Mutual Fund Behavior in Volatile Markets - a Study of the Swedish Premium Pension System

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Abstract

The Swedish Premium Pension system is constructed to allow investors the freedom to choose between a multitude of active and passive funds. Active funds carry higher fees in return for their activity while delivering meagre returns during the twelve years since the inception of the system. However, the opacity of the system makes it possible for managers to follow a closet indexing strategy while branding their funds as active. This thesis investigates the behaviour of actively managed funds and how their level of activity has been affected by the large shifts in market volatility of recent years. We construct several measures of activity and use both forward- and backward-looking measures of volatility. Our results prove inconclusive with two measures suggesting maintained activity and one indicating closet indexing. However, we argue that investors may want to consider choosing passively managed funds in light of the performance of active funds.

Keywords: Mutual funds, Volatility, Premium Pension System, Active Management, Closet Indexing

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Contents

1 Introduction

The Swedish pension system is one of a few in the world that allows for investors to choose how they want to invest their endowments. Active investors are encouraged to choose between over 800 funds that participate in the system, most of them actively managed. At the same time, the consensus view in financial literature has long been that active managers, on average, destroy value for their clients. The legitimacy of the system rests upon the assumption that the right to choose is so valuable that we are willing to accept a certain amount of risk that some of us make a bad choice. Due to the effects of the financial crisis, the system has come under fire for delivering inferior returns to too large a share of investors while fund managers are pocketing hefty fees at investors' expense.

The twelve years that the system has been in operation have been some of the most volatile times in recent history:

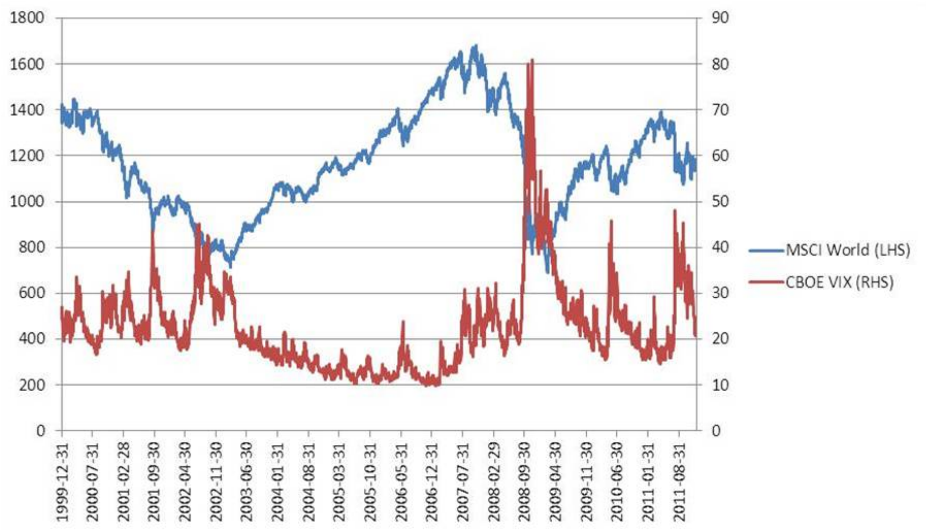

Figure 1: MSCI World and CBOE VIX indices

It is generally believed that the more volatile the market, the greater the opportunities for active fund managers.[1] Still, because of the opacity of funds' day-to-day operations there are incentives for managers to minimize their losses in bad times and simply stick to the benchmark in order to keep investors from fleeing, thus turning the fund into an expensive index fund. Given the large sums accumulated over a lifetime of hard labor, it is important both for individual investors and for the legitimacy of the system that the incidence of closet indexing is minimized.

This thesis aims to investigate the behavior of mutual funds in the Swedish premium pension system during volatile markets. Do they stick to their active mandate or hide behind an indexing strategy when the market turns sour?

We employ three different measures of activity: absolute excess return,

[1]The Big Myth: Active Managers Shine in Volatile Markets, http://money.usnews.com/money/blogs/On-Retirement/2011/09/22/the-big-myth-active-managers-shine-in-volatile-markets

Tracking Error and R^2. Although no similar studies have been done on the Swedish pension system, there is a large body of research on the topic of active management. Our results are less clear-cut than those of our main previous studies, proving inconclusive in the end. More specifically, we find that both the CBOE VIX index and the σ of benchmark returns have a positive relationship with activity when run separately, indicating that managers are either sticking to their active strategy or adjusting slowly to a more passive strategy. The results for R^2 suggest the contrary - that managers do engage in indexing behavior.

We proceed as follows: the introduction concludes with a run-down on the characteristics of the pension system. Section 2 presents previous studies of particular relevance to our topic, followed by a summary of concepts used in this paper. Section 3 presents our statistical methodology including variables of interest and specifications used, as well as a description of the dataset. Section 4 breaks down the results of our regression specifications by activity and volatility measures. Section 5 offers analysis of the volatility-adjusted performance record of our sample. Section 6 presents our conclusions and a discussion of potential flaws in our analysis. Finally, section 7 offers suggestions for future research on the topic.

1.1 The Swedish pensions system - a short introduction

In 1994, it was decided by the Riksdag that the pensions system needed a complete overhaul. The decision was driven in part by a realization that future demographic changes will put an unsustainable strain on the system, and in part by effects of the crisis of the early 90's that uncovered weaknesses in the current system. Implementation was finalized in 2000 with the inception of the pension fund system.

Currently, Swedish pensions are divided into *income pension*, *guarantee pension* and *premium pension*, where the latter will be the focus of this paper. 2.5% of Swedes' monthly gross (but net of social charges) salary up to SEK26,125 is retained in the premium pension system and may be distributed between up to five funds within the system. If an individual chooses not to invest, the money is invested in the AP7 Såfa fund, the state alternative, which has an all-equity component and a mixed fixed income and equity component. At the end of 2011, 2,764,852 investors (43.1%) had some or all of their premium pension invested with the state alternative. At SEK104.6bn, the default state alternative made up 26.6% of the total net assets in the system. Given that 43.1% of investors went at least partly with AP7, we can conclude that at least 56.9% of investors have made an active fund choice.

The SPA has taken a number of measures to make the system more accessible. Choosing funds and reallocating your investment is very easy, and each fund has a fact sheet readily available on the SPA web page. The fact sheet details fund characteristics such as "risk" (constructed as a function of annual standard deviation and placed into categories of green to red, low to high), "category" (there are a total of 30 categories; examples include Sweden index, Global, Telecoms & IT and "Pension in more than 20 years" which is constructed to deliver high risk to those investing for the very long term) and return compared to benchmark. However, despite the accessibility of information, most investors realize that making an informed choice demands a high level of understanding of financial markets. Media attention has exacerbated the belief that it is no use even trying to choose a fund because the counterparty (that is, fund managers) are not acting in investors' best interest, for example by levying higher fees than the state alternative. Moreover, because the system is relatively young, only a very small part of current and soon-to-be pensioners' pensions actually derive from the premium pension placements, thus making the upside to active choice very limited. On the other hand, the SPA argues that for those entering the labor market today, the premium pension will make up 10-40% of total pension benefits.[2] In conclusion, despite the SPAs efforts, there are still high barriers to becoming a truly active pension fund investor.

The system is constructed to give investors access to a multitude of funds at a lower cost compared to the open market (for detailed information on the fee rebate system, see ter Laak (2011)). However, an unintended consequence of the fee rebate system has been that it keeps index funds from entering the system - because they are already very cheap, further pressure on fees might make it unprofitable for these funds to participate. The SPA has acknowledged that this might be the case and notes that changes to the system might increase the amount of index funds, giving investors a high degree of diversification at low cost.[3]

2 Previous research

2.1 Studies of particular relevance

Literature in the field of mutual fund performance seems to suggest that actively managed mutual funds, in general, underperform their benchmark indices after fees. Petajisto (2010), however, found that even though the above is true for the average fund (and, indeed, a large set of funds) the most active ones seem to outperform the benchmark. He uses a combination of Tracking Error and Active Share to grade funds' activity and found that the most active fund managers by Active Share and Tracking Error consistently outperform the market, whereas "closet indexers" consistently underperform. He also found that the incidence of closet indexing increases with volatility. The Active Share measure, introduced in Cremers & Petajisto (2009) is defined as

$$ActiveShare = \frac{1}{2}\sum_{i=1}^{n}|w_{fund,i} - w_{index,i}|$$

Due to our lack of information about funds' holdings over time, we will not be able to replicate the study, nor do we have any way of distinguishing stock picking ability. However, other measures of activity exist and will be elaborated on in the methodology section.

Kacperczyk et al. (2011B) argue that average fund performance increases in a recession due to increases in volatility and in the price of risk. Moreover, they found that fund managers who displayed significant stock picking ability in times of low volatility also had significant market timing ability in recessions. Another notable result is that funds on average increase the cash proportion of

[2] Analytiskt testamente (2010), https://secure.pensionsmyndigheten.se/3325.html
[3] Analytiskt testamente (2010)

their portfolios in recessions, as well as shifting to lower-beta stocks and sectors. Albeit of some significance to our research question, we cannot test the latter result as we do not have sufficient data to notice any shifts in cash positions or short-term sector rebalancing.

Using their measures for stock picking and market timing, Kacperczyk et al. managed to find that for the top 5% of managers (by skill), the effect of recession on the deployment of skill (that is, variations in timing and picking skills) was much larger (quadruple and double for timing and picking respectively) compared to the median manager. This result confirms their hypothesis: given that a manager has skill, he or she will be using that skill for stock picking in good times and market timing in a recession.

Kacperczyk et al. also suggest that market timing could be captured by the R^2 of a regression of market excess returns on fund excess returns:

$$R_{i,t} = \alpha_i + \beta_i R_{I,t} + \sigma_{i,\varepsilon}\varepsilon_{i,t}$$

Using their sample of 3,477 funds between Jan 1980 to Dec 2005, they found a significant increase in R^2 of 3% (from 77% to 80%) in recessions, indicating that there might be evidence of market timing ability in the sample.

Amihud & Goyenko (2012) suggested another interpretation of the same measure. According to their paper, $(1 - \mathrm{R}^2)$ is a viable measure of "selectivity" and they find that lower R^2 significantly predicts higher fund alpha. They also find that R^2 is positively related to fund size and negatively related to expenses and the fund manager's tenure. Their R^2 is the result of a CAPM regression using a multi-factor (Fama-French-Carhart) index because they lack information on funds' benchmarks.

The basis for interpreting R^2 stems from the following:

$$\mathrm{R}^2 = 1 - \frac{RMSE^2}{VARIANCE} = \frac{SystematicRisk^2}{SystematicRisk^2 + RMSE^2}$$

Here, *RMSE* is idiosyncratic volatility. Thus with a lower R^2, a fund's returns are driven more by idiosyncratic volatility than systematic volatility, indicating that a manager is keeping his portfolio weights different from the index. Amihud & Goyenko (2012) further tested whether their results were simply the effect of R^2 was due to pricing of volatility. They did this by testing whether passively managed portfolios displayed the same characteristics and found that they did not. Thus, they concluded that R^2 is a good measure of activity.

2.2 Timing ability

It is generally assumed that managers who generate positive alpha do so through superior skill (indeed, this is a tautology given that skill is defined as alpha). "Skill", in turn, consists of two components: stock picking ability and market timing ability. The *timing* component of skill refers to the ability of a manager to forecast movements in the market and use these forecasts to his or her advantage, generating superior returns. Treynor and Mazuy (1966) constructed a model using a nonlinear component as a proxy for fund managers' market timing ability. They postulated that the returns of a manager with zero timing ability would be linearly related to the return of the market, and thus any nonlinear relationship would derive from timing ability. Their specification looked as follows:

$$r_i = \alpha_i + \beta_i r_m + \delta_i r_m^2 + e_i$$

The δ_i above would, if positive, signify market timing ability on part of the manager. Their results failed to show the existence of such a relationship - the managers in their sample did not display any significant market timing ability.

2.3 A short overview of portfolio theory

Much of the financial literature regarding portfolio theory originates from the model developed by Markowitz (1952). It is often boiled down to the two-fund separation theorem which means that an investor should hold a combination of the optimal risky portfolio (the ORP) and a risk-free asset depending on the risk aversion of the investor. The ORP is obtained through the allocation amongst risky assets which yields the best possible return-risk relationship, by maximizing the Sharpe Ratio, $S_p = \frac{[E(\tilde{r}_p)-r_f]}{\sigma(\tilde{r}_p)}$ (Sharpe, 1966). This combination of risky assets uses the concept of diversification. By combining a large number of securities with imperfect correlation, it is possible to construct a portfolio which reduces individual asset's risk and has a risk-return relationship superior to any individual risky security.

The Capital Asset Pricing Model, independently developed by Sharpe (1964), Lintner (1965) and Mossin (1966), builds on the mean-variance analysis (investors will only accept the largest possible expected return, given a level of risk). The model concludes that in equilibrium, everyone will hold the optimal portfolio, i.e. the market. This leads to the fact that investors should only be compensated for bearing systematic risk (beta), the risk of the market as a whole, not asset specific (idiosyncratic) risk. The market portfolio should include all assets in the world, it is in a sense unobservable, since it not only includes unequitized assets, but even more or less quantifiable assets such as human capital. Due to the unobservable nature of the market portfolio, standard practice is to use a proxy, such as a broad equity index.

The CAPM has received a lot of criticism over the years.[4] It seems like it is possible to obtain a return which is not entirely explained by a portfolio's exposure to the market, its beta. One of the most popular models exploring these anomalies is the three-factor model proposed by Fama and French (1996). It tells us that the expected excess return above the risk-free rate of a portfolio is due to the factor loadings (the slopes in a time-series regression) of the expected premiums of the market ($r_M - r_f$), a portfolio which is long small stocks and short large stocks (SMB), and of a portfolio which is long stocks with a high book-to-market value and short stocks with a low book-to-market value (HML). Additional factors has been proposed, such as momentum (Carhart, 1997) and macro factors (e.g. Chen, Roll & Ross, 1986; Jagannathan & Wang, 1996).

The Efficient Market Hypothesis (EMH), which is closely related to asset pricing models such as the CAPM, states that known information is reflected in assets' prices. By known information one usually distinguishes between past prices, public information and private information, which has resulted in the weak-form, the semi-strong form and the strong form of the EMH. Shiller (1981) challenges this theory since stock prices are too volatile to be explained by

[4]For an interesting discussion on the topic, see "The CAPM Debate" by Jagannathan and McGrattan (1995)

changes in dividends. The fact that momentum in stock prices exists, is also often used to reject the weak form of the EMH. Fama (1999) argues that the market is still efficient, only that there appears to be anomalies which are caused by use of the wrong methodology.

2.4 Active management

Active management is usually defined as a portfolio strategy which seeks to outperform a passive index. A manager of such a fund does not follow the efficient market hypothesis and tries to find undervalued assets to buy and overvalued assets to sell.

Models rely on theoretical assumptions and, given the anomalies found by empirical research, it is maybe not that strange that there is a large active management industry. However, several studies (e.g. Gruber, 1996; Fama & French, 2010) do in fact find that actively managed funds significantly underperform passive indices, which indicates that a passive market portfolio might be is the way to go after all. Although passive indexing has grown, it has not decreased the share of active management by much. One explanation to the size of the active management industry, though quite unsatisfying, is that investors are irrational. Pástor and Stambaugh (2012) propose another explanation: decreasing return to scale. They argue that an increasing number of active managers trying to generate returns above a passive index for their investors, dilutes the possibilities to do so. If all investors understand that there is a negative relationship between industry size and returns, but not exactly the degree of correlation, the result will only be a slow decrease of their invested share in actively managed funds, although the size of the industry will remain substantial.

When evaluating an actively managed fund, there is a shortcoming with the Sharpe Ratio, namely, the risk-free rate. By using the risk-free rate, the fund manager is assessed in the same way, irrespective of their investment strategy. If a fund's return is compared against an benchmark which better captures this, the comparison between funds will be more reasonable. If we put this excess return, the alpha, in relation to the standard deviation (the Tracking Error) of these returns we get the Information Ratio (also known as the Appraisal Ratio) $\mathrm{IR}_p = \frac{r_p - r_b}{\sigma(r_p - r_b)}$ (Treynor & Black 1973). It represents the active return in relation to the active risk, the consistency of alpha.

Sharpe (1991) reasoned that if costs are ignored, the average active return should be the same as the average passive return. Given the zero-sum game properties of the market, this would make sense. The theory requires that the active manager can only invest within the benchmark, which should be a viable assumption, given that the benchmark is appropriate. If a normal distribution of returns around the passive return is assumed, a positive IR would indicate that the fund manager is above average.[5] The problem with this reasoning is that the assumption of a normal distribution is not necessarily correct. This combined with survivorship bias, the fact that fund's that underperform too long will go out of business, makes it more difficult to interpret the IR.[6] A rule of thumb proposed by Grinhold and Kahn (1995) is that an IR of 0.5 is "good" and an IR of 1 is "exceptional".

[5]For more on how to interpret the IR, see Clement, C. (2009)

[6]Clement, C. (2009): Data between 2004-2009, on 247 funds with the S&P 500 as the benchmark, shows that more than 75% of the funds have an IR above 0.

2.5 Market uncertainty

The uncertainty, or the level of risk, in a market is usually measured by its volatility. It is either thought of as the standard deviation of past returns or derived from the prices of option contracts, yielding what is known as implied volatility. By using an option pricing model, such as the Black-Scholes, one can estimate the volatility which is required to yield a theoretical option price equal to the current market price. Thus, ceteris paribus, a higher price implies higher expected future volatility.

The standard deviation of past returns is a backward-looking measure of volatility, while the implied volatility is a forward-looking measure, as it is based on the current market estimate of near-future volatility.

Kaminski (2012) describes the cyclical behavior of volatility and distinguishes between cycles driven by positive and negative stimuli. The positive volatility cycles originate from overconfidence whereas the negative cycles are initiated and driven by fear and distress. The negative cycles are more extreme and long-lived due to the loss-averse nature of humans. Tversky and Kahneman (1992) found that the slope of the utility function of wealth is steeper by a factor of 2-2.5 for losses than for gains, that is, the negative utility of a loss is much greater than the positive utility of an equivalent gain in wealth for a given reference point.

The equities markets usually display a negative relationship with volatility. The correlation has been around -60%, since 1990, but during recent years it has increased to about -80% (Kaminski (2012), see Fig. 1 for an illustration). This relationship has for a long time been attributed to Black's leverage effect (Black, 1976). This suggests that when a company's stock price declines, its debt in relation to assets becomes larger, i.e. it becomes more leveraged. A higher leverage often leads to a higher volatility in equity returns. On the other hand, Hasanhodzic and Lo (2011) find that this "leverage" effect is even larger in all-equity financed companies. Their alternative explanations are, however, rather ambiguous. One of them centres on conditional risk-taking behaviour, which means that investors' assessment of a risky situation is based on previous experiences, such as a financial crisis.

Furthermore, during high volatility, the correlation between equities is generally amplified, especially during market downturns. This asymmetry relates to the disproportional relationship between return and volatility. Amira et al. (2011) argue that it is not volatility itself that drives the homogenization, but rather the market direction. A negative shock has a simultaneous effect on both the market trend, which affects the correlation, and the volatility. However, although the volatility decreased in 2010, the correlation between equities remained high.[7] The importance of macro related news and the popularity of exchange-traded funds (ETFs) could be an explanation.

2.6 Recessions

With the recent financial crisis fresh in memory, it is evident that the state of the economy is strongly linked to returns and volatility (see fig. 3 for an illustration). Apart from low returns and high volatility, there is also evidence of an increased price of risk, or risk aversion. People lose their jobs during recessions and the

[7] http://www.risk.net/asia-risk/feature/1895618/equity-correlation-volatility-sync

equity market simultaneously goes down, requiring investments to deliver a higher return per unit of risk. Investors are in other words willing to pay more for a high payoff.[8] This variability does not only concern the equity premium, but also premiums on other assets such as bonds and currencies.

Although recessions increase the aggregated risk, Kacperczyk et al. (2011A), could not find a noteworthy increase in stocks' idiosyncratic risk, further highlighting the presence of increased correlation between stocks.

3 Methodology

3.1 Variables

3.1.1 Dependent variables

In order for us to determine whether fund managers become more or less active during uncertain times, we have to use measures which capture their level of active management. Since we do not have any detailed information regarding funds' holdings, we are not able to use their Active Share (Cremers & Petajisto, 2009). Our measures will therefore focus on funds' deviation from their benchmark indices.

We believe that funds' absolute excess return ($|r_{i,t} - r_{I,t}|$, where subscript "I" represents the benchmark index) captures this deviation in a straightforward way - if a manager puts their weights in assets differently from their benchmark, we will see absolute excess return.

Another measure which captures how closely a fund tracks its benchmark is the fund's Tracking Error, which we, in line with Petajisto (2010), define as the standard deviation of the excess return ($\mathrm{TE}_{it} = \sigma(r_{i,t} - r_{I,t})$). Another approach would be to do a regression of a fund's return on the benchmark to measure the residual volatility. However, since a fund's performance more often is compared to its benchmark, rather than its beta times the benchmark, the volatility of the excess return better captures the active risk. Furthermore, Petajisto argues that if a manager for a short time holds a large amount of cash with the intent to time the market, this risk is not taken into account by the residual volatility, but it is captured by the first-mentioned definition.

As previously mentioned, Kacperczyk et al. (2011A), argued that the R^2 from a CAPM-regression at the fund level could capture fund managers' market timing. It measures how a fund's portfolio weights co-vary with the market premium. In other words, a low coefficient of determination indicates that the idiosyncratic volatility is high in relation to the systematic volatility. Amihud & Goyenko (2012) argued that $(1 - \mathrm{R}^2)$ may be interpreted as a measure of funds' *selectivity*. In this paper, we will look at both interpretations when conducting our analysis. We have calculated the R^2 by doing a 12 month rolling-window regression of a fund's return above the risk-free rate on the benchmark's return above the risk-free rate:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{I,t} - r_{f,t}) + \varepsilon_{i,t}$$

[8] For more information regarding the counter-cyclical variability of the equity premium, see Cochrane (2006)

We use the 3-month Treasury Bill as the risk-free rate ($r_{f,t}$) since shorter maturities are generally too volatile.[9] While the Kacperczyk et al. study was done on U.S. equity funds, our data covers funds from all over the world. In our regression we have replaced the general $r_{m,t}$ with $r_{I,t}$. Our motivation for using the benchmark as the "market" is that it should, more or less, represent a fund's investment universe and capture the level of co-variation between funds' weights and their benchmark. A change in a fund's R^2 should indicate a change in the portfolio's idiosyncratic risk relative to its total risk.

3.1.2 Independent variables

The independent variable is supposed to capture market uncertainty. In our first regressions we are using the price level of the Chicago Board Options Exchange Market Volatility Index, known as the VIX. It measures the weighted average of the implied volatility of options on the Standard and Poor 500 index for 30 days, quoted as the annualized standard deviation in percent.[10] Although it measures the market expectations of the volatility of the S&P 500 index, it is often seen as the fear index of the world, due to the importance of the S&P 500 index and its accessibility.

Our second proposal for an independent variable is to simply use the monthly volatility (i.e. the standard deviation of the returns) of a fund's benchmark index. This allows us to relate funds' level of activity to the uncertainty of the market, to which they are compared to and, presumably, where they primarily invest.

By using these two measures of market uncertainty, we can explore the impact of the market expectations of volatility, on a broader scale, as well as the ex-post effect of the benchmark-specific volatility.

Another aspect we want to explore is the impact of the state of the economy on the funds. Apart from an aggregate increase in volatility during recession, there is also an increase in the risk premium. The difficulty of implementing such a variable is that we have a large number of fund categories, of which some are not even specific to an economic region. The National Bureau of Economic Research Business Cycle Committee defines a recession as the period between the peak and trough of economic activity.[11] Following the methodology of Kacperczyk et al. (2011), we have created a dummy variable which takes the value of one during months of recession and zero otherwise. It should work as a proxy for a recession, regardless of where the majority of the funds' holdings are based, due to the importance of the US economy to the rest of the world.

We will also use the Chicago Fed National Activity Index (CFNAI) to robustness check our results. The CFNAI is a weighted average of 85 monthly indicators, categorized in the groups: production and income, employment, unemployment and hours, personal consumption and housing as well as sales, orders and inventories.[12] An advantage with the CFNAI is that it is a con-

[9] The data on the 13-week Treasury Bill was obtained from Yahoo Finance. Since it is quoted as a discount we have recalculated it to a monthly rate using a simplifying assumption that the maturity is 1/4 of a year

[10] For information on how the VIX is calculated, see `http://www.cboe.com/micro/vix/vixwhite.pdf`

[11] `http://www.nber.org/cycles.html`

[12] Further information about the CFNAI can be found at `http://www.chicagofed.org/webpages/publications/cfnai/index.cfm`

tinuous variable. Furthermore, its design makes it easy to interpret; when the index is zero, the economy is in line with the trend growth, a positive (negative) value means that growth is above (below) the trend rate of growth. In order to increase the readability of our results, we have transformed the CFNAI variable such that negative values are positive and vice versa.

3.2 Two-dimensional clustering and fixed effects

OLS assumes that each time period brings further information. By overlooking serial (between the same entity over different time periods - i.e. firm effects) and cross-sectional (between different entities during the same time period - i.e. time effects) correlation, there is a risk that the standard error is underestimated, which can result in overestimated t-statistics (Petersen, 2009). This can in turn lead the researcher to incorrectly reject a null hypothesis.

One approach which is often used to address cross-sectional correlation is the two-step Fama-MacBeth regression (Fama and MacBeth, 1973). The disadvantage with this method is that it does not take care of serial correlation and thus produces biased standard errors, which makes it less appealing for us.

A starting point to tackle the problem with correlation in our data, and get a more pure interpretation of our results, is to use a fixed effects regression. Although such a model enables us to control for time- and fund-specific effects, it will still leave some correlation errors untreated, if for example the factor sensitivities vary across funds (Thompson (2011)). Petersen (2009) showed that a regression with fixed effects leads to biased standard errors in the case of temporary firm effects, when the correlation across residuals varies over time. The same applies to non-constant time effects, i.e. when a shock has a larger impact on some funds than on others. Since we cannot rule out that there is such variation in our data (indeed, with a global fund universe this effect is likely to exist), we have to use additional specifications.

In order for us to compute standard errors which are robust for correlation across both time and funds, we have to use a two-dimensional clustering approach together with fixed effects. By using standard errors clustered by funds, the correlation between observations of the same fund in different years is taken into account. The standard errors clustered by time (in this case measured in months) captures the correlation between different funds in the same time period. This approach produces unbiased standard errors, whether the firm effects are constant or not.

Since most empirical data tend to suffer from heteroskedasticity, robust standard errors are often used by researchers. If, however, a fixed effects model is used, Stock and Watson (2006) showed that the cluster-robust estimator is more appropriate. Although this has been accounted for in more recent versions of Stata, it only works with one-way clustering.[13]

Thompson (2011) proposed the following calculation of the variance-covariance matrix:

$$\widehat{Var}\hat{\beta} = \hat{V}_{Firm} + \hat{V}_{Time,0} - \hat{V}_{White,0}$$

The variance estimate for an OLS estimator $\hat{\beta}$ is the sum of the standard errors clustered by firms and the standard errors clustered by time, which is subtracted

[13]In Stata version 10, vce(cluster id) is automatically applied when the robust option is used with xtreg, fe r (Baum, C.F., A. Nichols and M.E. Schaffer (2010))

by the White heteroskedasticity-robust OLS variance matrix, which includes the intersection of the two dimensions. The third variance matrix is subtracted in order to remove the double-counting of cross products, such as within-firm variance.[14]

The clustered standard errors are asymptotically consistent if both T and N are large.[15] Monte Carlo simulations done by Thompson suggest that 25 firms and time periods is sufficient if one does not allow for persistent common shocks. If we allow for persistent common shocks, a rule of thumb is between 50 to 100 time periods. Given our large data set (most funds have observations for 136 time periods), we can safely assume that we have enough clusters.

3.3 Regressions on monthly data

Our fixed effects model could be expressed in a general way as follows:

$$y_{i,t} = \beta_0 + \alpha_i + \theta_t + \beta_1 x_{i,t} + \varepsilon_{i,t}, i = 1, ..., N; t = 1, ..., T$$

Time (month) and entity (fund) fixed effects are represented by θ_t and α_i. However, since we suspect correlation in the error term, $\varepsilon_{i,t}$, we have to use two-way clustered standard errors, which are clustered on an entity (fund) and a time (month) dimension. It is especially important to use clustering when the variable is constant across all funds, such as the VIX and our recession variables. This is done with the Stata command `xtivreg2` (M.E. Schaffer, 2010), which allows for both fixed effects and multi-way clustering.

Our first fixed effects regressions allow us to investigate the impact of volatility on the absolute excess return of funds. It is specified as follows:

$$|r_{i,t} - r_{I,t}| = \beta_0 + \alpha_i + \theta_t + \beta_1 \text{Volatility}_t + \varepsilon_{i,t}$$

One regression is done with VIX_t as the variable for volatility. This will look at the effect of the forward-looking volatility on absolute excess return. The other regression will use the variable benchmark volatility $\sigma_{I,t}$, which determines the relationship of our backward-looking measure with funds' deviation from their benchmark. However, the regressions done with the VIX as a measure for volatility will not include time dummy variables due to collinearity.

The second type of fixed effects regression explores the effect of market volatility on funds' monthly active risk:

$$\text{TE}_{i,t} = \beta_0 + \alpha_i + \theta_t + \beta_1 \text{Volatility}_t + \varepsilon_{i,t}$$

The same variables for market volatility, used in previous regressions, apply here as well.

Our final activity measure, run as a dependent variable in our monthly data regressions will be the coefficient of determination:

$$\text{R}^2_{i,t} = \beta_0 + \alpha_i + \theta_t + \beta_1 \text{Volatility}_t + \varepsilon_{i,t}$$

By adding a variable for recession, we hope to separate the effect of decreased economic activity from the usually paired increase in market volatility. Since

[14] A more rigorous explanation can be found in Thompson (2011)

[15] Proof can be found in the appendix of Thompson (2011)

a recession itself may lead to a change in fund manager behaviour we want to control for this. The recession variable is either represented by a dummy for a month during recession in the U.S. or a continuous variable for the CFNAI. When a recession variable is used, time dummy variables are not used due to perfect correlation.

Furthermore, we will be running a combined specification in order to separate the effects of the VIX and the standard deviation of benchmark:

$$\text{Activity}_{i,t} = \beta_0 + \alpha_i + \beta_1 \text{VIX}_t + \beta_2 \sigma_{I,t} + \varepsilon_{i,t}$$

Finally, we will be looking at how our volatility and activity measures relate to funds' excess returns in order to determine whether they affect performance:

$$r_{i,t} - r_{I,t} = \beta_0 + \alpha_i + \theta_t + \beta_1 \sigma_{I,t} + \varepsilon_{i,t}$$

$$r_{i,t} - r_{I,t} = \beta_0 + \alpha_i + \theta_t + \beta_1 \text{Activity}_{i,t} + \varepsilon_{i,t}$$

3.4 Pre/post analysis on daily data

The Lehman Brothers bankruptcy in 2008 resulted in a huge spike in volatility. For us to test if this black swan event had any out-of-the-ordinary effect on funds' behaviour, we will perform a pre/post analysis using daily data. This will also serve as a robustness check of our previous findings from the monthly data. Since we have no access to intraday data on the funds, we cannot calculate their daily Tracking Error. Therefore, our study will focus on funds' daily absolute excess return.

Our model will be similarly specified as the ones used on monthly data, but with the addition of a post dummy variable, which equals to during and after the event, as well as an interaction term between the post dummy and the variable for volatility. Our belief is that a regression with the variable for volatility together with a post dummy will separate the effect of the general distress after the announcement from general market volatility. The logic behind this is to find whether there is something else, besides volatility, that has an effect on funds' deviation from their benchmark, i.e. their level of activity.

The specifications are as follows:

$$|r_{i,t} - r_{I,t}| = \beta_0 + \alpha_i + \beta_1 \text{Volatility}_t + \delta_0 \text{post} + \delta_1 \text{post} * \text{Volatility}_t + \varepsilon_{i,t}$$

The date of the event, the 15th of September, is included since the announcement was made in the morning and thus the market had time to react. We have decided to use a window of -45/+45 days around the event date, since this will capture the spikes in volatility after the event, as well as the relatively low volatility before the event.

The entity-fixed effects are applied at a fund level. We do not use any time dummy variables in this case, due to perfect collinearity with the post dummy variable. We are also clustering our standard errors on fund and date in order to adjust for serial and cross-sectional correlation in the error term.

3.5 Data description

The primary source of data is the Swedish Pensions Agency (SPA). The Agency maintains an online archive of all funds participating the pension system from

September 2000, as well as statistics and benchmarks from January 2006 (these will be elaborated on further below).

3.5.1 Funds

The full dataset comprises 1375 funds, identified by specific SPA six-figure identification numbers. These are funds that have been included in the system for at least one month during the full period. Funds are open-ended mutual funds, but the SPA imposes no other restrictions on them besides their fulfillment of the UCITS (Undertakings for Collective Investment in Transferable Securities) directives. With the exclusion of funds for which we have no benchmark figures and index funds (more on this under inclusion rules), 669 funds have been active during for at least twelve consecutive months over the eleven years and thus constitute our dataset. 443 funds have observations in the last month of 2011 and can be considered as having ongoing operations.

3.5.2 Inclusion rules

A number of modifications have been made to the original dataset; these modifications will be laid out and explained below.

Some funds are primarily or partially interest rate funds. These have been excluded for comparability reasons. Funds labeled "other countries" and "other sectors" were dropped due to the lack of a unifying benchmark. Funds in the categories "Europe/EMU index" and "Sweden index" were dropped because they are explicitly aiming to follow the benchmark index, thus falling outside the scope of this paper. The SPA decides which benchmark to use based on a fund's primary investing style. All funds within a certain category, except for the "other" categories, share the same benchmark (please see table 1 for categories and their respective benchmarks). These benchmarks are often, but not always, the same benchmark that the fund uses for internal performance measurement and in prospectuses. Thus, we have made sure to match funds with the benchmark that investors are presented with in choosing whether to invest, rather than that which funds use for their own evaluations. This also removes any bias from funds' choosing their own benchmark to look better by comparison.

3.5.3 Statistics

The SPA statistics database contains information on AUM, fees, categories and turnover. However, our use of some of these variables (AUM, fees and turnover) is very limited because figures are somewhat unreliable, prone to inconsistent formatting and exist for too small a subset of funds and time periods.

3.5.4 Returns

Returns are computed on daily close prices (which in turn are the average of bid/offer close prices) both for funds and indices and collapsed to monthly frequencies for the full dataset due to computing power limitations. The pre/post study uses daily data.

3.5.5 A note on currencies

The SPA data reports bid/ask prices both in local currencies and in SEK conversions at the prevailing rate. Although the case could be made that SEK returns better reflect the actual returns enjoyed by investors, this approach would make all our variables subject to unseen effects in currency markets, quite possibly skewing our results significantly due to the volatile nature of the Swedish Krona. Furthermore, maintaining local-currency returns makes for better comparability with indices as these are more often than not quoted in the correct currency (mainly SEK, USD and EUR). Errors arising from instances where the local currency changes over a fund's lifetime (as happens, for example, when the home market adopts the Euro) have been corrected for by elimination of erroneous values at the daily level.

4 Results

4.1 Absolute excess returns

The first set of regressions is done on absolute excess return. Although one could argue that it is a rather crude measure of a fund's activity we would expect it to decrease if a fund manager decides to reduce his active risk by shifting the portfolio weights more in line with the benchmark.

4.1.1 VIX

Our results done with the VIX as a measure for volatility can be found in table 2. When only the VIX variable is included (column 1), we find that a one point increase in the volatility index has an estimated effect of 0.144 percentage points on the absolute excess return and that the coefficient is significantly different from zero at a 1% level. A one point increase of the VIX represents a one percentage point increase in the annualized standard deviation, expected for the next 30 days.

If we add fund fixed effects to our basic regression (column 2), the coefficient is increased to 0.00146 and remained significant at a 1% level. Paired with the increased R^2, this implies that the firm fixed effects improves the model.

When we include the dummy variable for recession months in the U.S. (column 3) we find that the coefficient for VIX loses some of its magnitude, in relation to our regressions done in columns 1-2. It seems like there is other aspects of an economic downturn, other than increased volatility, which has an impact on funds' deviation from their benchmark.

In column 4, we have used the CFNAI variable as a measure of economic activity. Although the variable itself is insignificant, the inclusion of it increases the coefficient of the VIX, in comparison to the regression on column 2, (to 0.00152). Seemingly, the CFNAI reduces some of the noise in our data - it works as an unsuppressor variable. This would make sense as the market can sometimes react heavily on figures captured in the index. These include unemployment, housing and ordering data.

4.1.2 Standard deviation of benchmark

The use of the standard deviation of funds' benchmarks as a measure for volatility tells about the same story, which can be found in table 3. The coefficient is near 2 in all cases, which means that a 1 percentage point increase in the standard deviation is associated with almost double the effect on the excess absolute return.

The inclusion of both time and fund fixed effects (column 2) leads only to a small reduction in the coefficient for volatility but a higher coefficient of determination. Furthermore, the coefficient stays highly significant - i.e. we have reason to belive that its quite a robust measure.

If we add our recession varialbes (columns 3-4), the coefficients stays significant and stable above 2. However, the coefficients for the recession variables are not significant and thus do not seem to bring anything new to the table. Our interpretation is that funds' deviation from their benchmark is not really affected by other aspects of economic downturns, other than volatility.

Our main interpretation of the results done with the absolute excess return is that the fund managers in our dataset do not get less active, in the sense that they do not change their weights to more closely follow their benchmark. Whether managers get more active or remain at their previous level of activity during volatile markets is more difficult to tell. We would expect the absolute excess returns to be magnified, ceteris paribus, if market volatility increases.

4.2 Tracking Error

The Tracking Error measures a fund's active risk. Surely, if fund managers suddenly turn to closet indexing, it would decrease.

4.2.1 VIX

Results from our regressions done with the VIX as our volatility variable can be found in table 4. The standard OLS regression (column 1) shows a positive and highly significant relationship between volatility and funds' active risk.

When we control for time and fund fixed effects (column 2), we find that the coefficient for the VIX increases.

However, when add the NBER variable (column 3), the coefficient for the VIX is slightly reduced. The NBER variable has a positive and significant (at a 5% level) relationship with funds' active risk. In other words, the VIX does not fully capture the the effect on fund dispersion. If this result persists when we use our more robust measure for volatility, that could indicate that there is other factors in a recession, other than volatility, that play part in the dispersion.

4.2.2 Standard deviation of benchmark

As seen in table 5, we once again find that the standard deviation of the funds' benchmark is a more robust variable for volatility. It is highly significant in all cases with a coefficient of around 0.5-0.6. A one percentage point increase in the standard deviation of the benchmark, is associated with about half a percentage point increase in the Tracking Error.

Interestingly, the recession variables are both highly significant. During a month of recession in the U.S., the estimated increase on the Tracking Error is 0.116 percentage points. The CFNAI has a coefficient of 0.00063, which indicates that a decrease in economic activity has a positive effect on the active risk.[16] A one point decrease in the CFNAI would be associated with a 0.063 percentage point rise of the Tracking Error. When the economy slows down, there is usually great uncertainty. Our results indicate that there is something else, other than pure volatility, which has an effect on funds' Tracking Error. It might be related to an additional effect from negative volatility cycles with the accompanied increased correlation between stocks and increased risk premiums. If we look at fig. 2, we can see the latest two periods of recession in the U.S. and the CFNAI values at the time.

In contrast to our results from regressions done with the absolute excess return (in table 2 and table 3), we find that, apart from volatility, other factors captured in economic activity have an impact on funds' active risk.

However, the problem inherent in our activity measure persists. A closer look of the definition of the standard deviation of alpha will highlight our problem:

$$\sigma(r_p - r_I) = \sqrt{\mathrm{Var}(r_p) + \mathrm{Var}(r_I) - 2 * \rho(r_p, r_I) * \sigma(r_p) * \sigma(r_I)}$$

During high levels of volatility, the correlation between stocks usually increases. When the benchmark's variance increases, the portfolio variance will increase as well. In order for us to detangle these effects on the standard deviation of alpha, we need detailed information regarding funds' holdings.

4.3 R^2

The problem with our previous measures of activity is that it is difficult to tell if the increase in these measures during volatile markets is due to an actual increase in activity or simply because their holdings get relatively more volatile. Regressions done on the R^2 will hopefully remedy this dilemma or at least give it a helpful angle.

However, the interpretation of R^2 is not completely straightforward. As previously mentioned, it is the coefficient of determination of a regression of the index excess return on fund returns, using a twelve-month rolling window. One interpretation is that if R^2 is 1, variation in a fund's returns are fully explained by variation in index returns. Then, the fund would essentially be the index. Thus, it may be used as a measure of how well a fund tracks its benchmark and variations in R^2 over time could be interpreted as changes in how active a fund manager is.

Kacperczyk et al. (2011A) used the R^2 as a proxy for fund managers' timing ability. The reasoning is that an increase in R^2 in a recession would signify that managers are sensitive to changes in aggregate market conditions. However, it is not clear whether an increase in R^2 would actually be due to active management (managers in recessions rebalancing toward the benchmark) or whether it could simply be a result of the increased correlation across all asset classes that tends to be the result of a severe downturn.

The alternative interpretation, suggested by Amihud & Goyenko (2012), uses $\mathrm{R}^2_{i,t}$ as a proxy for selectivity, where lower $\mathrm{R}^2_{i,t}$ equals more selectivity, or portfolio deviation from benchmark in terms of weights. They find that lower

[16] We have reversed the signs of the index values for readability reasons

$R^2_{i,t}$ significantly predicts alpha and, somewhat contradicting Kacperczyk et al. (2011A), that this holds despite tests of $R^2_{i,t}$ as a proxy for market timing. Thus, they argue that funds that have market timing ability generate less alpha, that is, lower $R^2_{i,t}$ is *better*.

4.3.1 Recession dummy

First, we regressed $R^2_{i,t}$ on the NBER recession dummy. The results (table 7) suggest a significant (at the 1% level) 8.3 percentage points increase in R^2_i in a recession, from 66.8% to 75.4% (column 1). This result would tell us that managers do engage in market timing behavior when times get rough and is consistent with the findings in Kacperczyk et al. (2011A). Along with the alternative interpretation, the increase may be attributable to a decrease in managers' selectiveness - they are engaging in closet indexing.

4.3.2 VIX

The OLS regression (table 6 column 2) yields a significant coefficient of .00466, meaning that each one point (or, 1 USD) increase in the value of the VIX index is associated with a 0.466% increase in R^2_i. This result persists when adding NBER or CFNAI variables, which are both insignificant.

The effect of the VIX index on R^2_i is less clear-cut than that of the standard deviation. The effect is generally weaker than that of the standard deviation by about half (since the average value of the VIX is about 2000 times larger than the average standard deviation while the coefficient is only about a thousandth of that of the standard deviation). However, the results still indicate that managers do get less active as the VIX increases.

4.3.3 Standard deviation of benchmark

R^2_i displays a significant positive relationship with the standard deviation of the benchmark using all three specifications (table 7). The standard OLS regression (column 1) yields a coefficient of 4.823; with fund and time fixed effects and clustering (column 2) this is increased to 4.921, implying a 4.9% increase in R^2_i for each percentage point increase in σ_I. The NBER recession dummy (column 3) and the CFNAI variable (column 4), too, have significant (at 5%) positive coefficients.

The standard deviation has a significant effect on R^2_i in all of our regressions. This leads us to believe that managers do engage in some indexing behavior, maintaining a more active position when markets are calm and going toward the index as volatility rises.

4.4 The Treynor-Mazuy model

In order to further test managers' market timing ability, we employed the Treynor-Mazuy specification as laid out in a previous section (see table 8). Again, we first ran a standard OLS regression which yielded a significant negative coefficient for δ^2, implying *negative* market timing ability. When adding fund and time fixed effects, however, the coefficient is no longer significant. We interpret this as further evidence that the sample lacks significant market timing ability, and that we cannot credibly interpret R^2 as timing ability in the way that Kacperczyk et al. (2011A) do, instead leaning on the Amihud & Goyenko (2012) view of $(1 - R^2)$ as a proxy for selectivity/activity.

4.5 Results on daily data

As we previously mentioned, the regressions done on a daily data frequency will serve as a pre/post analysis of the Lehman bankruptcy in 2008. Additionally, a study on daily data will help us determine the robustness of our previous findings on monthly data.

4.6 Absolute excess returns

4.6.1 VIX

The results from the regression done with the absolute excess return as the explained variable and the VIX as an explanatory variable for volatility can be found in table 9.

Our robustness check is primarily the results reported in column 1-2. Firstly, by doing a standard OLS regression (column 1), we find a highly significant connection between the VIX and the absolute excess return. However, when we use a fixed effects specification (column 2) the coefficient is insignificantly different from zero. Moreover, the explained variance is increased when we control for time and fund fixed effects.

Once we turn to our pre/post analysis (column 3), we find that the coefficient for the VIX is positive (0.000685) and significant at a 5% level. The post dummy variable, which indicates if the Lehman bankruptcy has occurred, has a coefficient of 0.0138 and is also significant. This means that the absolute excess return is estimated to be 1.38 percentage points higher after the event. The insignificant interaction term implies that we could not find a change in the marginal effect of the VIX on the funds' absolute excess return. In other words, although the implied volatility, as well as the absolute excess return, most certainly increased after the Lehman bankruptcy, there was no statistically significant change in the relationship between the two.

The regression done on daily data does not give a uniform confirmation that there is a significant positive association between the absolute excess return and the VIX we found on monthly data. Given that the fixed effects specification (column 2) results in an insignificance of the VIX and the highest R^2, it seems like there are fund and time specific effects that have an impact on whether the funds' return differ from their benchmark, rather than the implied volatility, at this high frequency.

4.6.2 Standard deviation of benchmark

Table 10 includes the regression results using the standard deviation of the funds' benchmark as a measure of volatility. Once again, the main robustness check of our findings done on monthly data is to be found in column 1-2. The coefficient is highly significant and positive in both the standard OLS regression and our fixed effects specification.

In the pre/post analysis (column 3), we find that the coefficient is 0.117 and highly significant - an increase of the standard deviation by 10 percentage points is thus associated by a 1.17 percentage point increase of the absolute excess return. In this case, the coefficient for our post-event indicator is insignificantly different from zero. However, the interaction term at 0.247 is highly significant. This indicates that the standard deviation's marginal effect on the absolute excess return is noticeably increased after the event. A 10 percentage point growth in the standard deviation of a funds' benchmark is connected to a 3.64 percentage point increase in the absolute excess return after the event.

Although the aggregated monthly effect of the standard deviation of funds' benchmark on the absolute excess return is higher, we still find a positive relationship in the daily data. At this high frequency, there is probably more noise affecting the level of deviation from the benchmark - which is indicated by the low explained variance in all our regressions done on daily data.

4.7 R^2

In our study of daily data, the R^2 variable has been recalculated using the same rolling-window technique but rescaled to the higher frequency of data.

4.7.1 VIX

The post dummy (table 11 column 1) and VIX variable (column 2) both have significant coefficients using the standard OLS approach. VIX maintains significance but the coefficient decreases when we add fund and time clustering (column 3) and fund-fixed effects, and when we add post and interaction terms (column 4) both the post and VIX terms become significant only at 10%. We conclude that the VIX seems to have a positive relationship with R^2 at the daily level, corroborating our findings at the monthly level.

4.7.2 Standard deviation of benchmark

Again, the standard OLS (table 12 column 1) yields a significant positive coefficient, but when adding fund and time clustering (column 2) the coefficient is no longer different from zero. The interaction term (column 3) is significantly positive at 5%, indicating that there is a relationship between the benchmark standard deviation and R^2. It would seem that the effects from our monthly data do exist on a daily level as well.

4.8 σ of benchmark and VIX combined specification

Finally, we ran a regression on each of our dependent variables using both volatility measures. Results in table 13 show varying significance as well as signs. The VIX has a significant positive effect on activity as measured by Tracking Error, and a positive effect on *passivity* as measured by R^2. The standard deviation of benchmark has significant positive effects on absolute excess returns and the Tracking Error, but is insignificant in the regression on R^2. These results are somewhat contradictory and may cast doubt on our use of R^2 as a proxy for activity, given that we would expect global correlation to increase with volatility.

5 Implications for investors

Our results fail to give a conclusive answer as to whether managers are closet indexing, but we do find that deviation and dispersion measures increase with volatility. Given that their portfolios experience significant increases in these measures with increases in volatility, how does this affect their performance? Table 14 reports results of regressions done on excess returns using our measures of activity. None of the coefficients are significant. Even if fund managers stay active, we find nothing in our results to indicate that activity on average adds any value for investors - even before fees are taken into consideration.

Kacperczyk et al. (2011B) argued that fund performance improves in recessions, both due to the increased price of risk and volatility. Our simulation of these findings can be found in table 15. When we apply a standard OLS regression (column 1) we do find this is true for volatility but not for a recession itself. However, when we refine our model by including two-dimensional clustering and fund fixed effects (column 2), the coefficient for volatility also turns insignificant.

The yearly average returns on funds' benchmark, funds' excess return as well as other data can be found in table 16. The Eastern Europe, the Swedish Small Cap, the Latin America and the Emerging Markets indices are the top performers. However, they are also among the most volatile indices which is to be expected of such market types.

Turning to the funds themselves, the excess returns are lacklustre, to say the least, and surely confirm the academic world's view on active management. Although the time period was highly volatile, the above mentioned lack of significance in the relationship between volatility and performance means we could not expect the higher-than-average returns that Kacperczyk et al. (2011B) found. Only the categories Asia and the Far East, Global, Japan, Nordic countries, Emerging Markets and Russia have average returns above their benchmark. Note that fees have not been included in the analysis - if we consider an average fee of 2%, the average active management fund does not seem to add value to their investors in any of the categories.

If we instead were to take a mean-variance approach by looking at Sharpe Ratios, the best categories would be Eastern Europe, Emerging Markets, Swedish Small Cap Russia, Asia and the Far East and Latin America. Given the return above the risk-free rate in relation to the total risk, these categories should be chosen. Funds in these categories are also investing in the most profitable benchmarks. Although the state alternative, AP 7, has a high excess return, they have a low average Sharpe Ratio due to the low average returns of their broad benchmark index.

However, if we evaluate the fund categories with the Information Ratio, we find other results. Active fund managers under- and overweight their benchmark, based on their special information. The IR gives an indication of a manager's skill in relation to the additional risk taken. Given the rule of thumb set by Grinhold and Kahn (1995), not a single category achieves an average yearly IR near 0.5, which they determine as "good". On the other hand, Goodwin (1998) argues, based on a study on data stretching for 10 years, that 0.5 is too high. According to Kidd (2011), an asset manager herself, "the general consensus among the investment profession is that an IR of 0.20 or 0.30 is superior". If we take this into consideration, AP 7 is performing well with an average IR of 0.25. Furthermore, funds benchmarked against the Japanese index over the years 2007-2011, with a category average IR of 0.44. The fund managers in this category, together with AP 7, show the highest average skill.

Although the Japanese category displays a positive IR, one has to take the fact that the benchmark has a negative average return into consideration. We would expect these funds to be less inclined to invest in the stock market and instead hold cash, given the bad performance of the Japanese stock market. While IR is a good measure to determine which fund manager is the most skilled, the Sharpe Ratio is arguably more appropriate if an investor is choosing where to put all of his or her money, as this gives the highest return in relation to total risk. The optimum would of course be a fund with a high IR, benchmarked against an index with high return.

6 Conclusions

The aim of this thesis has been to determine whether funds in the Swedish pension system get less active during uncertain and volatile markets. We find some evidence that this would be the case. When volatility increases the deviation and the dispersion from the benchmark increases, leading us to conclude that managers maintain a certain level of activity. However, volatility also has a positive relationship with R^2, which we are interpreting as a measure of activity. We do realize that this measure might be flawed in that correlation would be expected to increase with volatility, thus yielding higher R^2 regardless. However, Amihud & Goyenko (2012) dismissed this explanation after finding that R^2 did not predict performance for passively managed portfolios, suggesting that it is a good measure of activity.

We are thus forced to admit that our results are inconclusive.

The regressions done with funds' Tracking Error as an explained varible show that it is not only volatiliy, as measured by our two variables, that has a positive effect on funds' active risk. This could indicate that they get more active. We argue that if they held their strategies constant, only an increase in volatility would have a significant positive relationship with Tracking Error whereas we find that an economic downturn also has an impact. They are in other words reacting to recessions. This conclusion is in line with Kacperczyk et al. (2011) who found evidence of fund strategy heterogenisation during recessions - uncertainty leads to a larger dispersion in trading ideas, i.e. funds do not closet index as Petajisto (2011) found.

While our results are ambiguous to say the least, perhaps this is not that strange given the sometimes contradictory conclusions found in previous studies.

It may still be the case that managers are closet indexing, only that other effects have a more prominent impact - they may, for example, be too slow in rebalancing their portfolios. By slow we mean that they are not fast enough to react to current volatility, yielding positive coefficients. However, tests with lagged volatility measures fail to support such a hypothesis.

A fund's benchmark should, if chosen appropriately, more or less represent its investment universe. When the volatility of their benchmark increases, we would expect an increased deviation and dispersion from their benchmark. Given that volatility is higher in negative volatility cycles than in positive ones, managers would want to depart from their active mandate/strategy in order to reduce downside risk. When moving from an active strategy to a passive one in times of high uncertainty, managers would have to sell and buy stocks at an increasing rate which would in and of itself lead to an increased dispersion of returns. This effect may be present in our sample, leading us to overstate managers' level of activity. Assuming that this is the case, the sample would be more prone to indexing behaviour than our results suggest. As we have pointed out previously, information on funds' holdings would remedy these types of bias in our study.

We find no evidence of any connection between volatility and excess returns, nor between activity and excess returns. In light of this, investors may be better off reducing the fees they pay by investing in passive funds. This view has also been expressed by the Swedish Pension Authority, which is currently searching for ways to incentivize index funds to join the system to a greater extent.

7 Future research

Pension systems and the added value of active management are hot topics both in the academic world and the media. The Swedish government is currently reviewing the pension system and its focus on actively managed funds. Naturally, there is a trade-off between giving investors the right to choose with whom to invest their pension endowments and maintaining the legitimacy of a system that consistently delivers inferior returns to those exercising that right (as opposed to passively investing in the default state fund). Furthermore, the value of research done on the premium pension system will only increase with time as the share of pensions deriving from it grows.

Throughout the writing of this thesis we have been highlighting the importance of information on funds' holdings. This would enable the calculation of Active Share, Timing and Picking measures used in Petajisto (2010) and Kacperczyk et al. (2011A). The problematic part is to find this data on a monthly basis for a large dataset, as it is usually reported per quarter or year.

Furthermore, our analysis of equity mutual funds can be expanded to mixed and pure fixed-income funds. These will normally be recommended to soon-to-be pensioners who cannot bear the high risk associated with all-equity funds. Currently, this smaller subset of investors have a very small share of their pension deriving from their investments, meaning that the economic significance of such research will be relatively low. Other measures of market uncertainty could for instance be credit and credit default swap spreads.

Another interesting topic is the performance of mutual funds. With more complete information on funds' fees, we could look into the actual value creation or as it seems to be in this case, value destruction. This topic is of especially high relevance now, with funds' fees having been scrutinized in several media reports lately.

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B Figures

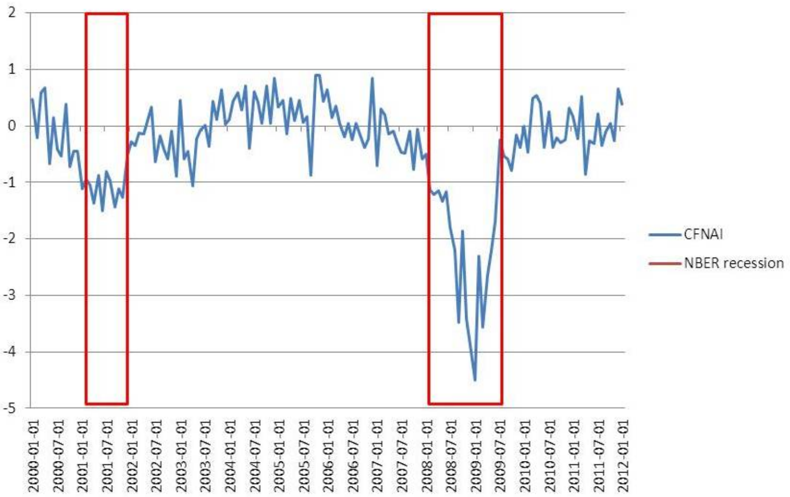

Figure 2: CFNAI index with recession indicator

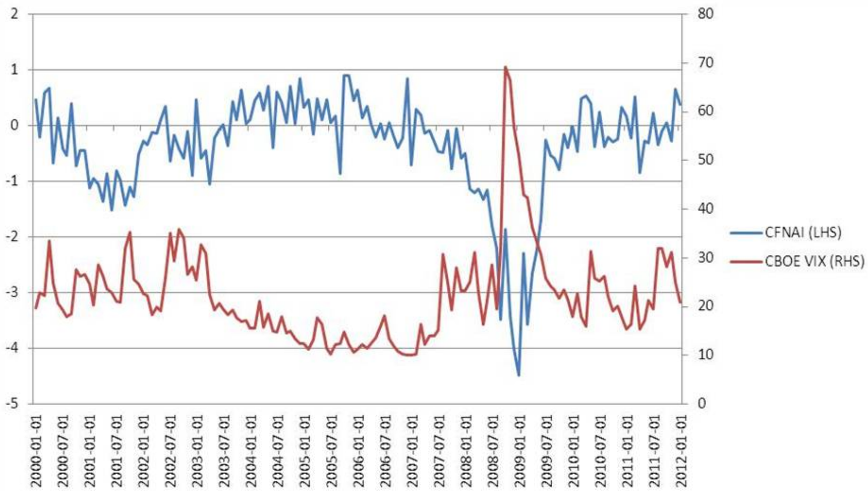

Figure 3: CFNAI and VIX indices

C Tables

Table 1: Fund categories and relevant indices

Category	Benchmark	Freq.	Percent
Asia and Far East	MSCI Pacific ex Japan	4792	8.64
Biotechnology	Nasdaq Biotechnology	276	0.50
EMU	MSCI EMU	1247	2.25
Europe	MSCI Europe	5543	9.99
Europe/EMU small cap	Dow Jones Stoxx Small (200)	1908	3.44
Global	MSCI World Free	7929	14.29
IT & Telecoms	MSCI ACWI Information Tech	3083	5.56
Japan	MSCI Japan	3570	6.43
China	MSCI China Free	956	1.72
Latin America	MSCI EM Latin America	550	0.99
Pharmaceuticals	MSCI Health Care	1792	3.23
North America & US	MSCI North America	4498	8.11
North America & US small cap	MSCI US Small Cap 1750	350	0.63
Nordics	MSCI NOrdic Countries	2295	4.14
Emerging markets	MSCI Emerging Markets	3226	5.81
Pension in >20 years	50% MSCI World, 50% SIX PRX	2190	3.95
Russia	MSCI Russia	614	1.11
Swedish & foreign equity	50% MSCI World, 50% SIX PRX	1454	2.62
Sweden	SIX PRX	5053	9.11
Sweden small cap	Carnegie Small Cap Return	1220	2.20
Eastern Europe	MSCI EM Eastern Europe	2933	5.29
	Total	55479	100.00

Table 2: The table reports regressions using absolute excess return as the explained variable and VIX as our measure of volatility using monthly data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Cboevix is the monthly average of the CBOE VIX index. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)
VARIABLES	absret	absret	absret	absret
cboevix	0.00144***	0.00146***	0.00122***	0.00152***
	(2.53e-05)	(0.000401)	(0.000427)	(0.000527)
	57.15	3.642	2.852	2.880
nber			0.0112	
			(0.00780)	
			1.439	
cfnai				-0.000834
				(0.00464)
				-0.180
Constant	0.0125***			
	(0.000506)			
	24.81			
Fixed effects	None	Fund	Fund	Fund
Observations	55,479	55,479	55,479	55,479
R^2	0.12104	0.12744	0.13630	0.12767
F	3266	13.17	7.229	6.741
Number of fondnummer		668	668	668

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: The table reports regressions using absolute excess return as the explained variable and $\sigma_{I,t}$ as our measure of volatility using monthly data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Sdindex is the monthly standard deviation of benchmark. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for increased readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)
VARIABLES	absret	absret	absret	absret
sdindex	2.269***	1.958***	2.046***	2.283***
	(0.0296)	(0.223)	(0.420)	(0.408)
	76.58	8.776	4.867	5.596
nber			0.00831	
			(0.00669)	
			1.241	
cfnai				-0.000536
				(0.00290)
				-0.185
Constant	0.0158***			
	(0.000342)			
	46.34			
Fixed effects	None	Fund, time	Fund	Fund
Observations	55,479	55,479	55,479	55,479
R^2	0.20706	0.50662	0.19579	0.19065
F	5865	183.2	15.03	17.05
Number of fondnummer		668	668	668

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The table reports regressions using Tracking Error as the explained variable and VIX as our measure of volatility using monthly data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Cboevix is the monthly average of the CBOE VIX index. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for increased readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)
VARIABLES	sd_AR	sd_AR	sd_AR	sd_AR
cboevix	0.000419***	0.000425***	0.000397***	0.000396***
	(5.12e-06)	(3.38e-05)	(3.55e-05)	(5.32e-05)
	81.92	12.56	11.16	7.433
nber			0.00131**	
			(0.000553)	
			2.380	
cfnai				0.000406
				(0.000388)
				1.045
Constant	0.000963***			
	(0.000100)			
	9.602			
Fixed effects	None	Fund	Fund	Fund
Observations	55,479	55,479	55,479	55,479
R^2	0.29868	0.39564	0.40010	0.39763
F	6710	156.5	78.20	89.51
Number of fondnummer		668	668	668

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The table reports regressions using Tracking Error as the explained variable and $\sigma_{I,t}$ as our measure of volatility using monthly data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Sdindex is the monthly standard deviation of benchmark. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for increased readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

VARIABLES	(1) sd_AR	(2) sd_AR	(3) sd_AR	(4) sd_AR
sdindex	0.593***	0.533***	0.580***	0.561***
	(0.00648)	(0.0347)	(0.0195)	(0.0199)
	91.48	15.36	29.78	28.19
nber			0.00116***	
			(0.000368)	
			3.153	
cfnai				0.000630***
				(0.000162)
				3.891
Constant	0.00276***			
	(7.13e-05)			
	38.69			
Fixed effects	None	Fund, time	Fund	Fund
Observations	55,479	55,479	55,479	55,479
R^2	0.41296	0.54917	0.51495	0.51748
F	8368	472.6	513.9	504.2
Number of fondnummer		668	668	668

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: The table reports regressions using R^2 as the explained variable and VIX as our measure of volatility using monthly data from 2000-09 to 2011-12. R^2 is extracted from a twelve-month rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Robust standard errors are shown in parentheses in columns 1-2 and cluster-robust standard errors, clustered on funds and months, are shown in columns 3-5. The t-statistic is shown below the standard error. Cboevix is the monthly average of the CBOE VIX index. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for increased readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)	(5)
VARIABLES	r2	r2	r2	r2	r2
nber	0.0829***			0.0238	
	(0.00238)			(0.0184)	
	34.87			1.294	
cboevix		0.00466***	0.00486***	0.00436***	0.00457***
		(9.75e-05)	(0.000623)	(0.000752)	(0.000855)
		47.84	7.798	5.791	5.341
cfnai					0.00406
					(0.00725)
					0.560
Constant	0.668***	0.580***			
	(0.00129)	(0.00259)			
	517.9	223.8			
Fixed effects	None	None	Fund	Fund	Fund
Observations	48,148	48,148	48,140	48,140	48,140
R^2	0.01650	0.03589	0.08048	0.08246	0.08078
p	0				
F		2289	60.32	31.03	31.27
Number of fondnummer			660	660	660

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: The table reports regressions using R^2 as the explained variable and $\sigma_{I,t}$ as our measure of volatility using monthly data from 2000-09 to 2011-12. R^2 is extracted from a twelve-month rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Sdindex is the monthly standard deviation of benchmark. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Cfnai is the monthly value of the Chicago Fed National Activity Index, the sign of which has been reversed for increased readability of the coefficient. A value above 0 is thus a sign of decreased economic activity and a value below 0 is a sign of increased economic activity. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)
VARIABLES	r2	r2	r2	r2
sdindex	4.823***	4.921***	4.423***	4.171***
	(0.125)	(0.930)	(0.995)	(0.965)
	38.73	5.289	4.444	4.323
nber			0.0416**	
			(0.0165)	
			2.525	
cfnai				0.0169***
				(0.00562)
				3.000
Constant	0.622***			
	(0.00207)			
	300.1			
Fixed effects	None	Fund, time	Fund	Fund
Observations	48,148	48,140	48,140	48,140
R^2	0.02603	0.25717	0.06845	0.06873
F	1500	12.61	27.12	36.34
Number of fondnummer		660	660	660

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: The table reports regressions using fund excess return above the risk-free rate as the explained variable applying the Treynor-Mazuy model using data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-3. The t-statistic is shown below the standard error. Indx is the benchmark excess return above the risk-free rate. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

VARIABLES	(1) ret	(2) ret	(3) ret
indx	0.808***	0.807***	0.660***
	(0.00336)	(0.0241)	(0.0209)
	240.4	33.52	31.61
indx2	-0.182***	-0.193	0.000387
	(0.0323)	(0.145)	(0.0959)
	-5.616	-1.325	0.00403
Constant	-0.000778***		
	(0.000164)		
	-4.752		
Fixed effect	None	Fund	Fund, time
Observations	55,479	55,479	55,479
R^2	0.69224	0.69299	0.76182
F	31621	661.1	168.2
Number of fund id		668	668

Table 9: The table reports regressions using absolute excess return as the explained variable and VIX as our measure of volatility using daily data 2008-08-01 to 2008-10-31. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-3. The t-statistic is shown below the standard error. Cboevix is the daily closing value of the CBOE VIX index. Post is an indicator variable equal to 1 on and after the 15th of September, the date of the Lehman bankruptcy. VIXinteract is defined as post multiplied by cboevix. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)
VARIABLES	absret	absret	absret
cboevix	0.000404***	0.000279	0.000685**
	(1.51e-05)		(0.000344)
	26.71		1.993
postdum			0.0138**
			(0.00685)
			2.021
VIXinteract			-0.000396
			(0.000325)
			-1.219
Constant	0.00225***		
	(0.000810)		
	2.776		
Fixed effects	None	Fund	Fund
Observations	31,684	31,684	31,684
R^2	0.02067	0.03853	0.02243
F	713.2	12.95	343.3
Number of fund id		499	499

Table 10: The table reports regressions using absolute excess return as the explained variable and $\sigma_{I,t}$ as our measure of volatility using daily data 2008-08-01 to 2008-10-31. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-3. The t-statistic is shown below the standard error. Sdindex is the standard deviation of benchmark. Post is an indicator variable equal to 1 on and after the 15th of September, the date of the Lehman bankruptcy. VIXinteract is defined as post multiplied by sdindex. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)
VARIABLES	absret	absret	absret
sdindex	0.444***	0.368***	0.117***
	(0.0185)	(0.108)	(0.0409)
	24.06	3.410	2.869
postdum			-1.02e-05
			(0.00109)
			-0.00942
sdinteract			0.247***
			(0.0360)
			6.863
Constant	0.00279***		
	(0.000852)		
	3.279		
Fixed effects	None	Fund	Fund
Observations	31,684	31,684	31,684
R^2	0.02543	0.03984	0.02327
F	578.8	64.06	576.9
Number of fund id		499	499

Table 11: The table reports regressions using R^2 as the explained variable and VIX as our measure of volatility using daily data 2008-08-01 to 2008-10-31. R^2 is extracted from a twenty-day rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-4. The t-statistic is shown below the standard error. Cboevix is the daily closing value of the CBOE VIX index. Post is an indicator variable equal to 1 on and after the 15th of September, the date of the Lehman bankruptcy. VIXinteract is defined as post multiplied by cboevix. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)	(4)
VARIABLES	r2	r2	r2	r2
postdum	0.0507***			0.101*
	(0.00348)			(0.0535)
	14.57			1.892
cboevix		0.00137***	0.000922***	0.00414*
		(9.11e-05)	(9.77e-05)	(0.00215)
		15.00	9.433	1.926
VIXinteract				-0.00338
				(0.00219)
				-1.542
Constant	0.540***	0.515***		
	(0.00247)	(0.00382)		
	218.7	134.8		
Fixed effects	None	None	Fund	Fund
Observations	31,609	31,609	31,609	31,609
R^2	0.00664	0.00703	0.10642	0.05725
F	212.3	225.0	3.367	26.60
Number of fund id			497	497

Table 12: The table reports regressions using R^2 as the explained variable and $\sigma_{I,t}$ as our measure of volatility using daily data 2008-08-01 to 2008-10-31. R^2 is extracted from a twenty-day rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in columns 2-3. The t-statistic is shown below the standard error. Sdindex is the standard deviation of benchmark. Post is an indicator variable equal to 1 on and after the 15th of September, the date of the Lehman bankruptcy. VIXinteract is defined as post multiplied by sdindex. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

	(1)	(2)	(3)
VARIABLES	r2	r2	r2
sdindex	1.850***	0.745	-0.593
	(0.0845)	(0.550)	(0.0893)
	21.89	1.354	-1.051
postdum			0.000417
			(0.0196)
			0.0213
sdinteract			1.472**
			(0.582)
			2.529
Constant	0.505***		
	(0.00334)		
	151.5		
Fixed effects	None	Fund	Fund
Observations	31,609	31,609	31,609
R^2	0.01311	0.10752	0.05872
F	479.1	7.005	13.95
Number of fund id		497	497

Table 13: The table reports regressions using a combined specification with both our measures of volatility as explanatory variables, the VIX and $\sigma_{I,t}$, using monthly data from 2000-09 to 2011-12. The explained variables are absolute excess return, Tracking Error and R^2. R^2 is extracted from a twelve-month rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Robust standard errors are shown in parentheses in columns 1, 3 and 5 while cluster-robust standard errors, clustered on funds and months, are shown in columns 2, 4 and 6. The t-statistic is shown below the standard error. Cboevix is the monthly average of the CBOE VIX index. Sdindex is the monthly standard deviation of benchmark. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

VARIABLES	(1) absret	(2) absret	(3) sd_AR	(4) sd_AR	(5) r2	(6) r2
cboevix	-5.90e-05*	1.97e-05	9.14e-05***	9.40e-05***	0.00404***	0.00417***
	(3.15e-05)	(0.000386)	(6.59e-06)	(2.20e-05)	(0.000161)	(0.000802)
	-1.875	0.0510	13.88	4.269	25.00	5.201
sdindex	2.325***	2.224***	0.507***	0.511***	0.968***	1.062
	(0.0442)	(0.499)	(0.00970)	(0.0258)	(0.194)	(1.016)
	52.64	4.457	52.32	19.80	4.997	1.046
Constant	0.0165***		0.00182***		0.582***	
	(0.000429)		(8.68e-05)		(0.00261)	
	38.31		20.93		222.5	
Fixed effects	None	Fund	None	Fund	None	Fund
Observations	55,479	55,479	55,479	55,479	48,148	48,140
R^2	0.20714	0.19053	0.41859	0.51772	0.03629	0.08125
F	2997	16.31	4552	549.1	1158	28.29
Number of fondnummer		668		668		660

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 14: The table reports regressions using excess return as the explained variable and our activity measures (absolute excess return, $\sigma_{I,t}$ and R^2) as explanatory variables using monthly data from 2000-09 to 2011-12. R^2 is extracted from a twelve-month rolling window regression with fund excess return above the risk-free rate as the explained variable and benchmark excess return above the risk-free rate as the explanatory variable. Cluster-robust standard errors are shown in parentheses. The t-statistic is shown below the standard error. The t-statistic is shown below the standard error. Significance is denoted as *** (p<1%), ** (p<5%) and * (p<10%).

VARIABLES	(1) AR	(2) AR	(3) AR
absret	-0.0672		
	(0.0920)		
	-0.730		
sd_AR		-0.112	
		(0.187)	
		-0.600	
r2			-0.00331
			(0.00423)
			-0.784
Fixed effects	Fund, time	Fund, time	Fund, time
Observations	55,479	55,479	48,140
R^2	0.22099	0.21956	0.22955
Number of fund id	668	668	660
F	10.42	81.26	92.75

Table 15: The table reports regressions using excess return as the explained variable and $\sigma_{I,t}$ as a measure of volatility using monthly data from 2000-09 to 2011-12. Robust standard errors are shown in parentheses in column 1 and cluster-robust standard errors, clustered on funds and months, are shown in column 2. The t-statistic is shown below the standard error. Sdindex is the monthly standard deviation of benchmark. Nber is an indicator variable equal to 1 during months of recessions in the U.S., defined by the NBER. Significance is denoted as *** ($p<1\%$), ** ($p<5\%$) and * ($p<10\%$).

	(1)	(2)
VARIABLES	AR	AR
sdindex	0.243***	0.315
	(0.0333)	(0.231)
	7.310	1.365
nber	-9.11e-05	-0.000858
	(0.000524)	(0.00490)
	-0.174	-0.175
Constant	-0.00488***	
	(0.000362)	
	-13.45	
Fixed effects	None	Fund
Observations	55,479	55,479
R^2	0.00312	0.00412
F	32.48	0.970
Number of fund id		668

Table 16: The table reports the yearly average (over the period 2001-2011) of benchmark returns, benchmark annualized standard deviation, fund excess return, fund annualized Tracking Error, fund Sharpe Ratio, fund Information Ratio and fund Information Ratio over the period 2007-2011.

Average performance	Benchmark		Fund				
Category	Return	Annualized Stdev	ER	Annualized TE	Sharpe	IR	IR ('07-'11)
Asia & Far East	9.06%	20.70%	1.63%	16.70%	0.39	0.10	0.12
Biotechnology	7.73%	19.89%	-6.23%	11.56%	0.02	-0.54	-0.99
China	6.35%	32.05%	-0.99%	14.35%	0.15	-0.07	0.03
Eastern Europe	19.24%	31.27%	-2.66%	19.56%	0.56	-0.14	-0.23
EMU	-1.45%	19.11%	-0.68%	7.12%	-0.21	-0.10	-0.47
Emerging markets	14.27%	23.19%	0.01%	11.86%	0.54	0.00	-0.18
Europe	3.01%	19.91%	-3.87%	12.20%	-0.17	-0.32	-0.19
Europe/EMU small cap	5.43%	18.33%	-0.93%	8.15%	0.14	-0.11	-0.17
Global	0.50%	14.73%	0.30%	9.89%	-0.07	0.03	0.07
IT & Telecoms	1.24%	25.08%	-2.24%	13.83%	-0.11	-0.16	-0.08
Japan	-3.97%	17.40%	0.99%	12.21%	-0.27	0.08	0.41
Latin America	15.09%	29.64%	-2.58%	12.18%	0.38	-0.21	-0.46
North America & US	2.11%	15.83%	-2.24%	10.62%	-0.12	-0.21	-0.20
North America & US small cap	3.78%	24.23%	-2.30%	10.12%	0.01	-0.23	-0.36
Nordics	6.30%	26.23%	0.04%	14.64%	0.20	0.00	-0.14
Pension in >20 years	6.06%	18.10%	-6.96%	7.61%	-0.18	-0.91	-0.98
Pharmaceuticals	2.10%	12.20%	-2.16%	14.02%	-0.13	-0.15	-0.26
Russia	9.90%	31.57%	1.03%	17.58%	0.32	0.06	-0.42
Swedish & foreign equity	6.10%	18.08%	-5.55%	5.91%	-0.08	-0.94	-1.25
Sweden	8.78%	20.62%	-4.35%	6.52%	0.12	-0.67	-1.35
Sweden small cap	16.35%	19.71%	-5.22%	7.59%	0.44	-0.69	-1.04
AP7 Såfa	0.50%	14.73%	1.60%	6.31%	0.01	0.25	0.23