An Evaluation of the Best Ideas of Swedish Fund Managers

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Abstract

We investigate the stock-picking ability of fund managers by comparing their portfolio weights to the corresponding market weight, creating portfolios based on the most overweighted stocks, called best ideas, and find that these in some cases outperform the market. The Swedish market exhibits properties which limit the usefulness of the best idea model, such as a heavy concentration in a few super-popular stocks that might be a reflection of liquidity management rather than the fund manager's view on future performance of the stocks. To adjust for this we exclude these stocks. The excess returns we then find co-vary with small, high-beta growth stocks that have recently not performed well. We find that less popular best ideas and less liquid best ideas tend to perform better, as well as best ideas from more concentrated funds. We do not find any clear evidence that smaller funds have better performing best ideas than larger funds. Best ideas that are fresh, where the last trade was a buy, performs better than non-fresh best ideas on average. The existence of positive alphas even after controlling for Fama-French factors suggests market inefficiencies exist in the Swedish fund market.

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1 Introduction

Do overweighted stocks in fund manager portfolios perform better than other stocks? The overall performance of different types and categories of funds have long been a topic of contention. Although general consensus among most studies today is that active fund managers do not generate positive returns in excess of relevant benchmarks, see e.g. Arnott et al. (2000), Bogle (2002) and Malkiel (1995, 2003, 2005), a number of authors still find evidence that many managers have significant stock selection talents. By investigating not the overall fund manager returns but a sub-selection of fund holdings, it is possible to investigate stock selection skills more directly, which is what we with this thesis aim to do for the Swedish market.

According to the Efficient Markets Hypothesis (EMH), stock prices should reflect all relevant information about a particular firm, and it should thus not be possible to exploit any kind of mispricing to make a profit. Only in case this does not hold is it possible to make a risk-adjusted profit by trading on information. One form of such information is the public information of what other funds are holding in stock, and how it changes from quarter to quarter. If it is thus possible to make a profit by trading on this type of information, we would find evidence against the Efficient Markets Hypothesis, which is one reason why this thesis topic is highly interesting.

There have been few papers covering this exact topic previously, and none covering the Swedish or European market. Cohen et al. (2010) did a study on the best ideas of funds, looking at the most overweighted stocks within U.S. mutual funds. This paper will use some of the methods applied by Cohen et al. (2010), but also extend their methodology in a number of ways, which will also be made clear later. For example, a small number of outlier stocks such as H&M have been excluded as they are often used as liquidity reserves by many funds, and are thus often going to be overweighted in the Swedish fund market. This has basis both in a number of the papers listed in the next section, as well as in information provided by industry insiders.

Our main hypothesis for this thesis is that some abnormal returns are possible for portfolios formed based on the stocks Swedish fund managers are the most confident about. It could potentially be positive in gross returns only, and might disappear as transaction costs and liquidity limitations are introduced.

The rest of the thesis will proceed as follows: Section 2 reviews the previous literature regarding active portfolio management and fund manager stock pick-

ing talents. Section 3 provides an overview of the data collection process and the sources used. Section 4 presents the methodology of our thesis. Section 5 contains a summary of our empirical results. Section 6 present a discussion of our results and our conclusions, overall thesis limitations and possible further extensions of the topic. Section 7 is the appendix with a list of references, tables and figures.

2 Previous Literature

It has been debated ever since the paper of Jensen (1968) whether fund managers that actively trade add value net of their transaction costs. The majority of the literature today agree that actively managed funds, on average, under-perform passive funds. Papers such as Gruber (1996) for example find that the average mutual fund under-performs passive market indices by about 65 basis points per year from 1985 to 1994. Carhart (1997) also finds lower benchmark-adjusted net returns the more actively a fund trades. Studies such as Arnott et al. (2000), Bogle (2002) and Malkiel (1995, 2003, 2005) all find results that suggest investors are better off investing in passive index funds than in actively managed equity funds. Busse et al. (2010) finds that domestic equity returns are not persistent and do not generate alphas in the long run.

2.0.1 Stock Selection Talents

Some papers, such as Berk et al. (2004), however argue that the poor overall performance of a fund is a suboptimal measure of a fund manager's stock selection skills, and that managers attribute high weights to some stocks they believe will outperform, but still are under pressure to diversify the idiosyncratic risk by holding other stocks which they hold neutral views on.

Other papers, such as Wermers (1997) and Grinblatt and Titman (1989, 1993) take an approach more in line with the arguments of Berk et al. (2004) and instead look at the stocks within the mutual fund portfolio. They find evidence that disagrees with the above conclusions of active mutual funds, actively trading managers possess significant stock selection talents, and that they are able to choose stocks that outperform benchmarks before expenses. Chen et al. (2000) investigates the return of stocks mutual funds buy and sell rather than their holdings, and find that the former outperform the latter by two percent per annum, adjusted for stock characteristics. Wermers (2000) and Cohen et al.

(2002) also find evidence that managers select stocks well.

2.0.2 Active Fund Management

Additionally, some studies disagree even on the point that active funds overall under-perform. For example, Kacperczyk et al. (2014) find that some fund managers significantly outperform benchmark indices and similar funds due to superior stock picking ability. Cremers and Petajisto (2009) also find that active managers significantly outperform their benchmarks, both before and after expenses. Wermers (2000) conclude that active mutual fund management has some value and that high-turnover funds beat their benchmarks, also after expenses. Shumway et al. (2009) keep track of fund managers' future performance beliefs for their holdings, and find that those managers whose beliefs are highly correlated with realized stock returns subsequently outperform those with low correlation.

The paper by Cohen et al. (2010) examines the performance of stocks in the U.S. market that active managers display the most conviction towards ex-ante, thus looking at investors' stock selection ability more directly, and find that they outperform both the market and the rest of the manager's portfolio by approximately one to four percent per quarter depending on the chosen benchmark. Pomorski (2009) shows that when multiple funds within the same company buy a stock, it outperforms benchmarks on average. Baks et al. (2006) conclude that more concentrated portfolios perform better, also highlighting the correlation between manager conviction and future stock performance. Kacperczyk and Zheng (2005) conclude that managers who concentrate in one area of expertise have better stock picking ability and perform better. Wermers et al. (2007) documents that trading portfolios consisting of other funds and with weights based on past fund performance outperform benchmarks after adjusting for factors such as momentum, value and earnings quality.

2.0.3 Role of Liquidity

Cohen et al. (2010) also highlights the significant liquidity service open end mutual funds provide to investors, and that papers such as Edelen (1999) find evidence that liquidity management plays a large role for fund managers, resulting in the dilution of portfolios with stocks managers are more neutral to, something most performance evaluation methods do not take into account. (Alexander et al., 2007) further discuss the liquidity-motivated buying within mutual funds

and its internal competition with valuation-motivated purchases.

3 Data

3.1 Data Selection

Our primary dataset is of Swedish fund holdings, and comes from Finansinspektionen (FI), a central administrative governmental authority with the responsibility of monitoring the financial market in Sweden. Firms managing funds are required report the holdings of their funds at the end of each quarter, and the holdings are then published publicly three to four weeks later. The responsibility of the correctness of the information lies with the firm reporting the holdings.

The stock data used is from Finbas, a database of stock price data, corporate actions and fundamentals from the Stockholm, Oslo, Copenhagen and Helsinki stock exchanges. The stock data comes at daily frequency. We also use the valuation of the total amount of stocks listed on the exchanges by Nasdaq OMX, the firm operating these stock exchanges, to enable us to calculate each stock's share of the total market.

3.2 Variables for Estimating the Idiosyncratic Risk

To estimate the idiosyncratic risk of each stock we need both a benchmark return, which is a relevant index, and a risk free rate. Since we are focusing on the Nordic stock holdings we use the Nasdaq OMX Nordic 40 as our main benchmark, an index consisting of the 40 most traded stocks from the Stockholm, Copenhagen, Helsinki and Rejkjavik exchange. While using the Nasdaq OMX Nordic 120 might have covered a greater part of the market, this index was not available for the majority of the period we had data from FI, and was thus ruled out. We used the index prices reported by Nasdaq OMX, which are given in Euros. For robustness we also use the OMXS30 and OMXSPI indices.

To keep the currency choice consistent and to avoid introducing the volatility of the exchange rates used exchange rates from Euros to the Swedish krona from the Swedish Central Bank, the Swedish central bank. We also chose to use the average risk-free one-month rate available on the market as reported by the Swedish Central Bank for our risk-free rate in these calculations. Since our funds are Swedish, using a different risk free rate would reintroduce the relative

volatility of the exchange rates.

3.3 Factors to Evaluate Performance

To evaluate the performance of the created portfolios, we control for the three main Fama-French factors of small-minus-big, high-minus-low and momentum, as provided for the European market on the Dartmouth Fama-French website. As the European dataset was calculated using the U.S. one-month risk-free rate, we recalculate the excess market return for the Swedish market using the Swedish one-month rate as provided by the Swedish Central Bank. The European dataset as it is provided by Fama-French is also calculated in U.S. Dollars, and the factors are therefore converted to a Swedish equivalent using the historical Swedish krona to U.S. dollar exchange rate, which is also provided by the Swedish Central Bank.

3.4 Our Sample

Our sample covers each quarter from the first quarter of 2002 to the last quarter apart from the third quarter of 2002 which is missing from the data set electronically available from the Swedish FI. While the electronic records starts at 2000, there is only data for one quarter during 2001 and for two during 2000, which is why these are excluded. The limit at the upper end of the time period is due to the Finbas stock data for market capitalization currently stops at the end of 2014.

For funds to be included in the sample they must have a total reported value of their holdings over 40 million SEK, have at least 20 reported stocks, of which at least 6 are listed at the Stockholm, Oslo, Copenhagen or Helsinki stock exchange at that time. The former is to exclude a small number of funds that are not considered mature enough for the sample. The later is to ensure not only that the fund is sufficiently large enough but also that it has enough positions within the target markets. These fund size limitations are common in the literature to filter out the most prevalent errors that appear in holdings data.

Table 1 on page 30 presents summary statistics on the properties of the funds in our final sample by the year end of each year. The number of funds range from 246 for the first year to 191 during 2013, the second to last year. The average number of stocks listed on the Nordic exchanges in the portfolio of each fund ranges from 35 to 48. The average number of stocks in total reported by

the funds starts at 140 in 2002, peaks at 224 in 2012 and falls to 192 in 2014, resulting in a decrease in the fraction of stocks held that are listed on the Nordic exchanges from 25% to 19% over the time period. The mean total value held by each fund, as self-reported by the funds, starts at 1.42 billion SEK in 2002 and increases by 368% to 6.65 billion in 2014.

4 Methodology

4.1 Defining Best Ideas

Our formal definition of the best ideas of fund managers is derived from the work of Cohen et al. (2010), where four different ways of measuring the relative overweight of a stock in a portfolio to the other stocks are used. Based on work by MacKinlay (1995), (Cohen et al., 2010) argue that weights adjusted by a benchmark is an appropriate way to measure fund managers views on mispricings. The idea is that the more overweighted a certain stock is in a portfolio relative the rest, the better the manager expects it to perform. For robustness all four measures used by Cohen et al. (2010) are used throughout the analysis here as well.

The first two measures of the relative over-weightings are fairly straightforward. The first one is defined as market tilt, using the whole market as the benchmark portfolio. Here we measure the relative weight in the portfolio compared to the weight in the market portfolio, based on the market capitalization of each stock. The second one is portfolio tilt, where the benchmark portfolio is replaced by a market portfolio constructed the same way as before but now only using the stocks the fund have investments in.

$$marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$$

$$portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$$

λ_{ijt} is the fraction of the total portfolio value held in stock i by the fund j at time t. λ_{iMt} is the market capitalization of stock i relative to the market capitalization of the full market at each time t. λ_{iVt} is the market capitalization of stock i divided by the sum of the market capitalization of all the stocks in the portfolio held by fund V.

Since this paper focuses on stocks listed on the Nordic exchanges, holdings not listed there are excluded and the portfolios are reformed as if they were only

containing the listed stocks. When the most popular best ideas are excluded the portfolios of the funds are once again reformed. The reason behind this is the limitations of the database used for stock data.

The second two measures scales the market tilt and the portfolio tilt by its idiosyncratic risk component, the mean square error,σ_{it}^2, obtained by regressing on a daily basis the excess returns of each stock on the market excess return over the quarter of which by the end the fund has reported its holdings. According to Cohen et al. (2010) this model is based on two strong assumptions: (1) that the model selected, here the CAPM model, reflects the factor structure of the returns and (2) that the manager of each fund aims at maximizing excess return relative to volatility. This is equivalent to the fund manager maximizing the information ratio of its portfolio. While Cohen et al. (2010) note that the second assumption would not seem restrictive, they chose to exclude certain funds that likely does not fulfil this criteria, such as index funds. Our sample does not exclude index funds, due to lack of classification of the funds in our data.

The estimation of the idiosyncratic risk component requires a choice of a market return for the regression. To overcome the lack of data of which benchmark for market return each fund uses we pick the listed index that for each fund correlates the highest with the daily returns of a portfolio consisting of the reported holdings over the month the holdings are reported for.

$$CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$$

$$CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$$

The four different tilts each provide a proxy for the funds relative view on the future performance of the stock, where a high tilt measure suggests a high conviction. The best idea of a fund is defined as the stock with the highest tilt.

All tilts are calculated on a quarterly basis. Since the holdings are published three to four weeks into the quarter we use the information on, this is an evaluation of the performance. It is not a test if it is possible to copy the results into a new trading strategy. All excess returns are in excess of the Swedish risk-free rate, unless the asset is a zero-investment portfolio.

4.2 Definition of Fresh Ideas

Most funds cannot take full use of new information on a stock immediately. Having large positions means that selling or buying to the optimal position immediately could result in price impact and less than optimal price levels for the transactions. There is also often tax implications of selling, which also might delay the offloading of the position.

To take this into account we define fresh positions as a position where the last action taken was a buy, assuming that the position then is based on new and fresh information. This allows us to exclude positions that a fund is slowly selling off as best ideas solely because it started off with a significant position.

4.3 Formation of Portfolios

After generating the different tilts, we create new portfolios every quarter for all fund holdings. This is based on the preceding quarter so that no data snooping occurs. Different portfolio weighting rules are used; for unique portfolios, the best idea of all funds each quarter is only included once, which means they are equally weighted between different managers that classify them as their best ideas. Dollar-weighted portfolios are also created, which weigh stocks based on the dollar amount invested into them. Both of these give alternative ways to utilize the information of what stocks fund managers show the strongest conviction towards.

The Swedish stock market is very concentrated compared to the U.S., something that is especially true for the most held stocks on the market, such as H&M. As many of these highly popular stocks are highly liquid and often used for cash management according to industry insiders, it is not possible to tell if an increase in a stock weight for a fund is because it is a new best idea by the fund manager this quarter or because they had an influx of capital they needed to invest into a liquid position. To handle this we also form portfolios with these outlier stocks excluded and calculate new tilts for these new portfolios. Thus, we exclude the five most popular stocks from our data set as these five exhibit characters such as a constantly extremely high popularity and high liquidity.

We also vary the weighting of the stocks in the created portfolios between value-weighted, equal-weighted, uniquely equal-weighted and weighted by market capitalization. Value-weighted entails a weighting based on the total capital invested into the stock by all funds where it is considered a best idea, while uniquely equal-weighted gives each unique stock among all funds' best idea an

equal weight. Equal-weighted simply entails an equal weight for each fund's best idea.

4.4 Different Portfolio Types

The best idea of each fund is the stock with the highest tilt measured each quarter. For each month, all stock weights are re-adjusted for any gain or loss in the portfolio during the previous month. In addition to looking at the best ideas of funds only, we also form and evaluate the performance of other portfolios. Zero-cost portfolios are also created where the best idea is bought and the remainder of the portfolio is sold.

For liquidity, different portfolios are created for the cases where a best idea stock is above, i.e. having a high spread, or below, i.e. having a low spread, the mean bid-ask spread as measured in percent of the ask price. We then look at the performance of the different portfolios and compare the two. Another potential way to create portfolios related to liquidity would be using trading volumes, but such data was unfortunately not available from our data sources.

For popularity, different portfolios are created for the cases where a best idea stock is below or above the median popularity for the portfolio at each point in time, with popularity measured by the tilt measure. Every quarter the stocks in each fund is sorted according to their tilt measures, and are assigned a rank, 1% for the stock with the lowest tilt measure, 100% for the one with the highest, 0% if the stock is not held. Each stock is then assigned its mean rank among the funds which gives an overall ranking each quarter of the popularity of the stocks.

We also look at the focus of each fund, with focus defined by the number of stocks a fund is invested in. The cutoffs are set by the 33rd and 68th percentiles, to give an even distribution and three different focus portfolios. Each focus portfolio contains the best ideas of the funds within the focus category each quarter. We look at the performance of the three different focus portfolios as well as the performance of a zero-cost portfolio: the high focus minus the low focus portfolio.

Portfolios are also created based on the size of the different funds having the best ideas. The cutoffs are set by the 33rd and 68th percentiles, to give an even distribution and three different size portfolios. Each size portfolio contains the best ideas of the funds within a size category each quarter. We look at the performance of the three different size portfolios as well as the performance of

a zero-cost portfolio: the large size minus the small size portfolio.

4.5 Performance of Best Idea Portfolios

After forming different portfolios, their performance is benchmarked against the Capital Asset Pricing Model (CAPM), as well as against the Fama-French model with controls for excess market return, small-minus-big (size), high-minus-low (value) and momentum factors. We also compare the average returns of the portfolios.

5 Empirical Results

5.1 Heavy Concentration on Most Popular Best Ideas

5.1.1 Overlap in Best Ideas

In our sample there are a few ideas that stand out as highly popular. Figure 1 and 2 on page 13 and 14 presents the distribution for portfolios containing all nordic-listed stocks held by the funds.

Depending on the tilt-measure use, 48% to 53% of the best ideas are unique at that time, which can be compared to the American market where more than 70% of the best ideas do not overlap between funds according to Cohen et al. (2010). 16% to 17% is shared by two funds and 8% to 9% by three funds. However, 9% to 10% of the best ideas are shared by more than ten fund at the same time, and 1% to 2% of the best ideas have more than 100 funds sharing the idea at that time. Some even have over 200 funds with the same best idea.

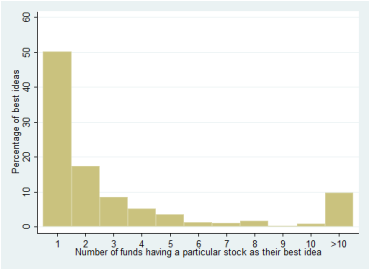
5.1.2 The Super-Popular Best Ideas

Figure 3 on page 15 presents the distribution of best ideas between the four overall most popular best ideas for the full time period and the rest of the stocks for each tilt measure. Between 56.7% and 73.8% of the best ideas is one of four most popular stocks, Ericsson, H&M, Nordea and Volvo. For the portfolio tilt Telia replaces Volvo.

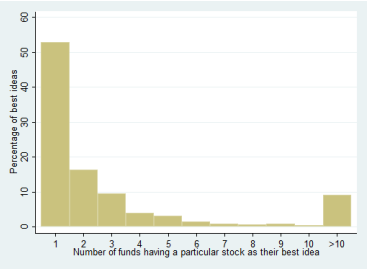
This heavy concentration in a few stocks for the best ideas is a concern for two major reasons. The first is that this causes the resulting portfolios formed on best ideas to be heavily overweighted in favour of these stocks. Several of the more basic portfolios have a weight of over 80% in one of these stocks during some quarters if the portfolios are weighted by number of funds with the stock

Figure 1: Overlap in Best Ideas

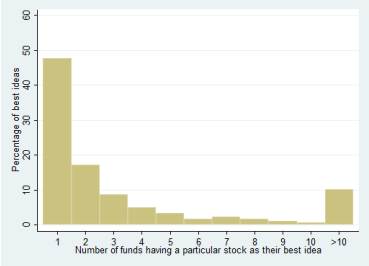
(a) Market Tilt



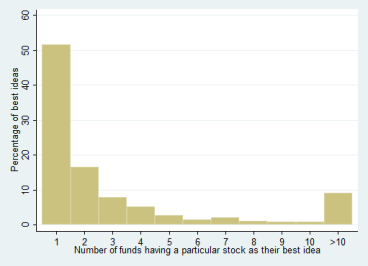
(b) Portfolio Tilt



(c) CAPM Tilt



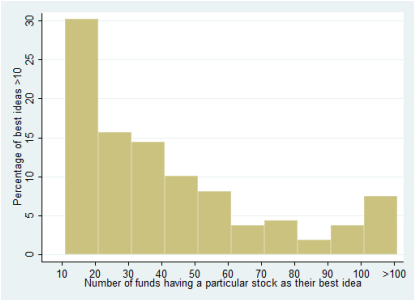
(d) CAPM Portfolio Tilt



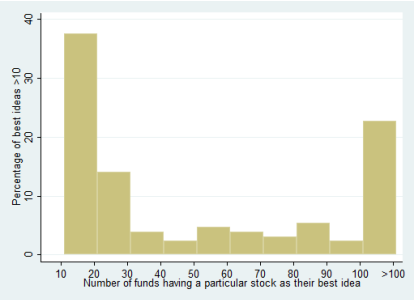
This figure displays the histogram of how much the best ideas overlap in the original data set. We count how many funds consider each particular stock their best idea for each quarter, and then how many times we have a best idea with only one fund, two funds and so one which consider it its best idea at a certain point in time. The best idea of a fund is the stock with the maximum value of the tilt measure in a fund that quarter. The sample period is 2002Q2 to 2014Q4.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$

Figure 2: Overlap in Best Ideas With over 10 Funds

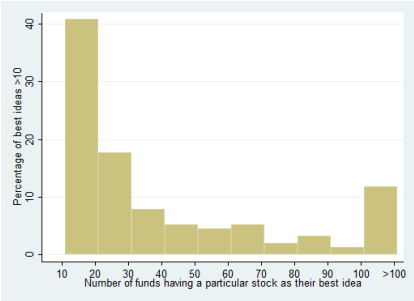
(a) Market Tilt



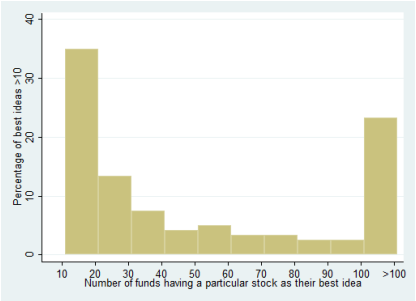
(b) Portfolio Tilt



(c) CAPM Tilt



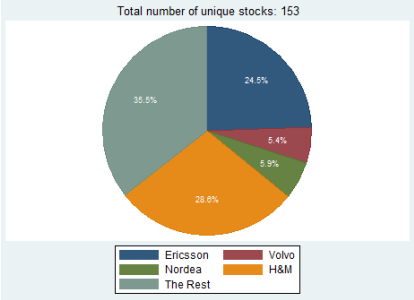
(d) CAPM Portfolio Tilt



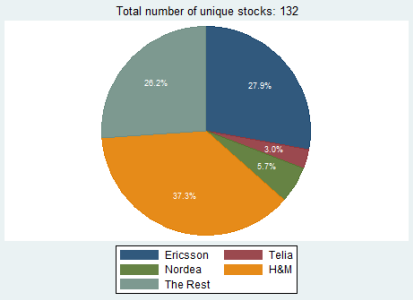
This figure displays the tail of of the histogram in figure 1. Figure 1 displays how much the best ideas overlap between the different funds in the original data set. Here we present the distribution of the best ideas with more than ten funds having the same best idea at the same time. We count how many funds consider each particular stock their best idea for each quarter and present the distribution of that. The best idea of a fund is the stock with the maximum value of the tilt measure in a fund that quarter. The sample period is 2002Q2 to 2014Q4.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

Figure 3: Overall Distribution for Super-Popular Best Ideas

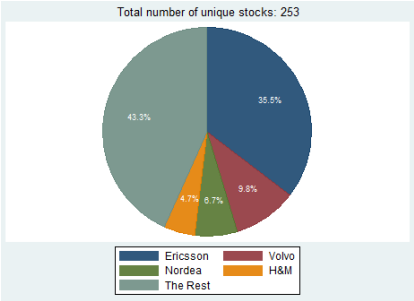
(a) Market Tilt



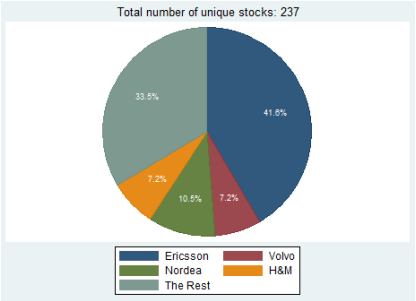
(b) Portfolio Tilt



(c) CAPM Tilt



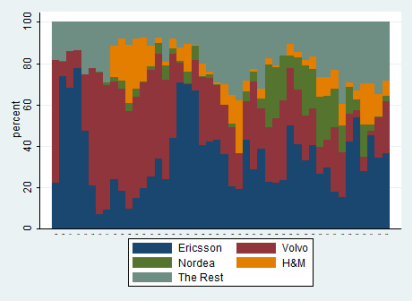
(d) CAPM Portfolio Tilt



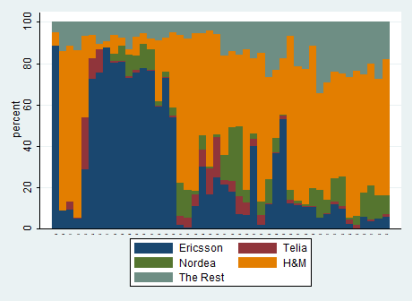
This figure presents the distribution of best ideas for the full time period, between the four most popular stocks for each tilt measure and the rest of the stocks. The four named stocks in each diagram are the four stocks that are chosen the most times as best idea for a fund. The best idea of a fund is the stock with the maximum value of the tilt measure in a fund that quarter. The percentage signifies the number of times the stock is being picked by a fund as their best idea using the specified tilt measure, divided by the total amount of best ideas selected over the time period. The sample period is 2002Q2 to 2014Q4.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

Figure 4: Distribution over Time for Super-Popular Best Ideas

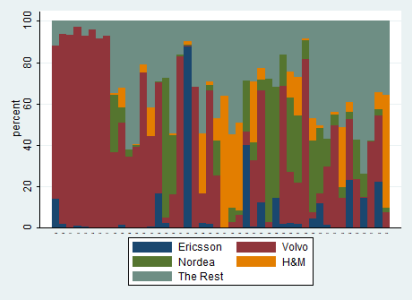
(a) Market Tilt



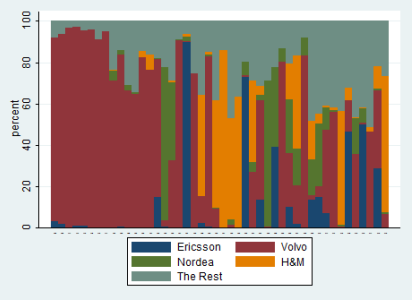
(b) Portfolio Tilt



(c) CAPM Tilt



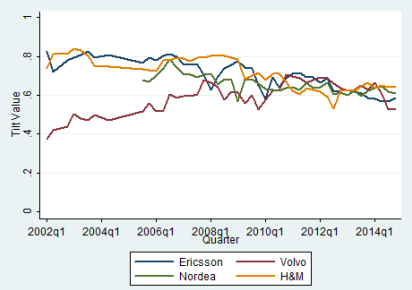
(d) CAPM Portfolio Tilt



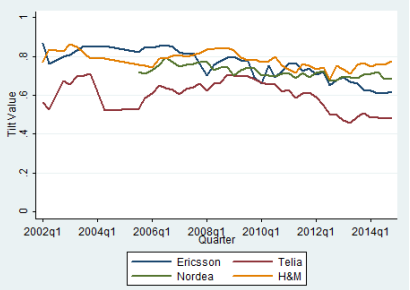
This figure presents the distribution of best ideas over the sample time period, between the four most popular stocks for each tilt measure and the rest of the stocks. The four named stocks in each diagram are the four stocks that are chosen the most times as best idea for a fund. The best idea of a fund is the stock with the maximum value of the tilt measure in a fund that quarter. The sample period is 2002Q2 to 2014Q4.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

Figure 5: Popularity Over Time for Super-Popular Best Ideas

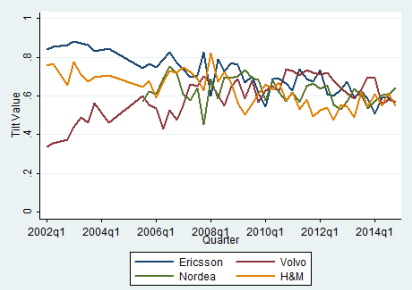
(a) Market Tilt



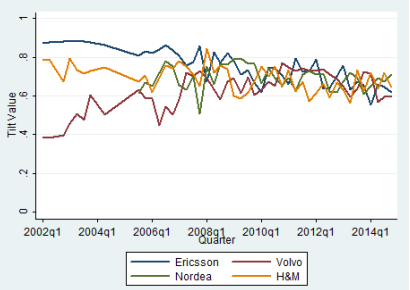
(b) Portfolio Tilt



(c) CAPM Tilt



(d) CAPM Portfolio Tilt



This figure presents the popularity metric for the top four most popular best ideas for each of the four tilt measures. These are the four stocks that are chosen the most times as best idea for a fund. Every quarter the stocks in each fund is sorted according to their tilt measures, and are assigned a rank, 1% for the stock with the lowest tilt measure, 100% for the one with the highest, linear inbetween and 0% if the stock is not held. This figure presents the mean value of that rank over the different funds for the stock each quarter.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

as best idea, either by value-invested in the stock or by the market capitalization of the stock.

Figure 4 presents the distribution of best ideas over time between the four most popular stocks and the rest. We can see that while which stock is the most popular there is a fairly consistent small portion of the best ideas that can be found outside these four highly popular stocks.

Figure 5 presents the popularity of the top four most popular stocks for each tilt measure over the time period. This is done using the popularity-metric described in the result-section. While the popularity is increasing some for stocks such as Volvo and Telia and decreasing some for H&M and Ericsson, the overall

level is fairly constant over the time period. Even if the stock which dominates the best idea selection changes the overall popularity is fairly constant. This supports the theory of these stocks being used for liquidity management.

5.1.3 The Problem

Now, this extreme overweighting of the super-popular stocks would not be an issue if we could be fairly sure that these stocks would be selected due to actually being best ideas in the sense considered in this thesis. However, according to Cohen et al. (2010) the more popular best ideas contribute less to the positive abnormal returns than the less popular ideas, which the data for this market provides support for too. This would suggest that it would be wiser to underweight the more popular ideas rather than overweight them the way an equal-weighting scheme or a weighting scheme based on dollars invested would do.

According to industry insiders it is highly common for funds to use these type of stocks to manage liquidity. Edelen (1999) and Alexander et al. (2007) both provide evidence that liquidity management is a major concern. Cohen et al. (2010) presents evidence for that less liquid best ideas outperforms more liquid, something that our data also supports. These five stocks all place in the top 1% of most liquid best ideas during at least some quarter and is in the top 9% more than 50% of the time. This would be another reason to underweight these overly popular stocks rather than over-weighting them.

The potential use of these stocks to manage liquidity would mean that the last action of a buy from a fund concerning a certain stock might well be a result of having extra cash at hand rather than new information to act on concerning the market. This means that these stocks might affect the results when focusing on fresh best ideas only too.

5.1.4 Exclusion as a Solution

Our solution is to exclude these five stocks and recalculate the tilts. This will focus the analysis on stocks with a higher probability that the position taken actually reflects the fund manager's view on the value of the stock. While this does not give much of an effect on the overlap for fewer funds per best idea, the number of best ideas with more than a hundred funds behind them decreases to 0.1-0.7% and eliminates the majority of their influence on our results.

5.2 Distribution of Tilts

Figure 6 presents the distribution over time for the different tilts for the best ideas. For the market and portfolio tilts there is no clear tendency over time. What is more noticeable if comparing to the results of Cohen et al. (2010) is that our minimum tilt value more or less is at the same level as their median. This could be due to our portfolios overall having fewer stocks, which would result in a larger percentage of the total value invested in each stock.

However, when instead investigating the CAPM tilt and the CAPM portfolio tilts we see that our tilts are far lower here compared to theirs. Since these tilts are a multiple of the idiosyncratic variance and the corresponding tilt calculated earlier, we are looking at a higher idiosyncratic variance for the best ideas picked using these two tilts.

To increase the chances that we are looking at actual active positions we focus most of our analysis on the top 50% of the tilts.

When investigating the data set it is clear that the CAPM tilt and CAPM portfolio tilts select a somewhat different set of stocks as best ideas compared to the market and portfolio tilt. Stocks that follow the index better have their tilt value scaled down, which allows for stocks that do not follow their index as closely to pop up as best ideas.

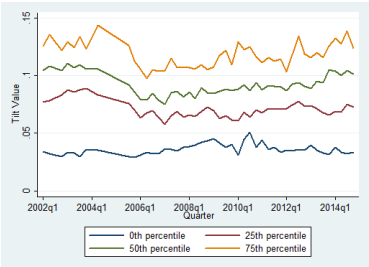
If these best ideas perform well they would have a greater chance of contributing to the alphas, since less of their alphas would be consumed by the market excess return coefficient. It is also worth noting that the popular stocks that are popular inclusions in the index portfolios would be weighted down, while those that are popular while not following the index would see their weights increased.

For the CAPM tilt and the CAPM portfolio tilt we have chosen to report regression results using a value-weighted portfolio, weighted by the value held by the funds in each stock. Weighting by market capitalization and unique-equal-weighting of the stocks produce overall qualitatively similar results, although slightly weaker in terms of actual returns.

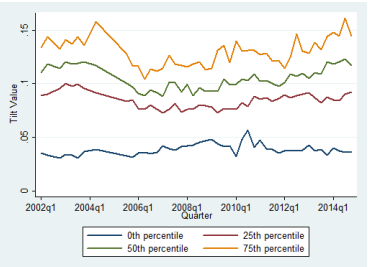
For the market tilt and the portfolio market tilt the problem experienced before still remains although to a lesser extent. The maximum weights in a stock each quarter is here almost 50% higher using an equal weighting compared to the same weighting scheme with the other two tilts. The extra weight on the more popular stocks still results in a drop in performance so we use the unique-equal-weighted portfolio for these two tilts. The performance overall utilizing

Figure 6: Distributions of Tilts over Time

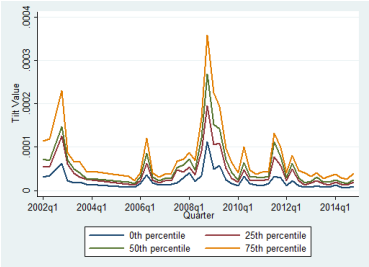
(a) Market Tilt



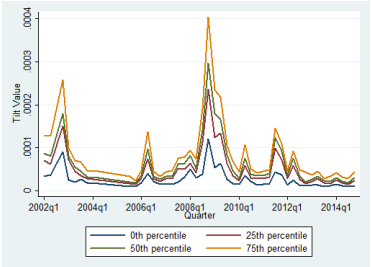
(b) Portfolio Tilt



(c) CAPM Tilt



(d) CAPM Portfolio Tilt



This figure presents the distribution of the tilts for best ideas over the entire sample time period for the modified data set, where the five super-popular best ideas were excluded. The best idea of a fund is the stock with the maximum value of the tilt measure in a fund that quarter. The sample period is 2002Q2 to 2014Q4.
(a) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
(b) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
(c) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
(d) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

either of the weighting combinations is very similar, but due to space constraints only this combination was chosen to be presented in the tables.

5.3 The Features and Performance of Best Ideas

We find that portfolios composed of best ideas are able to generate monthly positive significant alphas of around 100 basis points and that portfolios made of best fresh ideas tends to give a higher average return that those made of just best ideas. The effect of excluding non-fresh ideas are the greatest for the CAPM tilt and the CAPM portfolio tilt.

5.3.1 Returns

Table 2 on page 31 presents a comparison of portfolios formed by best ideas and best fresh ideas, both only using the top 50% of the ideas with the highest tilt. Table 3 and 4 presents the same results but for various subsets of the best and fresh ideas.

We have significant alphas of around 100 basis points for the market tilt and the portfolio tilt, and raw average returns of 126-127 basis points using best ideas. Looking at the fresh versions of these portfolios we have an increase of 8 and 13 basis points on the raw average returns but close to identical alphas for the Fama-French model. The CAPM-alphas increase marginally, though.

For the CAPM tilt and the CAPM portfolio tilt we go from an average return of 52 basis points to 104, and from 40 to 96, when looking at fresh best ideas compared to the best ideas in general. There is also a clear increase in the alphas, which are now significant for both regression models.

When limiting the portfolios to the subset of best ideas with a tilt-value above certain percentiles the average returns do in general increase, but we also lose in significance. Even though the fresh market tilt portfolio with the top 5% of the tilts have an average monthly return of 2.88%, the alphas are non-significant. This behaviour might be explained by the relatively small dataset that together with the coordination among the funds would result in portfolios that are very concentrated.

The significant alphas tells us that the extended Fama-French models do not explain all the factors in the returns and that there is something else driving the abnormal returns.

5.3.2 Factors

Using all of the best ideas all coefficients in the regressions are significantly different from zero. Exclusively looking at best fresh ideas it is only the value-coefficient for the CAPM portfolio tilt that is not. The significance of some coefficients does however drop the more we restrict which best ideas and best fresh ideas we use. For the market tilt and the portfolio tilt this is true for the momentum coefficient, for the CAPM tilt and the CAPM portfolio tilt this is true for the size-coefficient and the value coefficient. These two groups of tilts clearly capture slightly different market characteristics.

The signs are consistent, as we have positive market betas and size coefficients, while the value coefficients and the momentum coefficients are negative. The excess returns co-varies with small, high-beta growth stocks that have recently not performed well. This would suggest that the funds trade against the momentum when placing their strongest bets.

For momentum this is the opposite of what Cohen et al. (2010) find. Potentially Swedish fund managers are better at rebalancing their most prominent positions compared to their American counterparts, or they could just have a really good market timing.

5.4 The Most Effective Best Ideas

Looking into what makes a best idea well-performing we find that that less popular best ideas tends outperform highly popular stocks. Using the final subset of the funds portfolios there is a big divide in whether high-liquidity best ideas or low-liquidity best ideas do the best depending on the tilt measure used to define the best ideas.

5.4.1 Liquidity

The best ideas are split into two groups based on if their average bid-ask-spread over the quarter before was above or below the median bid-ask spread. The ones with a spread below the median are considered stocks with a higher liquidity, the ones above stocks with lower liquidity. Tables 7 on page 36 presents the results of the monthly regressions.

The market tilt and portfolio tilt gives the opposite result compared to the two CAPM-based tilts. For the first two the low-liquidity portfolios outperform the high-liquidity ones by 25-30 basis points and with a difference in the signif-

icant alphas from the regressions on the Fama-French model of around 40 basis points.

For the CAPM tilt and the CAPM portfolio tilt the low-liquidity portfolios gives a close to zero average return, while the high-liquidity portfolios perform at a level comparable to the low liquidity portfolios using the other two tilt measures in average returns. When it comes to significant alphas we instead have highly significant values of 161 and 123 basis points, beating the other two alphas both in level and significance. It seems as if the positive alphas for the CAPM and CAPM portfolio tilts are driven by the stocks with higher liquidity rather than lower, which would suggest that care should be taken to the type of tilt used when stockpicking based on liquidity.

5.4.2 Popularity

The idea would be that the value of new information would decrease the more others are acting on it, as the market reacts and would incorporate this new information. We would therefore expect less popular best ideas to outperform more popular best ideas, which is both supported by Cohen et al. (2010) and by industry insiders.

Table 8 on page 37 presents the results of portfolios divided on popularity, using the same ranking system as Cohen et al. (2010). Every quarter the stocks in each fund is sorted according to their tilt measures, and are assigned a rank, 1% for the stock with the lowest tilt measure, 100% for the one with the highest, linear inbetween and 0% if the stock is not held. Each stock is then assign its mean rank among the funds which gives an overall ranking each quarter of the popularity of the stock. The best ideas are then split into two groups, those below the median popularity level and those above.

Looking at the mean returns, less popular ideas outperform the more popular ideas by approximately 52 basis point on average for the market tilt and the portfolio tilt portfolios and by 37 for the CAPM portfolio tilt, while the difference is almost zero for the CAPM tilt portfolios. For the Fama-French model we have a difference of approximately 60 basis point for the significant monthly alphas for the market tilt and portfolio tilt, but no significance for both the low and high portfolios for the other tilts. This is expected since the CAPM portfolio tilt and the CAPM tilt both put less weight in stocks that follows the benchmarks by their construction, and the more popular best ideas have a tendency to follow the benchmarks.

5.5 Properties of the Funds

The best ideas are now split into groups depending on the properties of the fund to see if certain funds appear to be better at picking best ideas. We see that funds with more focused portfolios have better performing best ideas. For the size of the fund there seems as if it is the medium-sized funds that provide best ideas that tends to perform below the rest.

5.5.1 Focus

Table 9 on page 38 shows how the level of focus of the fund correlates with the performance. Focus is measured in how many different stocks the fund currently has investments in, a high focus fund meaning fewer stocks held and a low focus meaning more stocks held. Using the mean return all of the portfolios show a higher return the higher the focus of the portfolio, with a 70 basis point difference between the high and the low for the market and portfolio tilts, and around half of that for the CAPM tilt and CAPM portfolio tilt. Using the extended Fama-French model we have an alpha of 98 basis points with a t-statistic of 1.76, but no other significant alphas. For the low-focus portfolios there is also no significant alphas, while there are positive significant alphas for the medium focus and high focus portfolios, at 64 to 94 basis points for medium focus and at 101 to 148 basis points for the high focus portfolios. This might suggest a difference compared to the US-market where Cohen et al. (2010) found "no cross-sectional variation in the performance of best ideas as a function of fund focus".

5.5.2 Size

When we split up the best ideas into three equal-sized groups depending on the total value of the assets managed by the fund the results are not clearly pointing in any direction. Looking at the raw mean returns the small size-portfolios perform better than the large-size portfolios, but, on the other hand it is the medium-sized portfolios that perform the worst. There are no significant alphas for the spread portfolios, investing in the spread between the high-size and low-size portfolios.

5.6 The Rest of the Stocks

For our best minus the rest portfolios there are no significant alphas and average returns are close to zero. The results are qualitatively similar regardless of the weighting scheme used. This is in stark contrast to the results of Chen et al. (2000), who instead found that for the American market the alphas remained significant at the 1%-level for their 6-factor model. For our portfolios it appears as if the positive returns of the best ideas is being eaten up by going short the rest, suggesting that the rest of the stocks actually add to the performance.

6 Conclusion

The best ideas of the Swedish funds are heavily concentrated into a few highly popular stocks, which heavily skews the results. When ignoring these highly popular best ideas there is still a fairly large coordination among the fund managers. Portfolios formed by these best ideas in our Swedish fund dataset are able to generate monthly positive alphas of over 1%. The excess returns co-vary with small, high-beta growth stocks that have recently not performed well. We find that less popular best ideas and less liquid best ideas tend to perform better, as well as best ideas from more concentrated funds, in line with the literature.

The Swedish market exhibits some notably different properties compared to the American market described by Cohen et al. (2010). While some of these might be due to the smaller size, further analysis in how the market composition affects the stock-picking abilities of fund managers is needed.

Our results also support the industry-statements that funds use different benchmarks. We proved to significantly improve the results by finding and utilizing the most relevant benchmark portfolio for each fund in the calculation of tilts. This might well apply for other markets and might also be a potentially important extension of the framework set up by Cohen et al. (2010).

Another area of concern is how the framework set up by Cohen et al. (2010) with definitions and assumptions on best ideas and best fresh ideas does not seem to hold for this market. Best fresh ideas may be defined as fresh despite the freshness not being the result of new information but rather just results of day-to-day cash management. Best ideas might be defined as best without the holdings reflecting some specific view on mispricings but rather the view on its continuation as a highly liquid asset.

Our results show that Swedish fund managers are able to pick stocks that

outperform the market, despite the general consensus that funds are not able to beat the benchmark index with their overall portfolio. This points to the existence of market inefficiencies in the Swedish fund market.

6.1 Limitations and Future Topics

The main limitation of this thesis was the availability of data. The timespan of the FI fund dataset is only available from 2001 onwards, and this thesis thus only evaluates the stockpicking ability of fund managers past this point in time. FI potentially has a larger dataset available, in which case the results of this thesis could be extended to a larger sample. Also, we focused primarily on Swedish fund holdings in the Nordics, due to sparse availability of stock data outside the Nordics in the database used. A small number of best ideas of stocks outside the Nordics were thus not included in our portfolios due to a lack of stock price data, but their weights in the portfolios were generally small.

One extension of this thesis would be to do a similar study for European funds. This would require historical fund holdings data for the European market, as well as a more extensive historical stock price database than was used in our thesis.

It could additionally be of interest in a follow-up study to dive further into the portfolios with abnormal returns, and determine whether there is any alteration of the portfolio rule that could improve them. There is also significant room for qualitative studies to look into the underlying reasons for over- or underperformance of the different portfolios.

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7 Appendix

Table 1: Sample Summary Statistics

Year	Number of Funds	Fund Fund Value	Mean Number of Stocks	Mean Number of Nordic Stocks	Mean Fraction Nordic Stocks
2002	246	1,420,000,000	140	35	25%
2003	216	2,050,000,000	136	35	26%
2005	225	3,150,000,000	163	40	25%
2006	225	3,850,000,000	180	48	26%
2007	229	3,620,000,000	193	45	23%
2008	208	2,530,000,000	197	47	24%
2009	220	3,510,000,000	210	44	21%
2010	218	4,180,000,000	196	44	22%
2011	228	3,580,000,000	231	41	18%
2012	193	4,740,000,000	224	38	17%
2013	191	5,730,000,000	216	41	19%
2014	200	6,650,000,000	217	41	19%
Mean	217	3,750,833,333	192	42	22%

The table summarizes year-end statistics from 2002 to 2014 for all the funds in the sample. The sample consists of the funds who have reported their holdings to FI, have a total reported value of their holdings over 40 million SEK, have at least 20 reported stocks, of which at least 6 are listed at the Stockholm, Oslo, Copenhagen or Helsinki stock exchange at that time. Column 2 reports the total number of these funds each year end. Column three reports the average total value of the funds holdings. Column 4 reports the mean number of unique stocks held by funds, and column 5 the mean number of stocks listed on the Stockholm, Oslo, Copenhagen or Helsinki stock exchanges at the time. Column 6 reports the average fraction of such stocks in relationship to the total number of stocks held by each fund. The final row reports the mean of all of these variables, equal-weighted by year.

Table 2: Performance of Best Ideas

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. $r_{p,t}$ is the excess return on the portfolio formed by the best ideas from each fund in panel A and best fresh ideas in panel B. The best idea of each fund is the stock with the highest tilt measure each quarter. The best fresh idea is the best idea where the latest trade made by the fund for the stock was a buy. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. In this table the analysis is restricted to the funds whose maximum tilt is in the top 50% of all the tilts of all the best ideas at that time. The sample period is April 2002 to December 2014 for best ideas and July 2002 to December 2014 for best fresh ideas.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Best Ideas							
r_1	0.01259	0.640***	0.0103**	0.991***	0.640***	-0.577***	-0.183*
		(3.36)	(2.23)	(10.75)	(3.36)	(-3.10)	(-1.78)
r_2	0.01268	0.637***	0.0105**	0.997***	0.637***	-0.574***	-0.183*
		(3.15)	(2.14)	(10.20)	(3.15)	(-2.91)	(-1.68)
r_3	0.00517	0.0078	0.00877*	1.267***	0.306	-0.420**	-0.286**
		(1.52)	(1.76)	(12.73)	(1.49)	(-2.09)	(-2.57)
r_4	0.00393	0.0070	0.00786	1.262***	0.324	-0.373*	-0.345***
		(1.27)	(1.47)	(11.83)	(1.47)	(-1.73)	(-2.89)
Panel B: Best Fresh Ideas							
r_1	0.01342	0.00825*	0.00984**	0.975***	0.632***	-0.492***	-0.205**
		(1.78)	(2.21)	(10.82)	(3.40)	(-2.71)	(-2.07)
r_2	0.01398	0.00877*	0.0103**	0.971***	0.606***	-0.495***	-0.200*
		(1.86)	(2.27)	(10.56)	(3.20)	(-2.67)	(-1.98)
r_3	0.01044	0.0108**	0.0114**	1.195***	0.302	-0.326	-0.300***
		(2.13)	(2.31)	(11.99)	(1.47)	(-1.62)	(-2.74)
r_4	0.00956	0.00947*	0.00998*	1.205***	0.297	-0.288	-0.338***
		(1.75)	(1.89)	(11.29)	(1.35)	(-1.34)	(-2.88)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parentheses

* p<0.1, ** p<0.5, *** p<0.01

Table 3: Performance of Best Ideas at Different Threshold Levels

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. $r_{p,t}$ is the excess return on the portfolio formed by the best ideas from each fund. The best idea of each fund is the stock with the highest tilt measure each quarter. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Top 100% of Tilts							
r_1	0.01104	0.582***	0.00862**	0.977***	0.582***	-0.543***	-0.202**
		(3.75)	(2.29)	(13.00)	(3.75)	(-3.58)	(-2.40)
r_2	0.01145	0.568***	0.00912**	0.986***	0.568***	-0.535***	-0.189**
		(3.54)	(2.34)	(12.71)	(3.54)	(-3.41)	(-2.18)
r_3	0.00564	0.00712	0.00834*	1.226***	0.407**	-0.453**	-0.269**
		(1.46)	(1.77)	(13.03)	(2.09)	(-2.38)	(-2.55)
r_4	0.00478	0.00671	0.00795	1.243***	0.430**	-0.439**	-0.287**
		(1.30)	(1.59)	(12.45)	(2.08)	(-2.18)	(-2.57)
Panel B: Top 25% of Tilts							
r_1	0.01367	0.786***	0.0121**	1.021***	0.786***	-0.692***	-0.199
		(3.31)	(2.09)	(8.87)	(3.31)	(-2.98)	(-1.54)
r_2	0.0146	0.726***	0.0125**	1.005***	0.726***	-0.667***	-0.176
		(2.89)	(2.05)	(8.26)	(2.89)	(-2.72)	(-1.29)
r_3	0.00613	0.00891	0.00931*	1.212***	0.221	-0.229	-0.372***
		(1.61)	(1.74)	(11.37)	(1.00)	(-1.06)	(-3.12)
r_4	0.00584	0.00863	0.00905*	1.206***	0.233	-0.238	-0.393***
		(1.54)	(1.68)	(11.20)	(1.05)	(-1.10)	(-3.26)
Panel C: Top 5% of Tilts							
r_1	0.02656	1.770**	0.02730	1.195***	1.770**	-1.467**	-0.0718
		(2.33)	(1.49)	(3.26)	(2.33)	(-1.98)	(-0.18)
r_2	0.01003	0.2290	0.00605*	0.949***	0.229	-0.573***	-0.0622
		(1.60)	(1.73)	(13.65)	(1.60)	(-4.09)	(-0.80)
r_3	0.00160	0.00148	0.00203	1.050***	0.274	-0.2820	-0.412***
		(0.22)	(0.30)	(7.90)	(1.00)	(-1.05)	(-2.77)
r_4	0.00195	0.00224	0.00278	1.099***	0.237	-0.279	-0.339**
		(0.31)	(0.39)	(7.81)	(0.82)	(-0.98)	(-2.15)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parenthesess

* p<0.1, ** p<0.5, *** p<0.01

Table 4: Performance of Best Fresh Ideas at Different Threshold Levels

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. $r_{p,t}$ is the excess return on the portfolio formed by the best fresh ideas from each fund. The best fresh idea of each fund is the stock with the highest tilt measure each quarter, where the last trade by the fund in the stock was a buy. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value-weighted according to the funds investments in the stocks. The sample period is July 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Top 100% of Tilts							
r_1	0.01195	0.00675*	0.00826**	0.967***	0.586***	-0.519***	-0.209***
		(1.82)	(2.41)	(13.95)	(4.10)	(-3.71)	(-2.74)
r_2	0.01247	0.00736**	0.00884**	0.972***	0.574***	-0.521***	-0.208***
		(1.99)	(2.58)	(14.01)	(4.02)	(-3.73)	(-2.73)
r_3	0.00849	0.00824*	0.00904*	1.173***	0.382*	-0.350*	-0.298***
		(1.72)	(1.94)	(12.48)	(1.97)	(-1.85)	(-2.88)
r_4	0.00813	0.00794	0.00865*	1.168***	0.365*	-0.312	-0.306***
		(1.59)	(1.79)	(11.93)	(1.81)	(-1.58)	(-2.84)
Panel B: Top 25% of Tilts							
r_1	0.01527	0.0104*	0.0123**	1.012***	0.731***	-0.570**	-0.198
		(1.84)	(2.25)	(9.17)	(3.22)	(-2.56)	(-1.63)
r_2	0.01571	0.0105*	0.0125**	1.002***	0.740***	-0.600**	-0.188
		(1.74)	(2.12)	(8.44)	(3.03)	(-2.51)	(-1.44)
r_3	0.00813	0.0119**	0.0122**	1.259***	0.220	-0.235	-0.372***
		(2.07)	(2.17)	(11.11)	(0.94)	(-1.03)	(-2.99)
r_4	0.00952	0.00980*	0.0100*	1.244***	0.227	-0.216	-0.391***
		(1.66)	(1.76)	(10.77)	(0.96)	(-0.93)	(-3.08)
Panel C: Top 5% of Tilts							
r_1	0.02884	0.0229	0.0282	1.222***	1.884**	-1.456*	-0.0629
		(1.22)	(1.52)	(3.25)	(2.44)	(-1.92)	(-0.15)
r_2	0.01234	0.00678*	0.00781**	0.975***	0.286**	-0.512***	-0.054
		(1.96)	(2.35)	(14.51)	(2.07)	(-3.78)	(-0.73)
r_3	0.00858	0.0018	0.00264	1.077***	0.401	-0.427	-0.397***
		(0.26)	(0.39)	(7.82)	(1.41)	(-1.54)	(-2.62)
r_4	0.01239	0.00278	0.0036	1.133***	0.352	-0.434	-0.313*
		(0.38)	(0.49)	(7.65)	(1.16)	(-1.46)	(-1.92)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parenthesess

* p<0.1, ** p<0.5, *** p<0.01

Table 5: Performance of Best-Minus-Rest Portfolios

$$spread_{p,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. $spread_{p,t}$ is the return of an equal-weight portfolio, long one SEK in the best idea in panel A and one sek in the best fresh idea of each fund in panel B, and one SEK short in the rest of the stocks in the fund's portfolio. The best idea of each fund is the stock with the highest tilt measure each quarter. The best fresh idea is the best idea where the latest trade made by the fund for the stock was a buy. The results are qualitively similar regardless of weighting scheme. The sample period is April 2002 to December 2014 for best ideas and July 2002 to December 2014 for best fresh ideas.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Best Ideas							
r_1	0.00103	0.00007	-0.00057	0.048	-0.385***	0.107	0.347***
		(0.02)	(-0.18)	(0.770)	(-2.98)	(0.85)	(4.980)
r_2	0.00022	-0.00104	-0.00186	0.018	-0.430***	0.153	0.333***
		(-0.29)	(-0.55)	(0.260)	(-3.12)	(1.14)	(4.470)
r_3	-0.00549	0.0013	0.00077	0.311***	-0.128	0.162	-0.0601
		(0.28)	(0.16)	(3.23)	(-0.64)	-0.83	(-0.56)
r_4	-0.00657	0.00104	0.00035	0.350***	(0.162)	0.208	(0.051)
		(0.20)	(0.07)	(3.34)	(-0.75)	(0.98)	(-0.43)
Panel B: Best Fresh Ideas							
r_1	0.00005	-0.00007	-0.00063	0.073	-0.379***	0.109	0.312***
		(-0.02)	(-0.21)	(1.22)	(-3.08)	(0.90)	(4.73)
r_2	-0.00071	-0.00090	-0.00150	0.060	-0.393***	0.100	0.292***
		(-0.28)	(-0.49)	(0.97)	(-3.06)	(0.80)	(4.26)
r_3	-0.00354	0.00242	0.00181	0.275***	-0.153	0.213	(0.073)
		(0.54)	(0.40)	(2.99)	(-0.81)	(1.15)	(-0.72)
r_4	-0.00425	0.00203	0.00128	0.286***	(0.197)	0.254	(0.067)
		(0.42)	(0.27)	(2.94)	(-0.99)	(1.30)	(-0.63)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$ 3) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$ 4) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parentheses * p<0.1, ** p<0.5, *** p<0.01

Table 6: Performance of Best-Minus-Rest Portfolios

$$spread_{p,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. $spread_{p,t}$ is the return of an equal-weight portfolio, long one SEK in the best three ideas in panel A and one SEK in the best five ideas of each fund in panel B, and one SEK short in the rest of the stocks in the fund's portfolio. The best idea of each fund is the stock with the highest tilt measure each quarter. The results are qualitively similar regardless of weighting scheme. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Best Three Ideas							
r_1	0.00018	0.00055	-0.00032	0.090	-0.455***	0.117	0.301***
		(0.17)	(-0.10)	(1.480)	(-3.63)	(0.96)	(4.440)
r_2	-0.00071	-0.00032	-0.00114	0.087	-0.447***	0.081	0.283***
		(-0.10)	(-0.36)	(1.370)	(-3.42)	(0.63)	(4.000)
r_3	-0.00494	0.0015	0.00104	0.324***	-0.199	0.0288	0.0103
		(0.40)	(0.27)	(4.31)	(-1.28)	-0.19	-0.12
r_4	-0.00540	0.00111	0.000575	0.328***	-0.224	0.0401	0.0211
		(0.29)	(0.15)	(4.31)	(-1.42)	(0.26)	(0.25)
Panel B: Best Five Ideas							
r_1	0.00054	0.00076	-0.00023	0.073	-0.505***	0.116	0.293***
		-0.23000	(-0.08)	(1.21)	(-4.08)	(0.96)	(4.36)
r_2	-0.00019	0.00007	-0.00094	0.070	-0.512***	0.116	0.285***
		-0.02000	(-0.30)	(1.14)	(-4.00)	(0.93)	(4.11)
r_3	-0.00447	0.00165	0.00090	0.304***	-0.307**	0.071	0.043
		(0.49)	(0.27)	(4.55)	(-2.22)	(0.53)	(0.570)
r_4	-0.00446	0.00164	0.000856	0.301***	-0.321**	0.0813	0.0415"
		(0.48)	(0.25)	(4.43)	(-2.28)	(0.59)	(0.55)"

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parentheses

* p<0.1, ** p<0.5, *** p<0.01

Table 7: Performance of Best Ideas by Liquidity

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. The portfolios are divided depending on if the best idea stock is above, having a high spread, or below, having a low spread, the mean bid-ask spread measured in percent of the ask price. The best idea of each fund is the stock with the highest tilt measure each quarter. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Low and High Bid-Ask Spread Splits							
$r_{1.low}$	0.00977	0.00615*	0.00694**	0.958***	0.246*	-0.336**	-0.196***
		(1.76)	(2.06)	(14.29)	(1.77)	(-2.48)	(-2.62)
$r_{1.high}$	0.01266	0.00789	0.0108**	1.003***	0.930***	-0.760***	-0.206*
		(1.39)	(2.02)	(9.43)	(4.23)	(-3.54)	(-1.73)
$r_{2.low}$	0.01021	0.00632*	0.00699**	0.949***	0.198	-0.313**	-0.167**
		(1.77)	(2.01)	(13.70)	-1.38	(-2.24)	(-2.16)
$r_{2.high}$	0.01272	0.00835	0.0112**	1.024***	0.942***	-0.762***	-0.208*
		(1.42)	(2.02)	(9.24)	(4.11)	(-3.41)	(-1.68)
$r_{3.low}$	0.00507	0.00700	0.00797	1.229***	0.322	-0.415**	-0.288**
		(1.33)	(1.55)	(11.99)	(1.52)	(-2.01)	(-2.51)
$r_{3.high}$	0.00159	0.00280	0.00513	1.234***	0.797***	-0.705***	-0.362***
		(0.52)	(1.03)	(12.36)	(3.86)	(-3.50)	(-3.25)
$r_{4.low}$	0.00440	0.00690	0.00789	1.257***	0.351	-0.390*	-0.298**
		(1.23)	(1.44)	(11.49)	-1.550	(-1.77)	(-2.43)
$r_{4.high}$	0.00459	0.00489	0.00661	1.142***	0.643***	-0.518***	-0.388***
		(0.97)	(1.41)	(12.19)	(3.320)	(-2.74)	(-3.70)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parentheses

* p<0.1, ** p<0.5, *** p<0.01

Table 8: Performance of Best Ideas by Popularity

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. Every quarter the stocks in each fund is sorted according to their tilt measures, and are assigned a rank, 1% for the stock with the lowest tilt measure, 100% for the one with the highest, linear inbetween and 0% if the stock is not held. Each stock is then assign its mean rank among the funds which gives an overall ranking each quarter of the popularity of the stock. The portfolios are divided depending on if the best idea stock is below, $r_{p,low,t}$, or above, $r_{p,high,t}$ the median popularity for the portfolio at that time. The best idea of each fund is the stock with the highest tilt measure each quarter. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Low and High Popularity Splits							
$r_{1.low}$	0.01376	0.00895	0.0117**	0.996***	0.891***	-0.719***	-0.199*
		(1.58)	(2.17)	(9.27)	(4.01)	(-3.32)	(-1.66)
$r_{1.high}$	0.00854	0.00491	0.00579*	0.965***	0.265*	-0.371***	-0.189**
		(1.42)	(1.75)	(14.63)	(1.94)	(-2.78)	(-2.57)
$r_{2.low}$	0.01396	0.0097	0.0124**	1.021***	0.892***	-0.711***	-0.205
		(1.62)	(2.18)	(9.00)	-3.81	(-3.11)	(-1.61)
$r_{2.high}$	0.00889	0.00521	0.00595*	0.963***	0.215	-0.334**	-0.167**
		(1.51)	(1.78)	(14.49)	(1.56)	(-2.49)	(-2.25)
$r_{3.low}$	0.00526	0.00496	0.00635	1.161***	0.517**	(0.348)	-0.211*
		(0.93)	(1.20)	(11.03)	(2.38)	(-1.64)	(-1.80)
$r_{3.high}$	0.00577	0.00733	0.00855*	1.227***	0.399**	-0.469**	-0.276**
		(1.45)	(1.75)	(12.59)	(1.98)	(-2.38)	(-2.54)
$r_{4.low}$	0.00776	0.00678	0.00761	1.110***	0.341	(0.181)	(0.170)
		(1.35)	(1.51)	(11.05)	-1.640	(-0.89)	(-1.51)
$r_{4.high}$	0.00406	0.00620	0.00744	1.258***	0.417*	-0.457**	-0.280**
		(1.16)	(1.43)	(12.13)	(1.950)	(-2.19)	(-2.42)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$

2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$

3) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$

4) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$

T-statistics in parentheses

* p<0.1, ** p<0.5, *** p<0.01

Table 9: Best Ideas by Focus of Portfolio

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$
$$spread_{p,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. The best ideas are divided into three portfolios depending on the focus of the fund, using the 33rd and the 68th percentiles as cut-offs. Focus is measured by the number of different stocks the fund is invested in. Funds with less than the lower cut-off point is considered high focus, and fund with higher than the higher cut-off point low focus. Panel D presents the results of the same regressions run on the spread between the high focus return series and the low focus return series. The best idea of each fund is the stock with the highest tilt measure each quarter. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. In this table the analysis is restricted to the funds whose maximum tilt is in the top 50% of all the tilts of all the best ideas at that time. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Low Focus							
r_1	0.00721	0.00324	0.00440	1.009***	0.284*	-0.449***	-0.067
		(0.91)	(1.26)	(14.49)	(1.97)	(-3.19)	(-0.86)
r_2	0.00783	0.00350	0.00466	0.999***	0.268*	-0.459***	(0.042)
		(0.97)	(1.32)	(14.24)	(1.85)	(-3.24)	(-0.53)
r_3	0.00314	0.00483	0.00633	1.265***	0.478**	-0.511**	-0.234*
		(0.82)	(1.09)	(10.97)	(2.01)	(-2.20)	(-1.81)
r_4	0.00240	0.00623	0.00703	1.318***	0.322	(0.293)	-0.295**
		(0.96)	(1.09)	(10.29)	(1.22)	(-1.13)	(-2.06)
Panel B: Medium Focus							
r_1	0.01091	0.00588	0.00703**	0.917***	0.357**	-0.389***	-0.156**
		(1.63)	(2.01)	(13.18)	(2.48)	(-2.77)	(-2.01)
r_2	0.01076	0.00537	0.00637*	0.893***	0.314**	-0.346**	-0.149*
		(1.53)	(1.85)	(13.03)	(2.22)	(-2.50)	(-1.94)
r_3	0.00653	0.00892*	0.00935*	1.215***	0.141	(0.341)	-0.316***
		(1.67)	(1.81)	(11.81)	(0.66)	(-1.64)	(-2.75)
r_4	0.00452	0.00685	0.00733	1.202***	0.184	(0.335)	-0.347***
		(1.23)	(1.36)	(11.19)	(0.83)	(-1.55)	(-2.89)

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel C: High Focus							
r_1	0.01440	0.0116*	0.0142**	1.092***	0.810***	-0.720***	(0.202)
		(1.84)	(2.32)	(8.99)	(3.23)	(-2.94)	(-1.49)
r_2	0.01479	0.0123*	0.0148**	1.106***	0.831***	-0.718**	(0.209)
		(1.66)	(2.06)	(7.68)	(2.79)	(-2.47)	(-1.30)
r_3	0.00605	0.00931	0.0104*	1.279***	0.376	-0.457**	-0.356***
		(1.60)	(1.85)	(11.43)	(1.63)	(-2.02)	(-2.85)
r_4	0.00596	0.00906	0.0101*	1.244***	0.424*	-0.434*	-0.425***
		(1.50)	(1.76)	(10.81)	(1.78)	(-1.87)	(-3.30)
Panel D: High-Low Focus							
r_1	0.00720	0.00836	0.00976*	0.084	0.526**	(0.271)	-0.135
		(1.53)	(1.79)	(0.77)	(2.35)	(-1.24)	(-1.12)
r_2	0.00696	0.00876	0.01020	0.107	0.563**	-0.259	-0.167
		(1.31)	(1.52)	(0.80)	(2.03)	(-0.96)	(-1.12)
r_3	0.00291	0.00447	0.00405	0.014	(0.102)	0.0546	-0.123
		(1.19)	(1.07)	(0.19)	(-0.66)	(0.360)	(-1.46)
r_4	0.00356	0.00283	0.00311	-0.0741	0.102	-0.141	-0.13
		(0.72)	(0.78)	(-0.94)	(0.62)	(-0.88)	(-1.48)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
3) $CAPMTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iMt})$
4) $CAPMPortfolioTilt_{ijt} = \sigma_{it}^2 \cdot (\lambda_{ijt} - \lambda_{iVt})$
T-statistics in parentheses
* p<0.1, ** p<0.5, *** p<0.01

Table 10: Best Ideas by Size of Portfolio

$$r_{p,t} - r_{f,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$
$$spread_{p,t} = \alpha_4 + bRMRF_t + sSMB_t + hHML_t + mMOM_t + \epsilon_{p,t}$$

The table below reports the coefficients from monthly regressions of the model above, the alpha from regressions using the CAPM model and the mean portfolio return. The best ideas are divided into three portfolios depending on the size of the fund, using the 33rd and the 68th percentiles as cut-offs. Size is measured by the total value of the assets under the fund's management. Funds with less than the lower cut-off point is considered low size, and fund with higher than the higher cut-off point high size. Panel D presents the results of the same regressions run on the spread between the high size return series and the low size return series. The best idea of each fund is the stock with the highest tilt measure each quarter. For the portfolio tilt and the market tilt the portfolios are uniquely equal-weighted. For the CAPM tilt and the CAPM portfolio tilt the portfolios are value weighted according to the funds investments in the stocks. In this table the analysis is restricted to the funds whose maximum tilt is in the top 50% of all the tilts of all the best ideas at that time. The sample period is April 2002 to December 2014.

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
Panel A: Low Size							
r_1	0.01301	0.00904	0.0113**	1.036***	0.696***	-0.633***	-0.145
		(1.59)	(2.05)	(9.42)	(3.07)	(-2.85)	(-1.18)
r_2	0.01498	0.0108*	0.0129**	1.023***	0.663**	-0.562**	(0.129)
		(1.71)	(2.07)	(8.23)	(2.58)	(-2.24)	(-0.93)
r_3	0.00576	0.00434	0.00495	0.996***	0.255	-0.327*	-0.379***
		(0.94)	(1.14)	(11.50)	(1.43)	(-1.87)	(-3.92)
r_4	0.00692	0.00605	0.00647	1.025***	0.186	(0.286)	-0.355***
		(1.25)	(1.41)	(11.19)	(0.98)	(-1.55)	(-3.47)
Panel B: Medium Size							
r_1	0.00911	0.00443	0.00559*	0.916***	0.379***	-0.408***	-0.210***
		(1.26)	(1.67)	(13.72)	(2.75)	(-3.03)	(-2.81)
r_2	0.00819	0.00364	0.00471	0.918***	0.340**	-0.405***	-0.210***
		(1.01)	(1.38)	(13.49)	(2.41)	(-2.95)	(-2.76)
r_3	0.00308	0.00639	0.00736	1.238***	0.451**	(0.324)	-0.456***
		(1.12)	(1.35)	(11.42)	(2.01)	(-1.48)	(-3.76)
r_4	0.00373	0.00770	0.00847	1.268***	0.411*	(0.234)	-0.441***
		(1.32)	(1.50)	(11.29)	(1.77)	(-1.03)	(-3.51)

	$\bar{r}$	$\hat{\alpha_1}$	$\hat{\alpha_4}$	$\hat{b}$	$\hat{s}$	$\hat{h}$	$\hat{m}$
				Panel C: High Size			
r_1	0.01000	0.00736**	0.00860**	1.043***	0.353**	-0.483***	-0.173**
		(2.03)	(2.49)	(15.19)	(2.48)	(-3.48)	(-2.25)
r_2	0.00904	0.00617*	0.00739**	1.030***	0.347**	-0.484***	-0.174**
		(1.67)	(2.11)	(14.73)	(2.40)	(-3.43)	(-2.23)
r_3	0.00552	0.00833	0.00927*	1.287***	0.288	-0.433**	-0.256**
		(1.60)	(1.82)	(12.68)	(1.37)	(-2.11)	(-2.26)
r_4	0.00391	0.00706	0.00796	1.275***	0.319	-0.400*	-0.329***
		(1.25)	(1.45)	(11.66)	(1.41)	(-1.81)	(-2.69)
				Panel D: High-Low Size			
$spread_1$	-0.00301	-0.00169	-0.00269	0.008	-0.344*	0.150	-0.0281
		(-0.38)	(-0.60)	(0.09)	(-1.86)	(0.830)	(-0.28)
$spread_2$	-0.00594	-0.00465	-0.00551	0.007	(0.316)	0.0785	-0.0451
		(-0.88)	(-1.04)	(0.07)	(-1.45)	(0.370)	(-0.38)
$spread_3$	-0.00024	0.00399	0.00433	0.291***	0.032	-0.106	0.123**
		(1.44)	(1.57)	(5.29)	(0.28)	(-0.96)	(2.000)
$spread_4$	-0.00301	0.00101	0.00148	0.250***	0.133	(0.114)	0.027
		(0.36)	(0.52)	(4.43)	(1.14)	(-1.00)	(0.420)

1) $marketTilt_{ijt} = \lambda_{ijt} - \lambda_{iMt}$
2) $portfolioTilt_{ijt} = \lambda_{ijt} - \lambda_{iVt}$
3) $CAPMTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iMt})$
4) $CAPMPortfolioTilt_{ijt} = \sigma^2_{it} \cdot (\lambda_{ijt} - \lambda_{iVt})$
T-statistics in parentheses
* p<0.1, ** p<0.5, *** p<0.01