24-month windows. Then, by averaging the alpha values, we obtain a proxy for hedge fund performance in the cross-sectional regression analysis, and we name it "*alpha*." Taking p-value of alpha values into an account, we have slightly different performance measurement, which is named as "*palpha*." "Palpha" is the average value of alpha values regarded as zero when p-values of alpha values are greater than 0.1. We also obtain Sharpe ratio by averaging excess returns against a unit change in risk (standard deviation) for each individual hedge fund.

2.4.2.2 Cross-sectional Regression Analysis. In this section, we investigate factors that affect hedge fund performance. Following Ackermann et al. (1999), Liang (1999), and Agarwal et al. (2009) we conduct cross-sectional regression analysis using as dependent variable a performance measured in the previous section.

$$Y_i = \lambda_0 + \sum_{j=1}^{k} \lambda_j Z_{i,j} + \xi_i$$

Where Y_i denotes hedge fund performance measured by alpha, palpha or Sharpe ratio of hedge funds i. $Z_{i,j}$ and λ_j denote explanatory or independent variables and unknown parameters, respectively. As explanatory variables, we utilize hedge fund attributes: hurdle rate and high-watermark in dummy variables; lockup and redemption periods; management and performance fees; level of leverage; OFC; hedge fund size; and number of hedge fund return observations as a proxy for experience of fund manager.

Agarwal et al. (2009) measure managerial incentive fee by total delta, which is equal to the expected dollar change in compensation for one percent change in fund's net asset value. Total delta incorporates into itself a hurdle rate and high-watermark as well as performance fee. However, we separately consider impacts of those variables on performance. If necessary, we can examine the combined effect using interaction terms between a hurdle rate (and/or high-watermark) and performance fee. They also employ investment strategies into cross-sectional model, while we control for investment strategies in the process of measuring performance.

2.5 Empirical Results

2.5.1 Descriptive Statistics

Table 1 reports the summary statistics (Mean, Median, Standard Deviation, Minimum, Maximum, Skewness and Kurtosis) for hedge fund performance and attributes including location of headquarter (OFC), length of hedge funds' life, Alpha, Palpha, Sharpe Ratio, fund amount under management, management fee, performance fee and lockup period.

In Panel A, individual hedge funds are assigned to four different categories: hedge funds that offer none of hurdle rate and high-watermark; that offer hurdle rate only; that offer high-watermark only; and that offer both hurdle rate and high-watermark. These four categories are employed to avoid the potential endogeneity problem elaborated by Soydemir et al. (2012). About 77% of hedge funds provide with at least either of hurdle rate or high-watermark. But the proportion of hedge funds offering hurdle rate only appears to be relatively small. Also, more than half of hedge funds are headquartered in the offshore financial centre showing that those offering high-watermark or both of hurdle rate and high-watermark exhibit slightly higher rate of headquarters in OFC. For the mean length of hedge funds' life, funds offering none of hurdle rate or high-watermark survive longer than those offering a hurdle rate or high-watermark or both. If we assume that length of funds' life is positively related to the performance of hedge funds, we may expect superior performance of hedge funds not offering hurdle rate or high-watermark to that of hedge funds offering. From the mean amount of funds under management, we could observe that investors give their preferences in order of hedge funds offering hurdle rate, high-water mark and both. Funds offering none exhibit the smallest mean amount of funds under management. Lockup periods for hedge funds that do not offer hurdle rate, high-watermark or both appear to be shorter than other hedge funds that offer. Funds with longer lockup period seem to be necessary to signal that they surely achieve the targeted level of return as well as necessary to ensure that they wouldn't charge investors high performance fee unless targets are achieved.

For the management fee, we find little difference among the four categories of hedge funds with mean rate of management fee. However, maximum rate and positively skewed distribution of hedge funds not offering give a hint that they might have somewhat higher level of management fee compared to hedge funds in the other three categories. Performance fee clearly exhibits that hedge funds offering hurdle rate, high-watermark or both tend to require higher level of mean performance fee than hedge funds that do not offer. It supports that hedge fund managers ask higher performance fee as a reward for limiting their compensation because they can collect performance fee only when stated level of returns on hurdle rate and/or high-watermark are achieved. Taking the two types of fees – management and performance fees, we find that hedge funds requiring high performance fee tend to charge investors relatively low management fee. Even though management fee must be utilized for covering operating costs of the funds, it is possibly guessed that management fee might be inappropriately diverted to the compensation of managers.

In Panel B, hedge funds are categorized into five different groups on the basis of their investment strategies. Depending on the investment strategy, hedge fund exposure to risk factors may substantially vary. While RV pursues stable income by minimizing exposure to risk factors, DT takes relatively greater risk due to its investment style made upon prediction of market movement. So, it is reasonable to observe hedge fund performance using alpha and palpha that already involve exposure to risk factors. MP has the greatest alpha value and standard deviation, whereas FoF has the smallest alpha value and standard deviation. It is consistent with the idea that higher return accompanies greater risk. Palpha exhibits the same pattern as alpha. It is also consistent with investment styles of hedge funds. MP mainly takes positions on the transactional events, which usually involve high return and high risk simultaneously. On the other hand, FoF invests in the portfolio of other hedge funds and holds relatively well diversified investment portfolio, so that they could have lowest level of standard deviation. Low mean return of FoF can be attributed to the low risk as well as the fact that FoF has to pay high fees to hedge funds in its portfolio prior to the distribution of its returns to investors.

For attributes of hedge funds, there seems to be not a big difference between hedge funds with different investment strategy. Hedge funds in all four categories collect similar level of management fee and performance fee with an exception that FoF charges very low performance fee. For lockup period, MP limits investors from withdrawing funds for the longest mean periods, 4.72 months in average, and FoF does for the shortest mean periods, 2.43 month. Connecting it with the results of performance, we can expect that longer lockup periods may harm hedge fund performance.

2.5.2 Factors Affecting Fund Managers' Decision of Hurdle Rate and High-watermark

Table 2 reports the results from the multinomial logistic (MNL) regression analysis including coefficients and odds ratios for each variable as well as their standard errors. The model controls for size of hedge funds, experience of hedge fund managers, and education level of hedge fund investors using the mean amount of fund under management and number of employment, number of performance observations, and minimum required amount of investment, respectively.

To examine whether risky hedge funds are more likely to offer hurdle rate and/or high-watermark, different types of hedge fund investment strategies and level of leverage are included into the model. First, we controls for risk associated with investment strategies with dummy variables for hedge fund strategies announced by each fund at their inception. Then, we look at how levels of leverage that hedge funds take affect fund managers' decision to offer hurdle rate and/or high-watermark. The coefficients for leverage are significant and positive when offering high-watermark and both. The coefficient is insignificant but, at least, positive when offering hurdle rate. These results indicate that even after controlling for hedge fund investment strategies, level of risk taken by hedge funds have a significant positive impact on fund managers' decision to offer hurdle rate and/or high-watermark. It is consistent with the hypothesis and result of Soydemir et al. (2012). We can infer from this result that hurdle rate and high-watermark are offered to assure investors that they are protected from paying unreasonable fees. Furthermore, it is questionable whether fund managers intend to attract investors by showing their confidence in achieving the promised returns.

Management and performance fees appear to have significant impact on hedge fund managers' decision of whether to offer a hurdle rate and/or high-watermark. Because management fee has nothing to do with hedge fund performance, it should have no direct impact on the decisions of fund managers. But, we observe negative coefficients for all three categories of dependent variable and significant when offering a hurdle rate and both. It indicates that funds collecting high management fee are less likely to offer hurdle rate or both of hurdle rate and high-watermark. We conjecture that it is unnecessary to offer those with relatively low performance fee because they might misappropriate management fee for compensation for themselves. Performance fee has positive and significant coefficients indicating that as performance fee increases, the probability to offer hurdle rate, high-watermark or both increases as well. Therefore, the results associated with management and performance fee are also consistent with the second hypothesis that management fee is negatively or little related to offering a hurdle rate and/or high-watermark, while performance fee positively affects managers' decision to offer those.

Lockup period is well known as one of hedge fund's unique features. It limits investors' right to withdraw for a specified period of time with an aim of providing fund managers with a maximum discretion on using the funds. While providing more flexibility to fund managers, it puts more restrictions and risk on investors, so that managers might need to offer a hurdle rate and/or high-watermark. The results exhibit weak evidence supporting the third hypothesis. Only significant is coefficient for offering a hurdle rate while all three coefficients are positive. However, we can explain it with the average lockup periods in the Panel B of Table 1, which range from 2.43 months to 4.72 months. Because lockup periods are not that long, offering only a hurdle rate should be enough to alleviate investors' anxiety compared to high-watermark which requires recovering all previous loss to collect fee.

Hurdle rate and high-watermark are offered to investor by hedge fund managers. Offering those assures investors that they are protected from unfavorable conditions such as high risk and fees and strong restriction. Our results indicate that fund with higher level of risk and management fee, lower management fee, and longer lockup periods are more likely to offer those incentives. In addition, offering those incentives makes investors feel that fund managers are confident to earn positive return. However, Agarwal et al. (2009), Ray (2009), and Aragon and Nanda (2010) consider them to be an incentives for managers as well as for investors. Their argument is that fund managers would do their best to achieve a specified level of return and then collect fees. We examine effects of various hedge fund attributes on the performance of hedge fund managers in the cross-sectional regression analysis.

2.5.3 Cross-sectional Regression Analysis

Table 3 reports the results from the cross-sectional regression analysis to see how hedge fund attributes affect its performance using alpha, palpha and Sharpe ratio as a proxy for hedge fund performance. While alpha and palpha are obtained from the optimal models developed in the first essay controlling for hedge fund investment strategy and various risk factors, Sharpe ratio is adjusted only for standard deviation of hedge fund returns. In order to examine hypotheses, we control some of hedge fund attributes such as management fee, offshore centre, leverage, number of observations and minimum amount of investment.

First, we include a hurdle rate and high-watermark into the model to see whether they work as incentives for fund managers as majority of existing literature considers those. Otherwise they work as restrictions as Soydemir et al. (2012) claim. The coefficients of columns (1) for each analysis of different dependent variables are all negative and, particularly, coefficients for high-watermark are significant. These results indicate that hedge funds offering high-watermark underperform those that do not offer. In addition, the negative coefficients of hurdle rate prove that at least, offering hurdle rate does not positively affect hedge fund performance. Test results are consistent with Soydemir et al. (2012) well supporting the hypothesis that hedge funds that offer a hurdle rate and/or high-watermark should underperform or at best not better than those that do not offer. For the magnitudes of coefficients, we can observe that coefficients from the analysis using Sharpe ratio apparently differ from those using alpha and palpha. It can be attributed to the fact that Sharpe ratio does not control for risk associated with hedge fund investment strategies.

For all the three regression analyses, hedge fund performance fee exhibits significant and positive relationship with hedge fund performance as we expect. Performance fee is a critical incentive in the fund manager compensation system, and the high level of performance fee promotes performance of fund manager. This is consistent with Do et al. (2005) and Liang (1999). However, there is one thing that we should consider from the MNL regression analysis. It is that the performance fee has a significant and positive effect on fund managers' decision of offering hurdle rate and/or high-watermark. But, hurdle rate and high-watermark have negative impact on hedge fund performance, unlike positive impact of performance fee, in the cross-sectional regression analysis. Opposite impact of those attributes on hedge fund performance may involve interactions between hurdle rate and performance fee and between high-watermark and performance fee. So, we include interaction terms into the cross-sectional regression analysis, and the results are reported in the columns (2). Interaction terms for alpha and palpha are insignificant, but after controlling for the interaction terms, the coefficients for the individual variables increase. High-watermark and performance fee still have significant impact on hedge fund performance, but coefficient for hurdle rate turns into positive and remains insignificant. Therefore, we can conclude that hurdle rate has no significant effect on hedge fund performance whereas high-watermark has a negative effect.

If we argue that hurdle rate and high-watermark are restrictions on fund managers, we may also argue that lockup period is a restriction on fund investors. Since it provides fund managers with discretion on the use of funds for a certain period, longer lockup period tends to positively affect hedge fund performance. Our results from the analyses using alpha and palpha support the hypothesis. Lockup period has positive and significant coefficients, which are consistent with Aragon (2007), and Liang and Park (2007).

For the hypothesis that hedge funds with larger assets are more likely to outperform those with less, the positive coefficient of fund size, a proxy of fund amount under management (AUM), supports the hypothesis. As Xiong et al. (2007) argue, fund size exhibits positive relationship with hedge fund performance. It can be attributed in two different reasons. First, large amount of funds are ideal size for fund managers because of economy of scale, so that hedge funds with larger funds exhibit better performance. Second, investors in hedge fund industry are assumed to have relatively high education level, so that they are considered to be smart. They analyze and find funds that perform well or that are expected to perform well. Then, funds are invested in those hedge funds, which become larger.

2.6 Conclusion

In this study, we first conduct MNL regression analysis to see how hedge fund attributes affect hedge fund managers' decision of whether to offer a hurdle rate and/or high-watermark. The model controls for fund size, experience of fund managers and education level of investors including variables such as asset under management, number of employees, return observations and minimum amount of investment.

We find that hedge funds taking more risky positions are more likely to offer hurdle rate and/or high-watermark. It indicates that hurdle rate and high-watermark are offered to attract funds by assuring investors that their money will be safe. In addition, we reveal that performance fee and management fee significantly affect fund managers' decision. Performance fee is positively related to the probability of offering hurdle rate and/or high-watermark. It is attributed to compensating fund managers for offering hurdle rate and/or high-watermark. Therefore, we can conjecture that hurdle rate and high-watermark work as restriction for hedge fund managers on collecting fee rather than as incentives.

We also include lockup period to see how restriction on investors affects fund managers' decision, and find that funds with longer lockup period or stronger restriction are more likely to offer hurdle rate. However, lockup period does not exhibit significant relationship with the likelihood of offering high-watermark or both. Because lockup periods are not that long on average from 2.43 to 4.72 month by investment strategy, offering only a hurdle rate should be enough to alleviate investors' anxiety and then, to attract funds.

Second, we conduct cross-sectional regression analysis to see how hedge fund attributes affect hedge fund performance. The attributes examined in this test are hurdle rate, high-watermark, performance fee, lockup period and fund size. The first hypothesis aims to see the role of hurdle rate and high-watermark, and our results indicate that they are restrictions for hedge fund managers on collecting fee. This result is contrary to majority of existing literature, but consistent with Soydemir et al. (2012). Hurdle rate and high-watermark have negative or no effect on hedge fund performance, so that they cannot be considered to be incentives. We also find that hedge funds collecting high performance fee and having large amount of funds are more likely to outperform those collecting low performance fee and having small amount of funds. At last, we reveal that length of lockup period has a positive relationship with hedge fund performance. Lockup period provides fund managers with discretion to the use of funds, so that fund managers have more room to have more illiquid assets in their portfolio and earn illiquidity premium.

In the hedge fund industry, hurdle rate and high-watermark are generally considered to be incentives for fund managers, so that investors think of those attributes as signal that hedge funds offering those are confident to be in the money. As proven in this study, however, they are devised by fund managers to lure investors, but not to promote fund performance. While conducting cross-sectional regression analysis, we use three different measures of hedge fund performance: alpha, palpha and Sharpe ratio. Unlike Sharpe ratio only adjusted for standard deviation, Alpha and palpha are obtained from the optimal model by investment strategy controlling for hedge fund risk associated with risk factors different by its investment strategy. In addition, we control for survivorship and instant history biases. Using appropriate measures of fund performance may reduce the risk of biased results. So, our results from alpha and palpha are more credible than those of Soydemir et al. (2012) which employs only Sharpe ratio.

Table 2.1 Descriptive Statistics for Performance and Attributes of Hedge Funds

This table reports the summary statistics (Mean, Median, Standard Deviation, Minimum, Maximum, Skewness and Kurtosis) for hedge fund performance and attributes including Location of Headquarter (Offshore Financial Centre), Length of Hedge Funds' Life, Alpha, Palpha, Sharpe Ratio, Fund Amount Under Management, Management Fee, Performance Fee and Lockup Period.

Alpha values are obtained by averaging alphas from the time-varying regression analysis using Sharpe's multi-factor model. Since the different groups of risk factors are determined based on the hedge investment strategy, alpha values already reflect characteristics of each investment strategy. For collecting Palpha values, alpha values with p-values greater than 10% are considered to be zero; and otherwise to be as it is. Sharpe ratio is a change in an average excess return against a unit change in risk (standard deviation).

Offshore financial centre indicates the location of hedge fund headquarters. Significant number of hedge funds is located in the offshore financial centre where offers financial services to nonresidents on a scale that is incommensurate with size and financing of its domestic economy. Length of funds' life is measured by counting the number of monthly return observations for individual funds. In the analysis, it can be a proxy for experience of hedge fund managers. Fund amount under management is in a million and a proxy for size of hedge fund. Management fee and Performance fee charged by hedge funds are expressed in percentage. Lockup period, which is in the number of months, indicates the period during which investors are limited from withdrawing their investment, which works as a proxy for restriction on investors.

'*' denotes significance at the 5% level.

For Panel A, individual hedge funds are assigned to four different categories: hedge funds that offer none of hurdle rate and high-watermark; that offer only hurdle rate; that offer only high-watermark; and that offer both hurdle rate and high-watermark. These four categories are employed to avoid the potential endogeneity problem elaborated by Soydemir et al. (2012).

PANEL A: Performance and Attributes of Hedge Funds Depending on Whether to Offer Hurdle Rate and/or High-watermark

	Number of Funds	Offshore Financial Center		Life	Alpha	Palpha	Sharpe Ratio	Fund AUM ($Million)	Management Fee	Performance Fee	Lockup Period
None	1581	811	**Mean**	69.36*	0.6158*	0.4514*	0.1336*	148.554*	1.36*	8.24*	2.29*
	(22.3%)	(51.3%)	**Median**	58.00	0.4537	0.2354	0.1071	43.899	1.50	0.00	0.00
			Std. Dev	39.02	0.9918	0.7457	0.2892	350.820	0.58	9.77	5.55
			Min	24.00	-5.0532	-2.6072	-1.1642	0.011	0.00	0.00	0.00
			Max	180.00	11.6620	8.5630	3.9916	4530.915	6.00	50.00	60.00
			Skewness	1.16*	2.8649*	3.0550*	2.6926*	7.090*	0.96*	0.55*	3.31*
			Kurtosis	0.74*	22.2729*	18.4629*	25.1222*	66.547*	6.85*	-0.98*	16.34*
Only Hurdle	210	85	**Mean**	66.60*	0.4786*	0.3533*	0.1088*	159.312*	1.18*	13.24*	3.99*
	(3.0%)	(40.5%)	**Median**	59.00	0.3463	0.2087	0.0751	51.949	1.00	15.00	0.00
			Std. Dev	36.03	0.6917	0.5379	0.2410	295.329	0.48	8.43	8.61

			Min	24.00	-2.0311	-1.6595	-0.4634	0.037	0.00	0.00	0.00
			Max	180.00	3.7893	2.7565	0.9420	2574.356	3.00	50.00	60.00
			Skewness	1.18*	1.0766*	1.5188*	0.6344*	4.456*	0.10*	-0.07*	3.23*
			Kurtosis	0.98*	4.7357*	5.6596*	0.9782*	27.348*	1.09*	0.40*	13.55*
Only High-Watermark	4118 (58.0%)	2530 (61.4%)	**Mean**	66.67*	0.4692*	0.3352*	0.1091*	191.661*	1.41*	16.80*	3.98*
			Median	55.00	0.4345	0.2109	0.0812	67.924	1.50	20.00	0.00
			Std. Dev	38.06	0.6760	0.5428	0.4660	430.416	0.45	5.37	6.55
			Min	24.00	-4.6918	-3.4980	-0.7008	0.029	0.00	0.00	0.00
			Max	180.00	8.8258	8.0547	15.3432	7605.536	5.00	37.50	60.00
			Skewness	1.18*	1.6626*	3.1263*	17.5664*	6.383*	0.26*	-1.05*	1.90*
			Kurtosis	0.69*	22.4552*	35.4535*	474.9621*	57.485*	2.00*	0.12*	5.52*
Both	1139 (16.0%)	720 (63.2%)	**Mean**	66.70*	0.4373*	0.2950*	0.0932*	202.984*	1.36*	15.11*	3.12*
			Median	55.00	0.3668	0.1798	0.0547	64.495	1.50	15.00	0.00
			Std. Dev	38.17	0.6303	0.5013	0.4618	349.396	0.46	6.39	6.11
			Min	24.00	-7.0271	-6.6329	-0.4936	0.001	0.00	0.00	0.00
			Max	180.00	7.0249	4.2484	9.8324	214.771	4.00	65.00	60.00
			Skewness	1.18*	0.5214*	-0.1844*	12.6498*	3.332*	0.19*	1.33*	2.56*
			Kurtosis	0.71*	31.6816*	41.8360*	227.8078*	13.134*	2.54*	8.23*	10.59*

Table 2.1 (Continued) Descriptive Statistics for Performance and Attributes of Hedge Funds

For Panel B, individual hedge funds are assigned to five different hedge fund investment strategies. The first four investment strategies – Directional Traders (DT), Relative Value (RV), Security Selection (SS) and Multiprocess (MP) – are divided by Argarwal et al. (2009) based on investment strategy that hedge funds take. Argarwal et al. (2009) define that DT tends to bet on the direction of market prices of currencies, commodities and bonds in the futures and cash markets; that RV takes positions on spread relationships between prices of financial assets or commodities and aims to minimize market exposure; that SS takes long and short positions in undervalued and overvalued securities, respectively, and reduce the systematic market risk in the process; and that MP takes multiple strategies employed by funds, usually involving investment in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks.

Fund of hedge funds (FoF) is also one of widely known and used investment strategies. FoF holds portfolios of other hedge funds rather than directly investing in shares, bonds and commodities.

PANEL B: Performance and Attributes of Hedge Funds Depending on Investment Strategy of Hedge Fund

	Number of Funds	Offshore Financial Center		Life	Alpha	Palpha	Sharpe Ratio	Fund AUM ($Million)	Management Fee	Performance Fee	Lockup Period
DT	1069	615	**Mean**	68.02*	0.5058*	0.3444*	0.1117*	117.352*	1.51*	18.39*	3.43*
	(15.1%)	(57.5%)	**Median**	55.00	0.5016	0.1574	0.0959	50.967	1.50	20.00	0.00
			Std. Dev	39.54	0.9759	0.7357	0.2390	189.071	0.49	5.60	6.37
			Min	24.00	-7.0271	-6.6329	-0.6093	0.001	0.00	0.00	0.00
			Max	180.00	7.8946	6.0989	2.7571	1587.097	5.00	65.00	60.00
			Skewness	1.09*	0.0242*	0.7761*	2.9272*	3.469*	0.40*	-1.22*	2.44*
			Kurtosis	0.32*	10.4065*	18.1474*	22.6210*	15.287*	3.14*	10.58*	10.04*
RV	728	380	**Mean**	68.21*	0.5096*	0.4148*	0.2537*	164.956*	1.33*	18.54*	3.65*
	(10.3%)	(52.2%)	**Median**	56.00	0.5002	0.3525	0.0939	70.027	1.50	20.00	0.00
			Std. Dev	39.63	0.6443	0.5490	1.1048	315.517	0.50	6.31	6.81
			Min	24.00	-3.4980	-3.4980	-0.5889	0.815	0.00	0.00	0.00
			Max	180.00	7.4188	7.4188	15.3432	4530.915	2.60	65.00	60.00
			Skewness	1.09*	2.1106*	3.3103*	8.4944*	6.364*	-0.29*	-0.59*	2.79*
			Kurtosis	0.43*	25.9043*	42.5246*	89.6601*	62.559*	-0.09	9.38*	12.40*
SS	1667	786	**Mean**	69.88*	0.6133*	0.4085*	0.1170*	130.148*	1.35*	18.57*	4.34*
	(23.5%)	(47.2%)	**Median**	59.00	0.5437	0.2588	0.1170	45.398	1.50	20.00	0.00
			Std. Dev	39.29	0.7781	0.6077	0.2021	270.340	0.43	4.87	6.73
			Min	24.00	-2.2300	-2.0602	-0.7008	0.102	0.00	0.00	0.00
			Max	180.00	8.0899	8.0547	1.4127	4465.559	4.00	30.00	36.00
			Skewness	1.08*	1.9667*	2.9520*	0.2803*	7.276*	0.59*	-2.99*	1.55*
			Kurtosis	0.54*	14.7428*	21.2072*	2.4866*	80.118*	2.81*	8.51*	2.44*

MP	927	457	**Mean**	66.77*	0.7688*	0.5791*	0.2291*	218.481*	1.37*	18.20*	4.72*
	(13.1%)	(49.3%)	**Median**	57.00	0.6497	0.4453	0.1887	54.977	1.50	20.00	0.00
			Std. Dev	37.34	1.0750	0.8243	0.3589	480.569	0.53	6.03	7.35
			Min	24.00	-5.0532	-2.8188	-0.5124	0.149	0.00	0.00	0.00
			Max	180.00	11.6620	8.5630	6.3974	7605.536	4.00	50.00	60.00
			Skewness	1.13*	3.2466*	3.1095*	6.3128*	6.778*	0.02*	-1.47*	1.99*
			Kurtosis	0.69*	25.4807*	21.2921*	96.0688*	76.197*	1.26*	6.87*	6.11*
FoF	2711	1908	**Mean**	65.35*	0.3307*	0.2368*	0.0351*	235.226*	1.37*	8.07*	2.43*
	(38.2%)	(68.9%)	**Median**	54.00	0.2987	0.1318	0.0167	74.265	1.50	10.00	0.00
			Std. Dev	37.04	0.4177	0.3528	0.2320	496.898	0.50	6.19	5.43
			Min	24.00	-1.4958	-1.1940	-1.1642	0.037	0.00	0.00	0.00
			Max	180.00	4.6085	4.6085	2.5134	4941.644	6.00	35.00	60.00
			Skewness	1.31*	1.7498*	2.9813*	1.8327*	4.854*	0.82*	0.35*	2.98*
			Kurtosis	1.12*	14.0962*	21.3735*	14.4765*	28.657*	7.77*	-0.15	14.86*

Table 2.2 Multinomial Logistic Regression Analysis

This table reports the results from the multinomial logistic regression analysis to see what factors affect hedge fund managers' decision of whether or not to offer hurdle rate and/or high-watermark.

For this analysis, categorical dependent variable, Dummy_hr_hw, is used and coded as follows:
Dummy_hr_hw=0 if fund managers offer neither of hurdle rate or high-watermark (**used as a base category**); Dummy_hr_hw=1 if fund managers offer hurdle rate only; Dummy_hr_hw=2 if fund managers offer high-watermark only; and Dummy_hr_hw=3 if fund managers offer both of hurdle rate and high-watermark.

As the independent variables, dummy variables for four different hedge fund investment strategies including funds of hedge funds (DT, RV, SS and FoF) and level of hedge fund leverage are used as measures of risk that hedge funds take; hedge fund management fee and performance fee charged on investors are used as measures of rewards for hedge fund managers' performance; and lockup month is used as a measure of restriction put on investors funds.

In addition, this analysis controls for size of hedge funds with the mean amount of funds under management (Ln mean aum) and number of employees; experience of hedge fund managers with the number of performance observations (obs); and the education level of investors with the minimum required amount of investment.

This table consists of coefficients of each variable from the multinomial logistic regression analysis and odds ratios (denoted by RRR: relative risk ratios) along with their standard errors. '*' denotes significance at the 5% level.

	Coeff.	**Std. Err**	**RRR**	**Std. Err**	**Coeff.**	**Std. Err**	**RRR**	**Std. Err**	**Coeff.**	**Std. Err**	**RRR**	**Std. Err**
	Hurdle rate only				High-watermark only				Both			
DT	2.320*	0.504	10.179	5.134	1.462*	0.208	4.315	0.899	2.115*	0.266	8.286	2.206
RV	2.370*	0.529	10.700	5.658	1.122*	0.246	3.070	0.755	1.794*	0.303	6.016	1.820
SS	1.825*	0.485	6.203	3.006	1.416*	0.182	4.120	0.749	1.123*	0.252	3.074	0.776
FoF	3.998*	0.507	54.482	27.609	3.623*	0.215	37.433	8.054	5.102*	0.271	164.369	44.477
Management fee	-0.932*	0.191	0.394	0.075	-0.084	0.098	0.919	0.090	-0.328*	0.118	0.720	0.085
Performance fee	0.220*	0.019	1.246	0.023	0.304*	0.011	1.355	0.014	0.338*	0.013	1.403	0.018
Fund leverage	0.258	0.176	1.295	0.228	0.454*	0.107	1.574	0.168	0.491*	0.111	1.634	0.181
Lockup month	0.031*	0.012	1.031	0.013	0.008	0.008	1.008	0.008	0.007	0.009	1.007	0.009
Obs	0.002	0.002	1.002	0.002	0.001	0.001	1.001	0.001	0.003	0.001	1.003	0.001
Manager number of employees	0.001*	0.000	1.001	0.000	0.000	0.000	1.000	0.000	0.001*	0.000	1.001	0.000
Ln mean aum	0.078	0.054	1.081	0.059	0.142*	0.030	1.153	0.034	0.141*	0.035	1.151	0.040
Ln minimum investment	-0.112*	0.046	0.894	0.041	0.079*	0.025	1.082	0.027	-0.023	0.030	0.977	0.029

Constant	-6.392*	1.232			-8.848*	0.663			-10.014*	0.794		

Table 2.3 Cross-sectional Regression Analysis

This table reports the results from the cross-sectional regression analysis to see what factors including hurdle rate and high-watermark as well as other attributes affect hedge fund performance.

For this analysis, three different measures (alpha, palpha and Sharpe ratio) of hedge fund performance are utilized:
Alpha and ***palpha*** are obtained from the model by hedge funds' investment strategies proposed in the first essay.

$$R_{it}^{str} - R_{ft} = \alpha_i + \sum_{j=1}^{k}(X_{jt}^{str} - R_{ft})\beta_{ij} + \varepsilon_{it} \quad (i = 1, 2, \ldots, \mathrm{N})$$

,where R_{ft} and R_{it}^{str} denote the return on risk-free asset and hedge fund i with investment strategy *str* at time t, respectively. X_{jt}^{str} and β_{ij} denote the returns on selected risk factors and unknown parameters for hedge funds pursuing investment strategy *str*, respectively. Applying time-varying regression analysis with 24-month window, we obtain T alpha values, $\alpha_{i,,}$ for each hedge fund, where T denotes the number of 24-month windows. By averaging the alpha values, then we obtain ***alpha***. ***Palpha***, which takes p-value of alpha values into an account, is the average value of alpha values regarded as zero when p-values of alpha values are greater than 0.1. ***Sharpe ratio*** is an average of excess returns against a unit change in risk (standard deviation) for each individual hedge fund.

For the first cross-sectional regression analysis, hurdle rate, high-watermark, performance fee, lockup months and fund size (AUM) are examined controlling for management fee, risk (leverage), experience of managers (observations) and investors' education level (minimum investment). In the second analysis, interaction terms between hurdle rate and performance fee and between high-watermark and performance fee are added to the first analysis.

This table consists of coefficients of each variable from the cross-sectional regression analysis their standard errors. '*' denotes significance at the 5% level.

Independent Variables	Alpha				Palpha				Sharpe ratio			
	(1)		(2)		(1)		(2)		(1)		(2)	
	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
HR*Perform			-0.004	0.003			-0.003	0.003			0.001	0.002
HW*Perform			-0.001	0.003			-0.004	0.002			0.005*	0.002
Hurdle rate	-0.025	0.022	0.028	0.051	-0.030	0.017	0.008	0.041	-0.005	0.015	-0.021	0.036
High-watermark	-0.107*	0.025	-0.100*	0.039	-0.107*	0.020	-0.073*	0.031	-0.048*	0.018	-0.094*	0.028
Performance fee	0.013*	0.001	0.015*	0.002	0.011*	0.001	0.014*	0.002	0.007*	0.001	0.003*	0.002
Lockup month	0.009*	0.001	0.009*	0.001	0.006*	0.001	0.006*	0.001	-0.001	0.001	-0.001	0.001
AUM	0.026*	0.006	0.026*	0.006	0.025*	0.004	0.025*	0.004	0.004	0.004	0.004	0.004
Management fee	0.025	0.019	0.025	0.019	0.011	0.015	0.014	0.015	-0.015	0.013	-0.020	0.013
Offshore centre	-0.049*	0.019	-0.049*	0.019	-0.036*	0.016	-0.037*	0.016	-0.051*	0.014	-0.050*	0.014

Leverage	0.003	0.010	0.005	0.010	0.008	0.008	0.010	0.008	-0.002	0.007	-0.004	0.007
Observations	0.003*	0.000	0.003*	0.000	0.003*	0.000	0.003*	0.000	0.001*	0.000	0.001*	0.000
Minimum investment	0.008	0.005	0.007	0.005	0.011*	0.004	0.012*	0.004	0.007*	0.004	0.007	0.004
Constant	-0.457*	0.112	-0.467*	0.114	-0.552*	0.089	-0.581*	0.091	-0.144	0.079	-0.107	0.081
Adj. R-squared	*0.0687*		*0.0687*		*0.0789*		*0.0796*		*0.0242*		*0.0252*	

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