Risk Shifting and Mutual Fund Performance: A Swedish Perspective

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Abstract

This thesis examines the performance consequences of risk shifting in mutual funds on the Swedish market between the years 2000-2011. By constructing a risk shifting measure based on tracking error volatility, we conclude that the funds that increase risk the most have experienced better performance than funds which decrease or keep stable risk levels over the sample period. We also find that funds that engage in risk shifting behavior on average are younger, have less assets under management and charge higher expense rates. We suggest that Swedish fund managers who increase risk the most might have superior stock picking skill and market timing ability to their US colleagues.

Key words: Risk Shifting, Fund Performance, Tracking Error, CAPM, Fama-French, Carhart

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1. Introduction

A rational investor who faces the classic tradeoff between risk and expected return would seek to maximize return relative to his or her level of risk aversion. Among funds and fund managers there exists many investment strategies that over time have led to different returns through taking positions on different risk levels. The level of risk in mutual funds are of importance to investors as they want to know what return they can expect and how large losses they have to be prepared for. Our thesis aims to contribute to the field of research which provides investors with ways to identify funds that are more likely than others to deliver future returns in relation to risk and risk shifting. While our study is conducted using methods that are not immediately available for ordinary investors to replicate, our results serve to lend support to previous research on fund characteristics, which investors in turn can take into account when investing.

Tangible indicators of superior performance, for example size and expense rate, in mutual funds should reasonably be of great interest to Swedish investors, as savings in funds is central to the nation's public and private savings. The Swedish market for mutual funds has been growing rapidly since the late 1980's and early 1990's when favorable tax-regulations and credit market deregulations made it increasingly more attractive to invest money both domestically and internationally through funds. At the end of year 2011, the total fund assets amounted to 1819 billion SEK. Although this represents a reduction of 145 billion SEK compared to the previous year, total assets under management in funds have increased from 888 billion SEK since 2010 and from 120 billion SEK in 1990. Approximately 82 percent of Swedish citizens save in funds, and when taking into account saving in the premium pension system nearly the entire adult population saves in funds. Equity mutual funds are the most popular fund type, followed by Mixed funds (investing in equity and bonds) and Fixed Income funds.[1]

In our thesis, we examine the performance consequences of risk shifting in the Swedish mutual fund market. Huang, Sialm and Zhang (2011)[2] write about risk shifting by looking at performance consequences using a holdings-based measure to observe risk shifting in mutual funds and the subsequent effect on performance. Our intention is to replicate parts of the above mentioned article using a data sample of Swedish-based mutual funds between the years 2000-2011. By replicating this study with Swedish data, we are able to test the implications of risk shifting in a way that has not previously been done

[1] Swedish Investment Fund Association, (Fondbolagens Förening).
[2] Henceforth denoted *as HSZ (2011).*

in Sweden. We aim at providing an overview of the impact on performance in mutual funds when managers actively alter the level of risk in the managed fund. More specifically, our aim is to recreate parts of the article where results are not dependent on holdings data and parts where it is possible to make minor changes to fit our data. In comparison with research conducted in the massively documented US fund market, in terms of data available to researchers, we face certain limitations when using Swedish data obtained from Morningstar Sweden.[3] In absence of comprehensive holdings data for individual funds, we construct an alternative way of measuring risk shifting and apply it to selected tests from the above-mentioned article. The reasoning behind and construction of this measure is described in detail in the methods-section of the thesis. With support from established research on fund performance, we base the alternative risk shifting measure on tracking error volatility, i.e. deviation from a funds assigned benchmark. Furthermore, we compare our results to *HSZ (2011*) in order to discuss similarities and differences between the different markets, as well as confirming the validity of the alternative measure. While not pioneering the use of benchmark indices in fund research, we argue that the use of an extensive list of 62 benchmark indices add to the significance of our results.

Our thesis is structured as follows: We begin by reviewing existing literature and previous studies on fund research in order to provide the reader with a comprehensive overview of the subject in section 2, followed by data presentation and summary statistics in section 3. Section 4 describes our methods used to differentiate risk shifters and calculate performance measures. Section 5 covers empirical results of performance consequences of risk shifting. Sections 6 and 7 concludes, discusses limitations and offers our suggestions for future research. The Appendix lists fund categories and corresponding benchmark indices as well as presents regression tables.

[3] *http://www.morningstar.se/*

2. Previous Research

The topics surrounding the behavior of mutual fund managers and subsequent effect on fund performance have previously been extensively researched. Numerous studies have been devoted to examining the existence of skilled active managers that are able to persistently outperform the market using superior market timing ability and stock picking skill. Results of studies on the subject are often opposing in their conclusions, but there is an overall view that a small number of fund managers, often obscured in studies by the vast majority, possess superior skills. Kosowski et al. (2006) among others support this view. Carhart (1997) does not support the existence of skilled fund managers and relies on the efficient market hypothesis. Using a rational model of active portfolio management, Berk and Green (2004) find that active managers do not outperform passive benchmarks, but conclude that a majority has at least enough skill to earn back fees. Wermers (2000) supports the presence of stock picking skills in funds and argues that active management is beneficial to investors. On the same topic, Wermers (2003, Working Paper) conclude that fund managers who take larger active management bets show better stock picking skill in the long term, although the average manager tends to underperform their benchmarks. Baks, Metrick and Wachter (2001) conclude theoretically that even skeptical investors will allocate assets into active management. When using daily fund returns instead of monthly, Bollen and Busse (2001) suggest that timing ability in mutual funds might have been understated in previous research on the subject. Similarly, Jiang, Yao and Yu (2007) find positive market timing ability in US domestic equity funds when choosing a measure based on fund holdings instead of returns. They also find that market timing funds tend to exhibit higher industry concentration. This supports Kacperczyk, Sialm, and Zheng (2005) who suggest greater investment ability among managers holding portfolios that are focused on fewer industries. Furthermore, Elton, Gruber and Blake (2003) relate manager incentive fees in funds with higher stock picking skill.

Another major area of research related to mutual funds is the concept that funds that have experienced superior returns to investors in prior periods will continue to outperform and deliver high returns in the future. This also applies to whether or not funds that have underperformed in the past will continue to underperform in the future. In essence, researchers are looking at the track record of a fund assuming it contains information about the future performance. Brown and Goetzmann (1995) examine performance persistence in the US market between 1976-1988 and concludes that there is some persistence in relative risk-adjusted performance correlated across managers. They also find that poor performance over several years increases the likelihood of disappearance from the market through termination or merger of the fund. Carhart (1997) explains persistence in equity mutual funds with stock return-factors and investment expenses while Berk and Green (2004) find that past performance cannot be used to predict future returns.

Many articles identify the flow of invested assets in and out of mutual funds as a variable that helps explain and predict future performance, changes in manager behavior through incentives linked to asset flows, as well as increases in frequency of manager replacement. Gruber (1996) and Sirro and Tufano (1998) study flows in and out of equity mutual funds and conclude that consumers look to prior performance when investing, but do so in an asymmetrical manner by investing disproportional amounts into funds that have performed exceptionally in the prior period. When using a high expense rate as a proxy for higher marketing efforts, the latter also find that lower search cost for consumers through larger fund size and more media attention generates higher investments. Zheng (1999) observes a short-lived tendency of funds with large inflows to perform significantly better than funds that experience outflows, but the effect does not persist in the long run. Using the perspective of an individual investor, Ivkovic and Weisbenner (2009) find that in- and outflow is sensitive to performance, but in different ways. Inflow of assets is found to be related only to relative performance while outflow is related to absolute performance. There appears to exist a reluctance to sell a fund which has increased in value while there exists a willingness to sell a losing fund. They conclude that this might be due to tax considerations.

In the mutual fund industry, a fund manager is in a position to manipulate the performance, the characteristics or other factors related to the fund, in order to gain benefits or to prevent job loss. An agency conflict exists between investors and managers. This creates incentives for the fund company to adjust risk levels to increase inflow of new capital, reasons Chevalier and Ellison (1997). Khorona (2001) and Khorona (1996) find evidence of strategic risk shifting in fund portfolios prior to manager replacement, and also that returns improve when underperforming managers are replaced. Kempf, Ruenzia and Thielea (2009) uses bull/bear-market as a proxy for when manager employment risk is more important than incentives and show that low (high) employment risk make underperforming fund managers increase (decrease) risk to catch up with outperformers and prevent job loss.

Risk shifting among mutual fund managers is commonly examined in studies on tournament behavior, the tendency of interim-year underperforming fund managers to increase risk in the fund portfolio in the second interim-year period in an attempt to catch up to "winner" fund managers, when incentives are linked to performance. Brown, Harlow and Starks (1996) and Lynch Koski and Pontiff (1999) are among the first to view the mutual fund market as a tournament where manager payoff depends on performance relative to other managers, and find evidence that interim-year "losers" increase fund volatility in the latter part of an annual assessment period. This is supported by Brown, Goetzmann and Park (2001). Chevalier and Ellisson (1997) support tournament behavior with the conclusion that mutual funds alter portfolio risk between September and December depending on fund returns over the first nine months, with a negative relationship between performance and risk. Kempf and Ruenzi (2008) study tournament behavior in the context of larger fund families (i.e. mutual funds that belong to the same fund management company, for example Swedbank Robur in Sweden) and find that funds adjust risk depending on their relative position in the family. High expense ratios and single managers in particular are found to contribute to this behavior. Although the phenomenon of tournament behavior is well-established in the academic world, Busse (2001) and Basak, Pavlova and Shapiro (2007) argue that these increases in risk are due to biases in monthly volatility and find that underperformers increasing risk relative to better performing managers disappear with daily data. Schwarz (2009) explains these contradicting results with a sorting bias that, when corrected for, lends further support to the original conclusions on tournament behavior risk shifting among underperformers. Furthermore, in a recent job market paper on risk shifting, Jaiprakash (2010) finds that the originally hypothesized risk shifting behavior is reversed in a sample of US equity mutual fund between 2000-2007, meaning underperformers (winners) decrease (increase) risk in the second interim-year period.

There are relatively few papers published in higher financial publications on the characteristics and performance of the Swedish mutual fund market, which is the most relevant scope of this thesis. Previous literature on Swedish funds may serve to help us interpret empirical results. On a European level, Broihanne (2005) establishes tournament behavior as a phenomenon present in France, and Europe in general, by testing methods developed in the US on European funds between 1994-2003. When looking for differences in the European and US fund market by studying mutual fund performance in 27 countries including Sweden, Ferreira, Keswani, Miguel and Ramos (2011) find that country characteristics can explain performance. Their main findings show that liquid stock markets and strong legal institutions improve performance, and that the diminishing returns to scale typical in the US are not universal. As one of the most citied academic papers, Dahlquist, Engström and Söderlind (2000) study relations between fund performance and attributes in the Swedish market from 1993 to 1997 and find relations between good performance and small equity funds, low-fee funds and high trading activity. Engström (2003) examines the impact of geographical distance between the fund and the market on performance using a sample of funds available to Swedish investors. Various university theses originating from the Stockholm School of Economics give some further indication of general characteristics. For example, Garbalinska and Gustavsson (2007) support one-year performance persistence in Swedish equity mutual funds between 1993-2006. Bergström and Sundén (2008) find a positive relationship between asset flows into funds and risk-adjusted returns, i.e. the existence of "smart money" in a sample of funds between 2003-2007. Bikova and Tilgalis (2012) conclude that the Swedish fund market is characterized by high managerial turnover and that the replacement of an underperforming manager increases subsequent returns. Also on the topic of fund managers, Jerner and Wingårdh (2011) find a reversed U-shaped team size-performance pattern in Swedish funds, indicating that teams of two or three managers outperform both single managers and larger teams.

The above mentioned research uses a wide range of methods and data to reach their conclusions on fund market behavior. However, we find that there are two major groups into which one can divide the academic research: studies which use fund holdings-data (quarterly data is most common) and studies which use fund return-data (monthly). Among the latter group, tracking error volatility is a common return-measure being used in studies as a proxy for active management. Grinblatt and Titman (1993) are among the first to introduce holdings data in their study on mutual funds in the 1976-1985 period and find positive risk-adjusted returns for aggressively managed growth-funds. Looking at fund holdings has since become a frequently used method when studying funds, largely thanks to the extensive records of data that are kept in the US on holdings of domestic funds. Other notable research using holdings are Daniel, Grinblatt, Titman and Wermers (1997), Jiang, Yao and Yu (2007), Kempf, Ruenzia and Thielea (2009), Brown, Harlow and Zhang (2010) and Da, Gao and Jagannathan (2011). Interestingly, the rise of holdings-based research has inspired studies in itself, for example Elton et al. (2010) test the implications of reexamining prior research using higher-frequency holdings data (monthly) and find some changed or reversed results, mainly because quarterly holdings fails to capture roughly a fifth of trades that funds place on the market.

The other major group of research use ordinary monthly or daily return-data when studying fund behavior. Within this group, one of the more commonly used methods is to calculate the tracking error of funds and use the measure to draw conclusions on behavior. Notable research focused on tracking error include Mamaysky, Spiegel and Zhang (2007), Basak, Pavlova and Sahpiro (2007), Cremers and Petajisto (2009) and Chen and Pennacchi (2009).

3. Data

3.1 Data Description

The main part of the raw data used in this thesis is generously provided by Morningstar Sweden with a sample of Swedish-based Equity, Fixed Income and Mixed mutual funds available to Swedish private investors between January 2000 and December 2011. The funds in the sample invest both domestically and internationally, but originate in Sweden. The raw dataset contains 983 funds with a total of 79622 monthly returns observations. The dataset reports the following variables for each fund: monthly Net Asset Value returns, fund size in total managed assets, fund investment strategy specified as Morningstar categories[4], fund inception and termination date, fund ISIN code for identification purposes and in some cases the known manager history, as well as yearly standard deviation of returns. The monthly returns assumes dividends and other income to be reinvested into the fund. For additional control variables, we manually collect data on fund expense rates. We use the base expense rate that investors pay annually. Some funds charge an additional performance-related expense rate, which we do not include for comparison purposes. Our raw data sample provides monthly or quarterly observations on Total Net Assets (henceforth *TNA*) for most funds, with the earliest recordings of TNA starting in October 2005. A benefit of using a sample between 2000-2011 is that we are able to merge some data from the Swedish Financial Supervisory Authority[5] covering the same period. We expand the dataset with quarterly TNA from the public records of SFSA where applicable, allowing us to add complete quarterly TNA data to 18 funds. Average TNA over the sample period represents fund size and is included as a control variable. We choose not to include asset flows in this thesis, since we cannot properly do it justice with the data we have. Our primary concern is that quarterly data fails to capture the true nature of asset flows as invested assets

[4] Morningstar classifies each fund using the typical holdings reported by the fund to Morningstar from the past three years. Categories are mainly classified through choice of financial instruments, industry concentration or geographical region. New funds are appointed a category based on investment style according to their official fund statement.
[5] Henceforth denoted as the SFSA.

can be withdrawn or inserted on very short notice surrounding sudden changes in the market, which isn't captured with quarterly observations.

We extract every unique Morningstar category (for example: "Sweden Large Cap Equity) from the sample and tie them to their respective benchmark index according to classifications available to any private investor on Morningstar Sweden's website. In the raw dataset, there are 62 unique Morningstar categories, of which most have been assigned a benchmark index by Morningstar themselves. In some cases, we analyze the fact sheet of individual funds to identify the relevant benchmark. In most cases however, Morningstar clearly states which index is the benchmark (the above example matches the MSCI Sweden index) while in some cases we are forced to assign a relevant index with similar investment and geographical characteristics as the fund. The relevant indices used for benchmarking are mainly collected from MSCI, Bloomberg Inc and Thomson Reuters DataStream. In some cases, the benchmark index is weighted and comprised of two or more indices, which is mainly the case in Mixed mutual fund-categories. We then construct the index ourselves. The full list of categories and corresponding indices are listed in the appendix. The various benchmark indices specified by Morningstar are sometimes denoted in currencies other than SEK. Variables such as size of assets under management are converted to SEK where applicable, for comparison purposes.

To perform regressions on performance using the Fama-French[6] three-factor model, we obtain data on SMB (Small-Minus-Big, difference between average return of the smallest and largest stocks) and HML (High-Minus-Low, difference between the stocks with the highest and lowest Book-to-Market ratio) factors from the website of Kenneth French.[7] As is the case with many methods of measuring performance that have originated in the US or other international settings, there is unfortunately limited use when applied to a Swedish setting because of the lack of data. In the case of the Fama-French three-factor model, Kenneth French's website does not provide calculated SMB and HML factors for Sweden. To circumvent this, we either match monthly SMB and HML returns to the group of funds whose category most closely resembles the available country-factors, or we create our own SMB and HML factors using Swedish stock market data.

[6] The model developed by Eugene Fama and Kenneth French, 1993.
[7] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

3.1.1 Summary Statistics

Table 1 reports summary statistics of the sorted data sample. The total number of observations-figure refers to the number of monthly returns.

3.2 Data Screening and Sorting

To begin, we screen our raw dataset of 983 funds and start by dropping duplicates as well as all funds not listed in SEK. This eliminates 71 funds from the sample. We proceed with screening the remaining sample and manually remove all hedge funds since we cannot properly benchmark them against a benchmark index. This eliminates another 11 funds from the sample.[8] Of the 901 remaining funds, we drop another 434 funds due to insufficient data, nonexistent data or because we are unable to match the fund to a benchmark index. The most common case of insufficient data is when the fund has less than our minimum requirement of 36 consecutive monthly return observations[9], which means that funds started after December 2008 are automatically sorted out. Neither will some funds that are terminated before December 2002. Some funds in the raw dataset received from Morningstar lack data on returns entirely, and are not therefore not included in the study. Finally, remaining funds with or without sufficient data that cannot be tied to a relevant benchmark index are dropped. The specific index is either not available to us or it does not cover the same period as the fund. We end up with a sorted sample of 467 funds on which we perform our study. This sample consists of 350 Equity mutual funds, 65 Mixed mutual funds and 52 Fixed Income funds of which a small fractions consists of Fund-in-Funds. The 467 funds originate from 57 different fund companies that are or have been active in Sweden. As the largest actor on the Swedish fund market, Swedbank Robur Fonder AB has managed, or manages, 89 funds in the sample followed by SEB Investment Management AB, Nordea Fonder AB and Handelsbanken Fonder AB with 50, 41 and 32 funds respectively.

3.3 Data Issues

Although we believe our dataset to be robust, the issue of survivorship bias must be taken into account. Some funds which are established and terminated within the sample time period lacks observations on returns entirely, and some funds still active today that existed prior to year 2000 are also missing returns. Overall, the raw dataset has a slightly lower than desirable quality. However, the

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[8] The sample received from Morningstar inaccurately contained hedge funds which are sorted out. The identity of these are: Aktie-Ansvar Peritus, Cicero Hedge, Coeli Power Inc, Coeli Norrsken, DnB NOR Aktiehedgefond Primus, Hedgefonden Elexir inc, OPM Omega, SEB Hedgefond Equity Inc, Sector Hedge A/I, Tenglin Talent and Trevise Hedge Inc.

[9] We follow *HSZ (2011)* who also disregard funds with less than 36 months of return data.

amount of funds in the sorted dataset is comparable to amounts used in other papers cited in this thesis.[10] We consider the amount satisfactory for the purpose of this study. As noted by Jerner and Wingårdh (2011) who used a similar dataset, it is reasonable to assume that Morningstar has little incentive to keep records of discontinued funds that are of little interest to paying corporate or private customers. Similarly, some indices do not cover the same time span of a corresponding fund, and vice versa. Additionally, while *HSZ (2011)* use data covering the years between April 1983 and December 2009, our sample covers an eleven-year period between January 2000 and December 2011.

4. Method

In absence of complete data on the individual portfolio holdings in each fund for every month in our data sample, we construct an alternative measure of risk shifting based on how returns deviate from the benchmark assigned to the fund, i.e. the funds tracking error volatility, and the difference in risk between two non-overlapping periods. This section of the thesis describes the reasoning behind the methods and the construction of the measure we use to answer our main question.

4.1 Definition and Construction of Tracking Error

Risk and risk shifting behavior have been measured in many different ways in previous research on the subject. While some papers use in-depth holdings data to measure risk, others use more basic methods such as ordinary standard deviation of returns. *HSZ (2011)* use holdings data and compare realized and current holdings volatility and argue that comparing simple standard deviation of returns over two non-overlapping time periods may accidently capture exogenous market condition changes rather than manager-influenced changes in a fund portfolio. This might be the case in Lynch Kosti and Pontiff (1996) who use standard deviation of returns in their study on use of derivatives in funds and Busse (2001) who use standard deviation of returns in his article on tournament behavior. Standard deviation of returns is calculated as

$$Standard\ deviation = \frac{1}{T-1}\sqrt{\sum_{t=1}^{T}(R_{f,t} - \overline{R_f})^2}\ , \qquad \textbf{(1)}$$

where *t* symbolizes one period.

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[10] For example: Brown, Harlow and Starks (1996) use 334 funds, Engström (2003) uses 299 funds, Dahlqvist, Engström and Söderlind (2000) use 210 funds, Koski and Pontiff (1999) use 679 funds, Ferroera et. Al. (2011) use 242 Swedish funds and Sirro and Tufano (1998) use 690 funds.

To correct for exogenous market conditions, some papers have suggested using tracking error volatility instead of standard deviation of returns to measure risk. In order to explain tracking error volatility we define the term excess market return as

$$Excess\ market\ return = R_{f,t} - R_{m,t}\ . \tag{2}$$

As seen in equation (2), the excess market return for a portfolio is defined by the difference between its return and the return of the market in period *t*. *Tracking error volatility is defined as the standard deviation of the excess market return.* Unlike standard deviation of returns, tracking error volatility only captures the volatility in the funds deviations from its benchmark and therefore better describes the risk caused by active portfolio management. Tracking error volatility is in our study calculated as

$$Tracking\ Error\ Volatility = \frac{1}{T-1}\sqrt{\sum_{t=1}^{T}((R_{f,t} - R_{m,t}) - \overline{(R_f - R_m)})^2}. \tag{3}$$

Using tracking error volatility as risk shifting measure is supported by, among others, Cremers and Pretajisto (2007), Basak, Pavlova and Sahpiro (2007) and Chen and Pannacchi (2009) who all base their measure of risk on tracking error volatility. As noted by Cremers and Petajisto (2007), the beta between the fund and the benchmark index is assumed to be equal to one according to the tracking error definition, and subsequently any deviation from a beta equal to one will generate tracking error. In the calculations of tracking errors, we use a total of 62 benchmark indices which are each attached to funds in the corresponding Morningstar category. We argue that the broad selection of our benchmarks helps us better reflect the active fund manager decisions when there is deviation in returns from the benchmark. In comparison, it is common for studies originating from the US to only apply the broad S&P 500 index as the market proxy. Using only one broad index as a proxy for market return for all funds in a study may generate tracking errors for funds that deviate from index even though the deviation is not due to active management decisions. We avoid this problem by assigning each fund a benchmark index that is consistent with its investment strategy.

4.2 Construction of the Risk Shifting Measure and Formation of Fund Portfolios

Due to the lack of holdings data, we deviate from *HSZ (2011)* in the creation of a risk shifting measure. Instead of comparing the current holdings volatility of fund *f* at time *t* with the past realized volatility on returns, we base our risk shifting measure on tracking error volatility. To determine whether a fund has engaged in risk shifting behavior and to what extent, we calculate tracking error volatility in periods of six months for all funds over the entire sample period. As a result we end up with observations of the tracking error volatility in the past and the upcoming six months for each monthly observation on a rolling basis. For each month, we use the difference between the tracking error volatility in the prior and the upcoming six months to measure risk shifting for that month. The risk shifting measure is defined by

$$RS_{f,t} = TE_{f,t+6} - TE_{f,t-6}, \tag{4}$$

where *t-6* represents the six month-period before[11] month *t* and *t+6* represents the six month-period after[12] month *t*. A consequence of using a method with two non-overlapping periods (the six prior and upcoming months) is that we are not able to measure risk shifting for the first and last six months of our data sample as we don't have any prior or subsequent observations to compare them with.

When our risk shifting measure is created, we revert to the methods used by *HSZ (2011)*. For each month in our sample, we divide the funds into ten deciles depending on their degree of risk shifting in that month relative to the other funds. In each month, decile 1 includes the funds with the largest decrease in risk and decile 10 includes the funds with the largest increase in risk the same month. The deciles are sorted and used to create five fund portfolios consisting of funds with different risk shifting behavior. Table 3 displays how deciles are divided into portfolios. Portfolio 1 and 2 include the funds that decrease risk and portfolio 4 and 5 include the funds that increase risk. Funds that keep stable risk levels are included in portfolio 3.

With the risk shifting portfolios constructed according to degree of risk shifting, we begin by computing the characteristics of these portfolios. For each portfolio, we obtain average values of characteristics related to the funds, i.e. what they have in common in terms of traits observable to a private Swedish investor and the magnitude of risk shifting. Summary statistics of these can be found in Table 3. Furthermore, we present the five portfolios separated into fund-type in order to display the proportion of Equity, Fixed Income and Mixed funds in each portfolio in Table 4a and Table 4b.

[11] Henceforth denoted as Past Volatility.
[12] Henceforth denoted as Current Volatility.

4.3 Performance Measures

When evaluating the performance of the five risk shifting portfolios we calculate equally-weighted average excess return for the funds in each portfolio. The results are summarized in Table 5. We additionally report three different measures of performance, including the one-factor Capital Asset Pricing Model (CAPM), the Fama-French three-factor model and the Carhart four-factor model. We use the Swedish 10-year government bond rate as a proxy for the risk-free rate. The market return is the return of the assigned benchmark index.

4.3.1 Excess Market Return

Excess market is clarified above in the definition of tracking error.[13] It captures the part of the return of the funds that is in excess of the funds benchmark index and is a result of the managers choices of portfolio composition. Excess market return is calculated as

$$R_{f,t}^{Excess\ market} = R_{f,t} - R_{m,t}. \tag{5}$$

4.3.2 CAPM

CAPM (Sharpe, 1964) uses the return of the underlying market portfolio to measure the return for a portfolio. The model is defined as

$$R_{f,t} - RF = \alpha + \beta_f^m * \left(R_{m,t} - RF\right) + \varepsilon\ , \tag{6}$$

where R_m stands for the market return and β_f^m is the coefficient for the portfolios correlation with the market. The part of the return that is not attributable to the market return is denoted as α and is the value that we are interested in. RF is the risk-free rate.

4.3.3 Fama-French three-factor model

In their article from 1993, Eugene F. Fama and Kenneth R. French suggest an extension of CAPM by including factors to capture the significant effect on return from investments in small stocks and value stocks. They suggest the following model to measure portfolio performance

$$R_{f,t} - RF = \alpha + \beta_f^m\left(R_{m,t} - RF_t\right) + \beta_f^{SMB} * SMB_t + \beta_f^{HML} * HML_t + \varepsilon. \tag{7}$$

HML and SMB stand for High-Minus-Low and Small-Minus-Big. HML is the difference between the average return of the stocks with the highest Book-to-Market ratio and the stocks with the lowest Book-to-Market ratio. SMB is calculated as the difference between the average return of the

[13] See Section 4.1

smallest stocks and the largest stocks. The betas of these two factors show to what extent investments in small stocks and value stocks have affected the return of the portfolio.

4.3.4 Carhart four-factor model

The Carhart four-factor model (1997) is an extension of the Fama-French three-factor model where a factor that captures momentum has been added. The added factor is supposed to take into consideration the historically observed phenomenon that stocks with good past performance will continue performing well in later periods. The model is defined as

$$R_{f,t} - RF = \alpha + \beta_f^m\left(R_{m,t} - RF_t\right) + \beta_f^{SMB} * SMB_t + \beta_f^{HML} * HML_t + \beta_f^{MOM} * MOM_t + \varepsilon. \tag{8}$$

The MOM-factor is the difference between a portfolio of the stocks with the best return and a portfolio of the stocks with the worst returns over the past year. β_f^{MOM} explains the extent of which a portfolios return can be explained by investments in momentum stocks.

4.3.5 Regressions

To evaluate whether or not risk shifting behavior has an effect on performance, we run Ordinary Least Square-regressions on the portfolios and the performance measures. In the regressions on excess market return, we use fund age, fund size and fund expense rate as control variables. We also regress the risk shifting portfolios on additional measures of performance, and we test long-term performance using lagged risk shifting measures. For the one-factor CAPM, the Fama-French three-factor model and the Carhart four-factor model, we run regressions for each portfolio and obtain the intercepts, the alphas, for each portfolio, which represents the part of returns that cannot be explained by factor-models and thus should be a result of active portfolio management.

5. Empirical Results

This section covers our empirical findings from employing the methods described in section 3 on our sample of Swedish mutual funds. We follow *HSZ (2011)* in the calculations and regressions that are presented in this section, with some deviation where needed, mainly due to differences in data. A majority of the tests are replicated, with the exception of those which require holdings data or variables that are not covered in our dataset. We find that risk shifting funds in general are characterized as younger, smaller in size and charge higher expense rates. We also find that the funds which increase risk the most perform better than funds which decrease or keep stable risk levels. The latter is contrary to *HSZ (2011)* where funds that increase risk the most are found to perform subsequently worse.

5.1 Risk Shifting Persistence

We begin by looking into the short-term persistence of risk shifting, i.e. if a fund that is sorted into a certain decile of risk shifting is more or less likely to remain in the same decile over time. We test the probability that a fund in the sample will remain in the same decile one or three years after portfolio formation. Results are presented in Table 2. We find that over the shorter period of one year, funds are highly likely to remain in the extreme risk shifting deciles 1 and 10, with 26.6 percent of funds in decile 1 and 26.3 percent of funds in decile 10 still present after one year. Over the longer period of three years, funds are also likely to remain in the extreme risk shifting deciles, with 18.1 percent of funds in decile 1 and 18.7 percent of funds in decile 10 still present after three years. Funds in the central, more stable deciles are also more likely to remain there rather than switching to one of the extreme deciles. With support from the similar results presented in *HSZ (2011)*, we conclude that the funds in our sample are characterized by significant persistence in risk shifting over shorter horizons.

5.2 Characteristics of Risk Shifters

Having concluded that funds in the sample tend to exhibit persistent risk shifting strategies, we calculate the characteristics of funds in the five risk shifting portfolios. We present our results in Table 3. Funds in portfolios 1 and 5, which represents the funds with the highest tendencies to increase or decrease risk over time, are characterized as smaller in terms of size of average managed assets, younger in terms of fund age and they charge higher expense rates than funds that display more stable risk levels. Furthermore, we note that portfolio 5 exhibits a high current volatility and a low past volatility. The past volatility of portfolio 5 is relatively close to the mean past volatility (see summary statistics, mean past volatility is 3.711). Contrariwise, portfolio 1 exhibits a high past volatility and a low current volatility. The current volatility of portfolio 1 is relatively close to the mean current volatility (see summary statistics, mean current volatility is 3.747). This shows that funds in portfolio 5 increase risk significantly from the mean level of risk while funds in portfolio 1 decrease risk from high levels back towards the mean level of risk. We illustrate this relation graphically in Figure 1. In practical terms, this indicates that fund managers make an active choice to increase risk in pursuit of higher returns, but decreases risk when holding positions at relatively abnormal levels of risk. The above documented behavior is the same relationship between current and past volatility reported by *HSZ (2011)*. However, when examining performance consequences of risk shifting, we show that the implications of the above results are different in our study.

Regarding characteristics, our results are consistent with *HSZ (2011)* who report the same U-shaped or inverse U-shaped pattern in fund characteristics. This supports the concept that more active fund management charges higher expenses, which is signified by a higher degree of risk shifting in portfolio 1 and 5. Similarly, portfolios 2,3 and 4 charge lower expense rates, implying that funds which keep more stable risk levels represents less active fund management. We conclude that risk shifting mutual funds originating in the US and in Sweden share common characteristics.

5.3 Composition of Risk Shifting Portfolios

Compared to *HSZ (2011)* who only study US equity mutual funds, our sample consists of Swedish equity mutual funds, fixed income mutual funds and mixed mutual funds. We therefore break down the risk shifting portfolios into fund types to see how the funds are distributed. Distributions are reported in Table 4a and Table 4b. As expected, Table 4a illustrates that equity mutual funds make up the bulk of the portfolios, which is expected due to the high number of equity funds in the sample. More relevantly, Table 4b displays that fund types approximately follow a normal distribution across the five portfolios, thus indicating that funds, regardless of type, engage themselves in different degrees of risk shifting behavior. We note that the distribution of mixed mutual funds is slightly skewed towards the portfolios of funds that increase risk the most, but we consider this effect to be minor and should not affect results significantly.

5.4 Performance Consequences of Risk Shifting

In this section, we perform regressions related to performance. We deviate from the methods of *HSZ (2011)* where tests are not applicable for data reasons.

5.4.1 Excess Market Return

Table 5 displays monthly abnormal excess market return for the five portfolios. We regress performance on combinations of the portfolios and the control variables *Age*, *Fund Size* and *Expense Rate*. The central finding is that portfolio 5 consistently displays the best abnormal excess market return across all regressions, and that portfolio 1 consistently displays the worst abnormal excess market return across all regressions, including and excluding control variables. Abnormal returns for portfolio 5 vary between 0.17 basis points and 0.25 basis points per month and abnormal returns for portfolio 1 vary between -0.44 basis points and -0.36 basis points per month. All these regressions are statistically significant. Among the control variables, *Expense Rate* is the most economically significant with an abnormal excess return-contribution of -0.044 basis points per month when regressing in combination with other control variables (see columns 4, 6, 7 and 8), although the results are not statistically significant. We also note that portfolio 3 displays an excess return which is very similar to the sample mean excess return (see Table 2, Summary Statistics, mean excess return per month is -0.22 percent). These findings support Dahlquist, Engström and Söderlind (2000) who conclude that small equity funds in the Swedish market perform better than larger funds. They also find that actively managed equity funds perform better than funds under more passive management. We can relate their conclusions to the performance of portfolio 1 and 5 (which shift risk more actively and are smaller in size, see section 5.2) and find that active management can indeed generate positive returns, as is the case in portfolio 5. However, Dahlquist et al. (2000) base their results on an earlier sample period, which may affect comparability. Our results also mimic those of Wermers (2003, Working Paper) who find, in a sample of US funds between 1975-2000, a positive relation between the level of risk and performance for the majority of the sample period. Although fund managers who take on additional levels of risk do not always beat competitors, a minority of funds can provide additional value to investors, indicating the presence of superior stock picking skills. Wermers (2003, Working Paper) find these results using excess market return, the Fama-French model and the Carhart model.

5.4.2 Additional Performance Measures

In addition to excess market return, we also examine performance consequences of risk shifting using the CAPM-model, the three-factor Fama-French model and the four-factor Carhart model. Results are reported in Table 6. The same results are also displayed in graphical form in Figure 2. Regardless of performance measure, we observe that portfolio 1 remains statistically and economically significantly the worst performing portfolio. All regressions relating to portfolio 1, 2 and 3 remain statistically significant across all performance measures, while portfolio 5 is not as statistically significant when using CAPM and Fama-French. However, both portfolio 4 and 5 show positive returns and are statistically significant when using the Carhart model. We note that there seems to be a relation between performance consequences of increasing risk and the momentum effect. Overall, these results differ from *HSZ (2011)* who report the opposite – that portfolio 5 displays the worst performance instead of portfolio 1.

5.4.3 Long-Term Performance Consequences of Risk Shifting

Finally, we test performance of risk shifting-portfolios using lagged risk shifting-measures. While Table 6 reports performance based on the risk shifting measure of the prior month (one month lag), Table 7 reports performance based on the Carhart-model when the risk shifting measure is lagged by one to four months. We choose to perform this test using four lagged months instead of four lagged quarters as in *HSZ (2011)*. We select this approach because our raw data is based on monthly returns and because our sample time period is narrower than theirs. Results show that the positive performance of portfolio 5 disappears with lagged months. However, the negative performance of portfolios 1,2, and 3 are enhanced using lagged months and become highly statistically significant. Contrary to *HSZ (2011)*, we find that the lower performance displayed by portfolio 1 is statistically significant across longer periods than one month, indicating that one may predict poor long-term fund performance by observing active management choices of risk shifting when funds decrease risk. This might be the case since a fund would be unlikely to earn high returns if it decreases risk too much or decreases risk consistently, whereas it is possible for a fund which consistently increases risk to either earn higher or lower returns.

6. Conclusions

We find that risk shifting has a statistically and economically significant impact on fund abnormal returns in our sample. The funds that increase risk the most experience an average monthly abnormal excess market return of 0.24 percent. Inversely, the funds that decrease risk the most experience an average monthly abnormal excess market return of -0.37 percent. These finding are the opposite to those of *HSZ (2011)*. In terms of overall characteristics of the funds that are more likely than other to shift risk, we find results very similar to those of *HSZ (2011)*, which suggests that the global mutual fund industry is homogenous in some regards. Compared to funds that keep stable risk levels over time, the funds that shift risk significantly are smaller in terms of managed assets, younger and they charge higher expense rates. These tangible characteristics are observable to a private investor, but the degree of risk shifting is not, implying that there a problem for individual investors who cannot draw conclusions on performance without making an assessment of the fund managers risk shifting preferences. Thus, there exists a principal-agent-problem since the fund manager knows if the fund increases or decreases risk while the principal investor does not. Our findings suggest that increasing risk in funds might not have been negative to investors in the Swedish fund market over the past decade. However, increasing risk is always hazardous as it is associated with both lower and higher realized returns. One explanation of the contrary findings might be that Swedish fund managers have, on average, displayed superior stock picking skill or market timing ability in comparison to their US colleagues over the past decade. To further conclude if this is the case, additional research is required.

7. Limitations, Discussion and Suggestions for Future Research

7.1 Limitations and Discussion

The large amount of equity mutual funds we use in our sample, in relation to mixed mutual funds and fixed income funds, might contribute to some bias in results. Additionally, we cannot rule out that the datasets obtained from Morningstar Sweden and Thomson Reuters DataStream contains unseen errors. This would in particular apply to the raw Morningstar data which, as far as we are aware of, has been manually assembled and erroneously contained hedge funds. Additionally, survivorship bias in the data sample can influence results, as discussed in section 3.

Furthermore, we are unable to test and explain the economical motivation behind risk shifting of Swedish fund managers. The reason for this is that we do not have access to holdings data which would enable us to observe how managers alternate between high- and low-risk stocks, how the idiosyncratic risk is managed within the fund, and how fund managers behave in the market when trading and placing orders. It would also be beneficial to have access to data related to the explicit compensation to fund managers in terms of fixed payment and incentive programs. Associated with this, we note that *HSZ (2011)* have access to a larger amount of control variables which help them isolate the actual effect of risk shifting on fund performance. However, despite this, the control variables we use in our thesis only have minor effects on our regressions.

7.2 Suggestions for Future Research

An extension of our research would be to look for ways to assess the economical motivations behind risk shifting in the Swedish fund market, as our dataset has only enabled us to focus on the performance consequences. As previously mentioned, this would require holdings-data.

As discussed above, although our dataset allows us to draw significant conclusions, there is much room for future research to expand upon our findings on risk shifting in the Swedish fund market. In particular, the lack of comprehensive data on equity-, bonds- and cash holdings in individual Swedish funds prevents many previously conducted studies in the US from being replicated in detail with Swedish data. Future theses could strive to merge the limited holdings data that is available publically from the SFSA with other sources of holdings data on a fund-by-fund level. The resulting dataset would allow many exciting studies to be conducted. Furthermore, the main supplier of fund statistics in Sweden today is the company Morningstar, who have little monetary incentives to keep detailed records of fund that have been terminated in the past and are thus not available for paying customers, which leads to some degree of survivorship bias in any sample obtained from them. Finally, with daily return-observations instead of monthly, it would be possible to revisit previous studies and look for differences in results, as was the case in Busse (2001) and Elton et al.(2010).

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Appendix

Appendix A
Fund categories and assigned index

Category	Assigned index
Global Large-Cap Blend Equity	MSCI World Free
SEK Money Market	Citigroup World Money Market 3 Month Euro Deposit
Sweden Large-Cap Equity	MSCI Sweden
SEK Bond	Citigroup World Government Bond Index Sweden
Global Emerging Markets Equity	MSCI Emerging Markets
Europe Large-Cap Value Equity	MSCI Europe Value
China Equity	MSCI China
Sweden Small/Mid-Cap Equity	MSCI Sweden Small Cap
Sector Equity Technology	MSCI World/Information Tech
Australia & New Zealand Equity	MSCI Australia
Property - Indirect Other	Carnegie Real Estate Index (SEK)
Japan Large-Cap Equity	MSCI Japan
SEK Bond - Short Term	Barclays Global Inflation-Linked Sweden
Russia Equity	MSCI Russia
Asia-Pacific inc. Japan Equity	MSCI All Country Asia Pacific
Eurozone Large-Cap Equity	MSCI EMU
Global Large-Cap Value Equity	MSCI World Free Value
US Large-Cap Growth Equity	MSCI USA Growth
Sweden/Global Equity	50% MSCI World Free / 50% MSCI Sweden
Europe Large-Cap Blend Equity	MSCI Europé
SEK Cautious Allocation	75% Citigroup World GBI Sweden / 12.5% MSCI Sweden / 12.5% MSCI World
EUR Flexible Allocation	50% Barclays Global Aggregate Treasury (Euro) / 50% FTSE World
Sector Equity Energy	MSCI World/Energy
Nordic Equity	MSCI Nordic Countries
Global Flex-Cap Equity	MSCI World Free
Emerging Europe Equity	MSCI Emerging Markets Eastern Europé
BRIC Equity	MSCI BRIC
Global Bond	Barclays Global Aggregate Treasury (USD)
Africa Equity	S&P Pan Africa
India Equity	MSCI India
Greater China Equity	MSCI Golden Dragon
Africa & Middle East Equity	S&P Mid-East and Africa Broad Market Index
Sector Equity Biotechnology	MSCI World/Biotechnology
SEK Flexible Allocation	40 % MSCI World Free / 20 % SIX PRX / 40% Risk-free
EUR Aggressive Allocation	Barclays Pan Euro High Yield Euro
SEK Inflation-Linked Bond	Barclays Global Inflation-Linked Sweden
Emerging Europe ex-Russia Equity	HSBC Emerging Markets Europe (Excluding Russia) Euro
Sector Equity Financial Services	MSCI World/Financials
Turkey Equity	MSCI Turkey
US Large-Cap Blend Equity	MSCI USA
Sector Equity Healthcare	MSCI World/Health Care
Property - Indirect Global	Carnegie Real Estate Index (SEK)
Asia ex Japan Equity	MSCI AC Asia Excluding Japan
Global Large-Cap Growth Equity	MSCI World Free Growth
Sector Equity Alternative Energy	S&P Global Clean Energy
Sector Equity Ecology	MSCI World
Latin America Equity	MSCI EM Latin America
EUR Diversified Bond	Barclays Euro Aggregate Treasury
Asia-Pacific ex-Japan Equity	MSCI All Countries Asia Pacific Excluding Japan
Europe Large-Cap Growth Equity	MSCI Europe Growth
Sector Equity Private Equity	S&P Listed Private Equity
US Mid-Cap Equity	MSCI US Mid Cap 450
US Small-Cap Equity	MSCI USA Small Cap
Europe Small-Cap Equity	MSCI Europe Small Cap
Sector Equity Industrial Materials	MSCI World/Materials
Switzerland Large-Cap Equity	MSCI Switzerland
Brazil Equity	MSCI Brazil
Europe Mid-Cap Equity	STOXX Europe Mid 200
EUR Moderate Allocation	50% Barclays Euro Aggregate Treasury / 50% FTSE World
Europe Bond	Barclays Pan Euro Aggregate Treasury
Sector Equity Natural Resources	S&P Global Natural Resources
Sector Equity Consumer Goods & Services	50% MSCI World Consumer Goods / 50% MSCI World Consumer Services

Table 1. Summary Statistics

Variable	Mean	Std. Dev	Median
Total Net Assets (in million SEK)	2099.1	3355.3	962.6
Fund age (in Years)	13.48	7.58	12.8
Expense Ratio	1.24	0.58	1.4
Investor return (per month)	0.210	5.239	0.420
Excess return (per month)	-0.220	4.345	-0.086
Current Volatility (per six months)	3.747	2.051	3.484
Past Volatility (per six months)	3.711	2.058	3.439
Risk Shifting (per month)	0.050	2.098	0.033
Total Number of Funds	467		
Total Number of Equity Funds	350		
Total Number of Mixed Funds	65		
Total Number of Fixed Income	52		
Total Number of Return Observations	55166		

This table provides summary statistics of variables related to the sorted sample of mutual fund, years 2000-2011.

Table 2. Transition Matrix

One Year After Portfolio Formation					**Decile**					
Current Decile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**26.6**	11.8	7.5	5.9	6,0	5.1	5.9	6.9	8.9	15.4
2	10.7	**14.8**	11.3	9.9	8.6	8.5	8.1	9,0	9.9	9.2
3	7.5	11.6	**13.5**	12,0	11,0	10.5	8.7	9.8	9,0	6.5
4	6,0	8.7	12.2	**14,0**	12.9	12.2	11.4	9.8	7.7	5.2
5	6.2	8.1	10.3	12.4	**14.3**	13.6	12.3	9.5	7.9	5.3
6	5.4	7.7	11.1	11.7	13.2	**14.4**	12.6	10.2	8.1	5.6
7	5.9	8.8	9.5	10.9	11.3	12.8	**14.7**	11.6	8.5	6,0
8	7.5	9.2	9.4	9.9	9.8	10,0	11.7	**14.9**	11.3	6.3
9	9.1	10.4	8.8	7.8	7.6	8.5	8.9	10.8	**16.8**	11.3
10	16.3	9.3	6.8	5.5	5.1	5.1	6,0	7.5	12.1	**26.3**

Three Years After Portfolio Formation					**Decile**					
Current Decile	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**18.1**	10.5	8.3	6.9	6.4	6.4	7.3	8	10.9	17.3
2	10.4	**11.4**	11.1	8.9	8.6	9.4	8.9	9.6	11.6	10.1
3	8	10.8	**11.2**	11.1	10.4	10	10.2	10.7	9.8	7.9
4	6.6	9.2	11.1	**12.6**	11.9	12.3	10.9	10.4	8.9	6.1
5	6.5	8.3	9.9	12.2	**13.2**	12.2	11.2	10.6	8.9	7.1
6	6.6	8.6	9.8	11.1	12.3	**12.5**	13	11	9.1	5.8
7	7.4	9.1	9.7	11.5	12	12.3	**12.1**	10.4	8.9	6.8
8	8	10.7	10.9	10.8	10.1	10.3	11.3	**11.6**	9.6	6.8
9	10.8	11.6	10	9.1	9.7	8.7	8.7	9.9	**12.1**	9.6
10	18.2	10.1	8.7	6.7	6.1	6.7	7	7.7	10.1	**18.7**

This table shows the probabilities that a fund in the sample transitions from one decile to another after one or three years, conditional on the funds surviving for one or three years. Probabilities are reported in percentage.

Table 3. Fund Characteristics by Risk Shifting Portfolio

RS-Portfolio	RS-range	RS-mean	Current Volatility	Past Volatility	Fund Size	Age	Expense rate
Portfolio 1	Decile 1	-2.43	3.15	5.57	2054.02	14.09	1.33
Portfolio 2	Decile 2-3	-0.97	3.13	4.10	2347.95	15.37	1.21
Portfolio 3	Decile 4-7	0.03	3.59	3.56	2676.60	15.97	1.20
Portfolio 4	Decile 8-9	1.10	4.17	3.07	2302.39	15.06	1.21
Portfolio 5	Decile 10	2.60	5.56	2.95	2013.29	13.55	1.28

This table provides summary statistics on the average characteristics of the risk shifting portfolios of the mutual fund sample, sorted according to the most recent risk-shifting measure. *RS-mean* shows average risk shifting per portfolio and month. *Fund Size* shows average assets under management in million SEK. *Expense rate* is percent of invested assets. All regressions are significant at a 99% level. All regressions are estimated by OLS using robust standard errors. In line with *HSZ (2011)* we rerun regressions following Fama-MacBeth (1973) and find highly similiar results to the above.

Table 4a. Composition of Risk Shifting Portfolios

RS-Portfolio	Equity	Fixed Income	Mixed	Sum
Portfolio 1	69%	11%	20%	100%
Portfolio 2	73%	14%	13%	100%
Portfolio 3	84%	9%	7%	100%
Portfolio 4	73%	13%	15%	100%
Portfolio 5	61%	14%	24%	100%

The above table summarizes how the risk shifting portfolios are composed over time by different fund types, expressed in percentage.

Table 4b. Distribution of Fund Types

RS-Portfolio	1	2	3	4	5	Sum
Equity	9%	19%	44%	19%	8%	100%
Fixed Income	10%	25%	31%	22%	12%	100%
Mixed	16%	20%	23%	23%	19%	100%

The above table summarizes how the different fund types are distributed over time in the different risk shifting portfolios.

Table 5. Performance Consequences of Risk Shifting. Excess Return

RS-Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio 1	**-0.4115*** **	**-0.4390*** **	**-0.4255*** **	**-0.3586*** **	**-0.4224*** **	**-0.3656*** **	**-0.3866*** **	**-0.3660*** **
	(0.0543)	(0.0668)	(0.0632)	(0.0772)	(0.0734)	(0.0797)	(0.0845)	(0.0865)
Portfolio 2	**-0.2509*** **	**-0.2809*** **	**-0.2633*** **	**-0.1908*** **	**-0.2600*** **	**-0.2062*** **	**-.2219*** **	**-0.2066*** **
	(0.0371)	(0.0565)	(0.0461)	(0.0608)	(0.0613)	(0.0635)	(0.0718)	(0.0734)
Portfolio 3	**-0.2280*** **	**-0.2592*** **	**-0.2587*** **	**-0.1830*** **	**-0.2553*** **	**-0.2141*** **	**-0.2156*** **	**-0.2146*** **
	(0.0290)	(0.0538)	(0.0344)	(0.0522)	(0.0540)	(0.0553)	(0.0657)	(0.0672)
Portfolio 4	**0.0423**	**0.0129**	**0.0153**	**0.0911**	**0.0186**	**0.0699**	**0.0607**	**0.0695**
	(0.0467)	(0.0633)	(0.0461)	(.0606)	(0.0608)	(0.0633)	(0.0712)	(0.0730)
Portfolio 5	**0.1957** **	**0.1692***	**0.1797** **	**0.2540*** **	**0.1826***	**0.2361***	**0.2270** **	**0.2357** **
	(0.0839)	(0.0920)	(0.0638)	(0.0765)	(0.0732)	(.0789)	(0.0834)	(0.0852)
Age		**0.0020**			**-0.0002**		**0.0022**	**0.0000**
		(0.0027)			(0.0030)		(0.0027)	(.0030)
Fund Size			**0.0104***		**0.0105***	**0.0107***		**0.0107***
			(0.0057)		(0.0062)	(0.0057)		(0.0062)
Expense Rate				**-0.0420**		**-0.0440**	**-0.0444**	**-0.0440**
				(0.0349)		(0.0357)	(0.0351)	(0.0359)

All regressions are estimated by OLS. * indicates significance on a 10% level, ** indicates significance on a 5% level and *** indicates significance on 1% level. This table presents the monthly mean excess market return of the risk shifting portfolios of the mutual fund sample, sorted according to the most recent risk shifting-measure. *Age, Fund Size* and *Expense rate* are included as control variables. Robust standard errors are shown in brackets. We perform a F-test and find that the portfolioas are jointly different from zero. For comparison reasons, fund size is measured in billion SEK.

Table 6. Performance Consequences of Risk Shifting

RS-Portfolio	Excess return	CAPM	Fama-French	Carhart
Portfolio 1	**-0.366*** **	**-0.272*** **	**-0.220*** **	**-0.183*** **
	(0.087)	(0.045)	(0.044)	(0.046)
Portfolio 2	**-0.207*** **	**-0.221*** **	**-0.171*** **	**-0.139*** **
	(0.073)	(0.029)	(0.030)	(0.030)
Portfolio 3	**-0.215*** **	**-.230*** **	**-0.137*** **	**-0.078*** **
	(0.067)	(0.022)	(0.022)	(0.022)
Portfolio 4	**0.070**	**-0.025**	**0.024**	**0.115*** **
	(0.073)	(0.034)	(0.033)	(0.034)
Portfolio 5	**0.236** **	**0.087**	**0.089* **	**0.209*** **
	(0.085)	(0.055)	(0.054)	(0.055)

All regressions are estimated by OLS. * indicates significance on a 10% level, ** indicates significance on a 5% level and *** indicates significance on 1% level. This table presents abnormal monthly returns of the risk shifting-portfolios of the mutual fund sample, sorted according to the most recent risk shifting measure. We summarize the mean excess return over the assigned benchmark index including control variables, and the intercepts from factor regressions based on the CAPM, Fama-French and Carhart models. Robust standard errors are shown in brackets.

Table 7. Long-Term Performance Consequences of Risk Shifting

	Number of Lags in Months			
RS-Portfolio	**1**	**2**	**3**	**4**
1	**-0.183*** **	**-0.279*** **	**-0.368*** **	**-0.263*** **
	(0.046)	(0.046)	(0.047)	(0.046)
2	**-0.139*** **	**-0.250*** **	**-0.296*** **	**-0.254*** **
	(0.030)	(0.031)	(0.030)	(0.031)
3	**-0.078*** **	**-0.238*** **	**-0.289*** **	**-0.231*** **
	(0.022)	(0.023)	(0.022)	(0.022)
4	**0.115*** **	**0.018**	**-0.098*** **	**-0.035**
	(0.034)	(0.037)	(0.035)	(0.034)
5	**0.209*** **	**0.065**	**-0.016**	**0.021**
	(0.055)	(0.059)	(0.057)	(0.057)

This table presents Carhart-adjusted monthly returns of portfolios of mutual funds sorted according to the prior risk shifting measure. Performance of the fund portfolio is computed based on the risk shifting measures of funds over the prior one to four months. All regressions are estimated by OLS. * indicates significance on a 10% level, ** indicates significance on a 5% level and *** indicates significance on 1% level. Robust standard errors are presented in brackets.

Figure 1. Risk Shifting Surrounding Mean Volatility

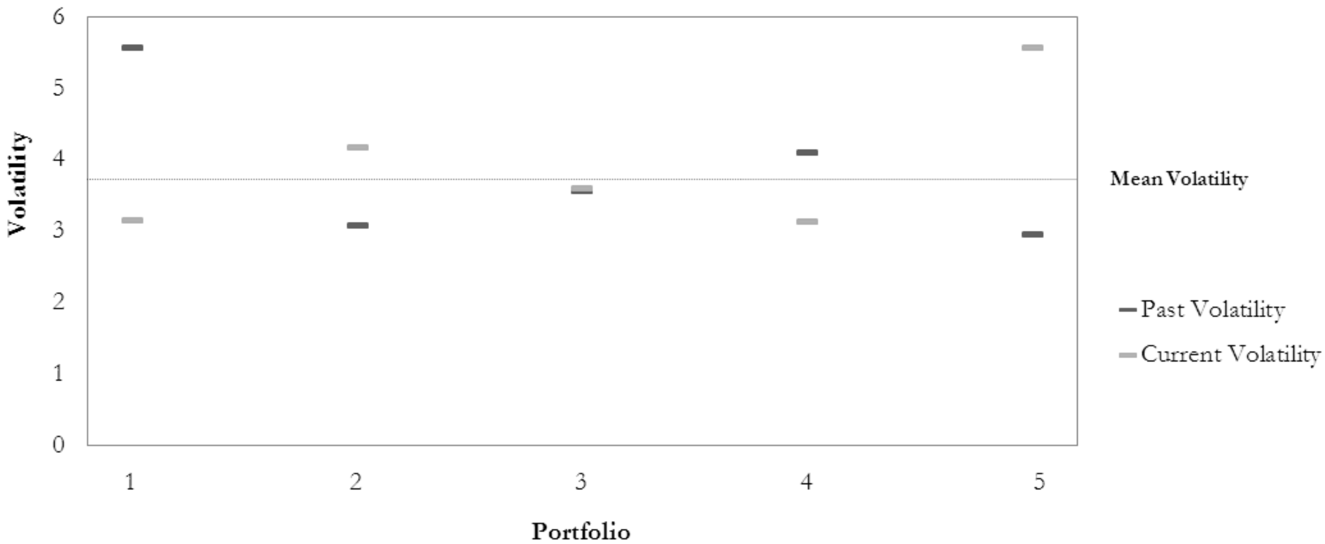

Figure 1 shows the average level of risk shifting in terms of past and current volatiliy for the five fund portfolios. The horizontal line illustrates the mean volatility of all funds over the sample period.

Figure 2. Risk Shifting and Performance

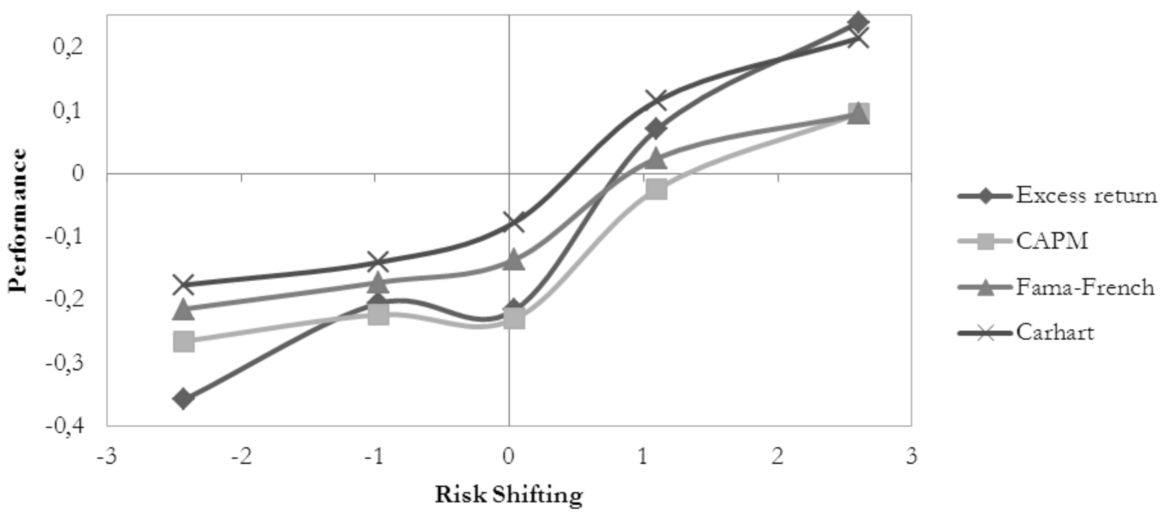

Figure 2 presents graphically the abnormal monthly returns of the risk shifting-portfolios of the mutual fund sample, sorted according to the most recent risk shifting-measure. We summarize the mean excess return over the assigned benchmark index, and the intercepts from factor regressions based on the CAPM, Fama-French and Carhart models.