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Survivorship Bias in the Norwegian Mutual Fund Market: Impact, Causes and Methodical Differences

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Abstract

This paper systematically accounts for the survivorship bias in the Norwegian mutual fund market and the impact of its existence. Survivorship bias has been researched in-depth in the US market and other large economies, however it remains a relatively unexplored topic in smaller economies such as Norway. Although research on survivorship bias can be found in the literature, most research addresses the survivorship bias as a sub-category. The paper contributes to previous research with a newly constructed dataset of Norwegian equity mutual funds from 1997 until 2017. We measure the survivorship bias using different methodical approaches, and show that different combinations of methods yield different result. Additionally, we analyse the relationship between performance, size and disappearance. Overall, the evidence points to a substantial survivorship bias in the Norwegian mutual fund market regardless of method applied. In general, we find the relationship between fund size and performance to be positive, however, in some cases the smallest fund group outperform larger funds. The disappearance rate of funds increases with decreasing fund size and is accelerating.

1 Introduction

Survivorship bias, in finance, is the error that comes from excluding closed assets in performance studies. Since most common datasets on mutual fund returns only include past records of currently existing funds, there is a possibility that significant bias is present in the return data. Survivorship bias tends to cause overestimation of the performance of funds, as poor performing funds are more likely to be closed and merged with better performing funds (e.g. Malkiel, 1995; Brown and Goetzmann, 1995; Elton, Gruber and Blake, 1996; Rohleder, Scholz and Wilkens, 2010). Such upward bias is likely when the poor performing funds are closed, thus making the surviving funds appear to perform better than what is actually the case. For example, Rohleder et al. (2010) find a Jensen alpha of 0.48% per year for their equal-weighted biased portfolio in the period 1993-2006, indicating that the average fund outperforms the passive benchmark. However, for their equal-weighted unbiased portfolio for the same period, they find an alpha of -1.09%, which indicates that the passive benchmark beats the average mutual fund. The difference in Jensen´s alpha between the biased and the unbiased portfolio is referred to as survivorship bias. Brown, Goetzmann, Ibbotson and Ross (1992) show that survivorship bias can "give rise to a substantial probability that statistical tests based on risk-adjusted return data will give rise to the false inference that there is, in fact, dependence in security returns". Furthermore, Brown et.al (1992) demonstrates with a numerical example that even very mild survivorship criteria are sufficient to induce strong persistence in performance for a reasonable specification of the distribution of returns across managers. This is problematic since studies of consumer behaviour and the money flow into mutual funds indicate that investors select funds based on past performance[1]. Moreover, failure to correct survivorship bias can also lead to false inferences about the impact of fund characteristics on fund disappearance. Lastly, the survivorship problem also relates to other studies dealing with groups and portfolios of assets and other financial instruments such

[1] See Patel, Hendricks, and Zeckhauser (1990) and Sirri and Tufano (1992), for examples.

as stocks (e.g. Brown and Goetzmann, 1995) or other aggregated data where survivorship bias-free data is not available[2].

Due to its relevance, a large number of articles address the survivorship bias either as the main subject or as additional research. Besides Berk and Green (2004), most performance studies only deal with survivorship bias from an empirical perspective. The results in these studies range from 0.01% in the US market during the period 1975-1984 (Grinblatt & Titman, 1989), to 2.71% in the Canadian market during the period 1988-1998 (Deaves, 2004). Apart from differences in the datasets employed, the different results can be explained by the different methodical approaches. The most common differences lie in the weighting schemes, definitions of surviving funds and even in the definition of the survivorship bias itself[3]. Since very few studies use the same set of definitions and methods to compute the survivorship bias, it is difficult to compare results. In order to interpret and compare results from previous studies, it is important to look into these various methodical approaches, as well as the characteristics of surviving and non-surviving funds. Rohleder et al. (2010) fill this gap in the US market by examining the survivorship bias using different combinations of survivor definitions and weighting schemes. This paper tests the same hypotheses which has previously been addressed by Rohleder et al. (2010) using US data and constitutes the first comprehensive study of the survivorship bias using Norwegian data. The main objective is to quantify the survivorship bias using different methodical approaches. Overall, we test if survivorship bias has a statistically significant impact on return data from Norwegian mutual funds and whether different estimation techniques yields significantly different results. Additionally, we analyse fund characteristics in order to determine the major causes of the survivorship bias and why different weighting schemes and survivor definitions yield different estimates of the survivorship bias, i.e. which factors affect the decision of fund mergers and liquidations. In particular, we test if small funds are more likely to close/merge than large funds, and the relationship between fund performance and fund size

[2] For the US market survivorship bias-free data is available through the Center for Research in Security Prices (CRSP), however in most countries (including Norway) such data is not available.

[3] See section 3 for further details on methods and definitions.

and the impact on fund disappearance.

The remainder of this paper proceeds as follows: In section 2, we present an overview of the Norwegian fund market. Section 3 presents related literature, including the most common definitions and methods prevailing in the literature. In section 4, we report summary statistics and a description of the fund identification process as well as the construction of the fund sample and the market factors. Section 5 presents different approaches to computing the survivorship bias and performance models and the relations to fund characteristics. In section 6 we present empirical results. Section 7 provides a summary and conclusive thoughts.

2 The Norwegian Mutual Fund Industry

The Norwegian Mutual Fund Association (VFF) has statistics on assets under management and fund flows. Table 1 reports some descriptive statistics on the Norwegian equity mutual funds. The table shows that the positive growth in the Norwegian market was reversed around 2000 and this trend lasted until 2008. In 2008, assets under management were approximately halved compared to the previous year, while the average number of customers and fund flows remained more or less unchanged. This implies that the massive reduction in assets under management was caused by the large negative returns due to the financial crisis and not because of a large withdrawal of funds. After the crisis in 2008, the net inflow stabilized and average assets under management have more than doubled since before the crisis.

In 1997, VFF reported assets under management in Norwegian equity mutual funds of approximately NOK 32 billion in total. In 2017, VFF reports assets under management of nearly NOK 128 billion in total. Total numbers can be found in appendix A. During the same time, the average number of customers per fund has decreased from an average of 13,736 in 1997, to an average of 4,389 in 2017. Also, there has been a negative net flow in Norwegian equity funds from the year 1997 until 2017 as the total net flow has decreased from a total of NOK 8.4 billion (1997) to a total of NOK 4.8 billion (2017). This increased the interest of saving in mutual funds, i.e. the increase in assets under management, can be explained by higher savings in general in 2017, due to private pension plans, increased wealth etc. However, the reduction in average customers per fund and the negative net flow also implies that investors have changed focus from Norwegian equity funds to funds with international mandate due to diversification benefits. Nevertheless, the Norwegian equity mutual fund market is still substantial, which demonstrates the importance of considering matters such as survivorship bias.

Table 1: Descriptive Statistics of the Mutual Funds

The table shows descriptive statistics per year for the Norwegian equity mutual funds in our sample. Column two shows the number of funds included in the sample at the end of each year. Column three shows the average number of customers per fund. Column four shows the average fund size in million NOK. Column five through seven show average inflows, outflows, and net flows per fund in million NOK.

Year	Funds Included	Average Number Customers per Fund	Average Fund Size	Average Inflow	Average Outflow	Average Net Inflow
1997	52	13472	620	301	139	162
1998	62	13048	358	116	122	-6
1999	60	14323	572	111	100	11
2000	68	11959	462	114	149	-36
2001	67	12227	387	84	97	-13
2002	67	10625	239	77	90	-13
2003	67	9960	354	61	63	-2
2004	66	9088	428	101	157	-57
2005	70	7431	507	165	230	-65
2006	75	6621	645	214	192	22
2007	66	7235	765	186	220	-34
2008	64	7288	381	214	213	1
2009	64	7518	868	322	155	167
2010	67	6843	1122	348	283	65
2011	67	6556	874	234	256	-22
2012	63	6550	916	333	309	24
2013	68	5109	1171	240	248	-9
2014	71	4543	1171	372	396	-24
2015	68	4439	1244	320	380	-59
2016	66	4717	1586	349	250	98
2017	66	4389	1939	449	376	73

3 Literature Review

This section will review some literature on the survivorship bias. Most research addresses the topic of survivorship bias as a sub-category, usually related to research on fund performance, however, this section will also review literature that specifically addresses survivorship bias.

The majority of studies define the survivorship bias as the performance difference between a biased and an unbiased portfolio of funds. A few studies use a different definition of the survivorship bias (e.g. Malkiel, 1995; Blake and Timmermann, 1998; Deaves, 2004) which define the survivorship bias as the performance difference between survivors and non-survivors.

Malkiel (1995) utilizes a dataset including all equity mutual funds that existed each year during the sample period. This approach enabled more precise examination of mutual fund performance and the extent of survivorship bias, and his results showed that survivorship bias appeared to be considerably more important than other studies (e.g. Grinblatt and Titman, 1989; Brown et.al, 1992) had estimated. Early studies of mutual fund performance were less concerned with biases in the data and more concerned with new methods for measuring performance (Elton et al., 1996). Since then, many other studies (e.g., Brown, Goetzmann, 1995; Elton et al., 1996; Dahlquist, Engström and Söderlind, 2000; Deaves, 2004; Sørensen, 2009; Rohleder et al, 2010) have shown that survivorship bias has a significant impact on studies on mutual fund performance.

Studies also indicate that differences in estimation methods yield different measures of the survivorship bias. The differences typically lie in the definition of surviving funds, weighting schemes used to aggregate fund performance and in some cases even in the definition of survivorship bias. There are two predominant definitions of survivors in the literature; end-of-sample survivors and full data survivors[4]. End-of-sample survivors are defined as all the funds that exist at the end of the sample period and this approach is followed by e.g. Dahlquist et al. (2000), Carhart, Carpenter, Lynch and Musto (2002), Deaves (2004), Sørensen (2008), and Rohleder et al. (2010). The full data survivors are a sub-sample of the end-of-sample survivors and are defined as funds that have existed throughout the entire sample period. This approach is used by e.g. Grinblatt, Titman (1989), Malkiel (1995), Brown, Goetzmann (1995), Elton et

[4] Also have look-ahead conditioning which requires funds to survive some minimum length of time after a reference date. End of sample can be thought of as look-ahead conditioning with longer look-ahead periods for earlier reference dates.

al., (1996) and Rohleder et al. (2010). The other common difference in estimating the survivorship bias prevailing in the literature lies in the weighting schemes. Most studies use equally weighted estimates for the aggregated fund performance (e.g. Grinblatt and Titman, 1989; Elton et al., 1996; Sørensen, 2008) whereas Brown, Goetzmann (1995), Malkiel (1995) and Deaves (2004) aggregates fund performance based on fund size (value-weighted). Dahlquist et al. (2000) and Rohleder et al. (2010) uses both equally weighted and value weighted estimates.

Rohleder et al. (2010) systematically examine the survivorship bias using different combinations of alternative survivor definitions and weighting schemes. They find that regardless of the methods applied, significant survivorship bias exists, in form of the performance difference of an unbiased and a biased portfolio of funds. However, the different estimation methods provide significantly different results. Their results show survivorship bias estimates twice as high for full data survivors and four times as high for end-of-sample survivors when equally-weighted portfolios are used compared to value-weighted portfolios. Other studies from the US market, such as Grinblatt and Titman (1989), Brown and Goetzmann (1995), Elton et al. (1996) also show that the survivorship bias estimates are higher when returns are scaled by the funds market capitalization. Their estimates vary from 0.5%, 0.8% and 1.0% (and above) per year respectively using equal weighting, while estimates are reduced to 0.2% for the former two and 0.7% per year when value weighting aggregation is used. Dahlquist et al. (2000) found similar results for their measures of the survivorship bias in the Swedish market using both equally-weighted and value-weighted portfolios of funds and find that value-weighted aggregation yields a slightly smaller bias than their equally weighted estimate of 0.7% per year. Sørensen (2009) found similar results for the Norwegian market with an estimate of 0.84% per year using an equally weighted portfolio and end-of-sample survivor conditioning.

In general, the major reason for the closing of funds lie in inferior performance, and consequently, survivorship bias tends to overestimate the performance of fund portfolios that do not take the inferior performance into account (i.e. only include currently existing funds). Rohleder et al. (2010) show that closed funds underperform surviving funds years before they are actually closed and conclude that performance, as well as size, are important drivers for survivorship bias, as the small funds are more likely to get closed than bigger funds. Thus, it exists a causal relationship between performance and fund size, however, large funds are less likely to get closed, even if returns are temporarily low. Elton et al. (1996) has carried out similar research. They examined the frequency of mutual fund disappearance and the impact of this on investor return as well as the characteristics of funds that merge and their partner funds. They found that the impact of size on performance in their biased portfolio is more or less non-existent, while the unbiased portfolio clearly shows that large funds tend to outperform small funds. They also conclude that large funds are more likely to survive than small funds. The majority of studies find similar results and are consistent across countries[5].

4 Data

This section provides the process of data collection needed to complete our analysis. This includes the selection process of funds and daily prices (Net asset values), assets under management and fund flows of each fund. Prior to 1997, reports from VFF are of unreliable quality and an apparent lack of funds in their reports[6]. We therefore find it reasonable to start our sample period in 1997. Thus our dataset consists of all Norwegian funds that have been ordinary members[7] of the Norwegian Mutual Fund Association (VFF) in the period 1997-2017[8]. In this period, the number of funds in existence each year have ranged from 52 (1997) to 75 (2006).

[5] Cuthbertson, Nitzsche and O`Sullivan (2008) investigates the UK market, Deaves (2004) studies the Canadian market and Dahlquist et al. (2000) have conducted similar research in the Swedish market. Sørensen (2009) looks into the Norwegian market.

[6] For example, in 1996 we were only able to identify 32 funds operating within the boundaries of this paper.

[7] All Norwegian companies that manage securities in accordance with current regulations can become ordinary members of the VFF. Companies that do not meet these criterions can become associated members. Associated members cannot be represented in the board of VFF and have no voting rights (VFF.no).

[8] Similar studies usually use sample periods ranging from 10 to 20 years (e.g. Elton et al., 1996; Deaves, 2004; Rohleder et al., 2010). Dahlquist et al. (2000) only include 5 years in their sample.

4.1 Identification of Funds

The Oslo Stock Exchange (OSE) operates with four different classifications of mutual funds according to their respective investment universe. The categories are 1) Norwegian equity funds, 2) Norwegian/international equity funds, 3) international equity funds and 4) sector equity funds. Following Carhart et al. (2002), Sørensen (2008) and Rohleder et al. (2010) we exclude pension funds, sector funds and funds with an international mandate. By only including Norwegian equity funds (category 1) we can obtain a precise estimate of the survivorship bias strictly in the Norwegian mutual fund market and it is a clear definition which refines our selection of funds. The Norwegian Mutual Fund Association has data available on all funds in existence each year, which allowed us to identify any new funds and funds that disappeared from year to year. The funds not meeting the criteria for category 1), as well as pension funds, closed-end funds and funds without available data have been identified and excluded from the dataset. Additionally, some funds have been excluded due to unresolved fund mergers. The remaining funds in the sample have at least 80% of the funds capital invested in the Norwegian equity market.[9] The selection process left us with a total of 64 active funds and 50 inactive funds adding up to a total of 114 funds in our sample. Successfully merged funds are given the name to which it was last registered. Appendix B contains further details on the data processing and consolidation as well as tables disclosing name changes and acquisitions and excluded funds. Appendix C present summary statistics for the sampled funds.

4.2 Market Factors

Since our measure of the survivorship bias will be the difference in performance of the unbiased and biased set of funds, we need market factors for the different performance models described below. Ødegaard (2018) has collected market factors on the Norwegian equity market and are made available through the Oslo Børs Information. We obtained daily data of risk-free rate, market return, SMB, HML, and PR1YR. The interest rates are forward-looking and are the borrowing

[9] Definition from VFF.

rate on any given day. Market return is the returns of a portfolio constructed from most stocks at the OSE (Oslo Stock Exchange). SMB (small minus big) is a factor which is long small-cap stocks and long big-cap firms. HML (high minus low) is a portfolio which is long value stocks and short growth stocks. The last factor is a momentum factor, PR1YR (prior one-year), and is calculated the same way as Carhart (1997) using Norwegian data. It is a portfolio that is long the stocks with the highest one year lagged return and is short the lowest ones

Table 2: Summary statistics - market factors

This table show descriptive statistics for the market factors used in this analysis. Numbers are based on daily return in percent.

	$R_m - R_f$ (EW)	$R_m - R_f$ (VW)	SMB	HML	PR1YR
Average return	0.08 %	0.07 %	0.06 %	0.04 %	0.04 %
Std. Dev.	0.89 %	1.51 %	1.47 %	1.71 %	1.95 %
Cross-correlations					
$R_m - R_f$ (EW)	1.0000				
$R_m - R_f$ (VW)	0.7768	1.0000			
SMB	-0.3130	-0.5255	1.0000		
HML	-0.1305	-0.1303	0.4335	1.0000	
PR1YR	-0.0190	0.2073	0.0324	0.0020	1.0000

4.3 Construction of Dataset

To our knowledge, there is no existing up-to-date survivorship bias-free dataset of the Norwegian mutual fund market. We have used OBI and Bloomberg Financial to acquire the necessary data for all funds, both active and inactive, that have been operating within our sample period. OBI has daily return data available, however, their feed only includes funds that existed at the time when the data was published, which implies that survivorship bias is present in the data.

Our dataset consists of daily Net Asset Values (NAV) from all of our identified funds and market returns. NAV is gross of taxes. Our estimates are calculated using daily returns of all funds allocated to each respective portfolio (Carhart, 1997; Rohleder et al. 2010). This method allows us to include all funds regardless of the length of their price histories. To correctly calculate the return on our funds we have dropped weekend-days and common holidays from our dataset. Furthermore, our dataset suffers from gaps in observations without obvious reasons or reasons common to all funds in our dataset. However, our sampled funds have 0.84 % (Appendix C) missing values on average out of their respective price history so we expect the impact to be insignificant. We will use estimates to fill those gaps rather than dropping entire dates and losing valuable information. Following Rohleder et al. (2010) we will calculate our estimates as the average monthly growth in price for each fund separately. Filling gaps is not optimal and could potentially result in imprecise outputs. A robustness check was done in order to investigate to what extent it will influence our results. By replicating the analysis, both with filling in the missing values and without doing so. There were a few variances in our estimates, however the overall interpretation remained the same[10]. From the Net Asset Values of each fund, we compute the return of fund *i* at day *t* as follows,

$$R_i = \frac{NAV_t}{NAV_{t-1}} - 1$$

This method of calculating returns corresponds to the way Oslo Stock Exchange calculate returns and its assumed that dividend payments are reinvested in the fund. We therefore also assume that dividends are reinvested[11]. This formula will account for the change in Net Asset Value (price of the fund) that occur when funds merge and we will get an accurate return for each fund. The data on assets under management is collected from VFF and consist of yearly data at the end of each year.

5 Methodology

In this section we will disclose the methods used in this paper in order to successfully perform our analysis. Our approach and choices of methods will be justified in this chapter.

5.1 Approaches to Survivorship Bias

Following most studies (e.g. Elton et al., 1996; Dahlquist et al., 2000; Rohleder et al., 2010), we construct a measure to quantify the survivorship bias by

[10] The results from the robustness check is reported in appendix E
[11] Only a couple of funds reports reinvested dividend in the data from VFF. For instance, in 2017, Landkreditt Utbytte was the only fund that had reinvested dividend.

comparing the difference in return of a biased portfolio versus an unbiased portfolio consisting of historical returns from Norwegian mutual funds from 1997 to 2017. This definition is preferred when evaluating the historical performance of a portfolio that includes all funds investors were able to buy over time.

We estimate performance measures for seven different portfolios, where for each portfolio both an equal-weighted and a value-weighted portfolio are examined to show how different methodical approaches result in different measures of the survivorship bias. The portfolios of funds are (1) *End-of-sample survivors*, (2) *Full-data survivors,* (3) *Non-full-data survivors,* (4) *Unbiased portfolio,* (5) *Non-surviving,* (6) *New funds* and (7) *Initial funds*. Portfolio (1) consists of all funds existing at the end of our sample period, i.e. all the funds that were operational on June 30th, 2017. Portfolio (2) includes the funds that have been active throughout the entire sample period. Portfolio (3) consist of all the funds that have been created during our sample period. Together, portfolio (2) and (3) add up to the *end of sample survivors* (1). The *unbiased portfolio* (4) consists of returns of all funds that have existed at any point in time during the sample period (e.g. Elton et al., 1996; Blake and Timmerman, 1998; Carhart et.al, 2002, Sørensen, 2008; Rohleder et al., 2010)[12]. *Non-surviving funds* (5) is the set of funds that have discontinued operations during our sample period which combined with *full data survivors* and *non-full data survivors* adds up to the *unbiased* portfolio. *New funds* (6) consist of funds that started operating at some point during our sample period and *initial* funds (7) includes funds that was alive at the beginning of our sample period. Together they add up to the *unbiased* sample. The measures are constructed using time series of daily returns for all funds in the respective portfolios. This approach is followed by e.g. Carhart (1997) and Carhart et.al (2002) but with monthly returns. This method has the advantage that it lets us use data on all funds, regardless of the length of their return history which is particularly important for two reasons; 1) the Norwegian market is small, which means we need to include as many funds as possible, and 2) funds with short return histories are usually a sign of poor performance (e.g.

[12] Grinblatt and Titman (1989) and Elton et al. (1996) exclude new funds from their unbiased portfolio. Following our definition of an unbiased portfolio, a portfolio that does not include new funds are not unbiased.

Elton et al., 1996) which is what causes the survivorship bias in the first place. For the purposes of this study, it makes sense to include short-lived funds in order to obtain as correct measures as possible of the survivorship bias.

All of our portfolios tested negative for normal distribution with the Shapiro-Francia normality test (Appendix D). However, when visually assessing the distribution of our portfolios visually they appear seemingly normal with very few/no extreme outliers. Following Rohleder et al. (2010), we will, despite of test results, rely on parametric tests in our analysis without any adjustments to our time series. Figure 1 shows the distribution of the unbiased and the end of sample portfolio´s[13]. We test for heteroscedasticity using Breusch-Pagan and White tests and a Breusch-Godfrey test for autocorrelation[14]. We cannot reject the null hypothesis that heteroscedasticity exists in our sample with a White test, nor can we reject Breusch-Godfrey test for autocorrelation. However, on equally weighted portfolios Breusch-Pagan shows signs of no heteroscedasticity, but not for value-weighted portfolios. For our analysis we will correct this by using heteroscedasticity and autocorrelation consistent (HAC) standard errors in our regression estimates after Newey and West (1987). Additionally, we will use the automatic selection rule implemented by Newey and West (1994). This will allow us to use OLS estimates and thereby avoid potential problems considering our small sample of funds.

[13] The distribution of our remaining portfolios can be found in appendix F.

[14] Full report of tests can be found in appendix D

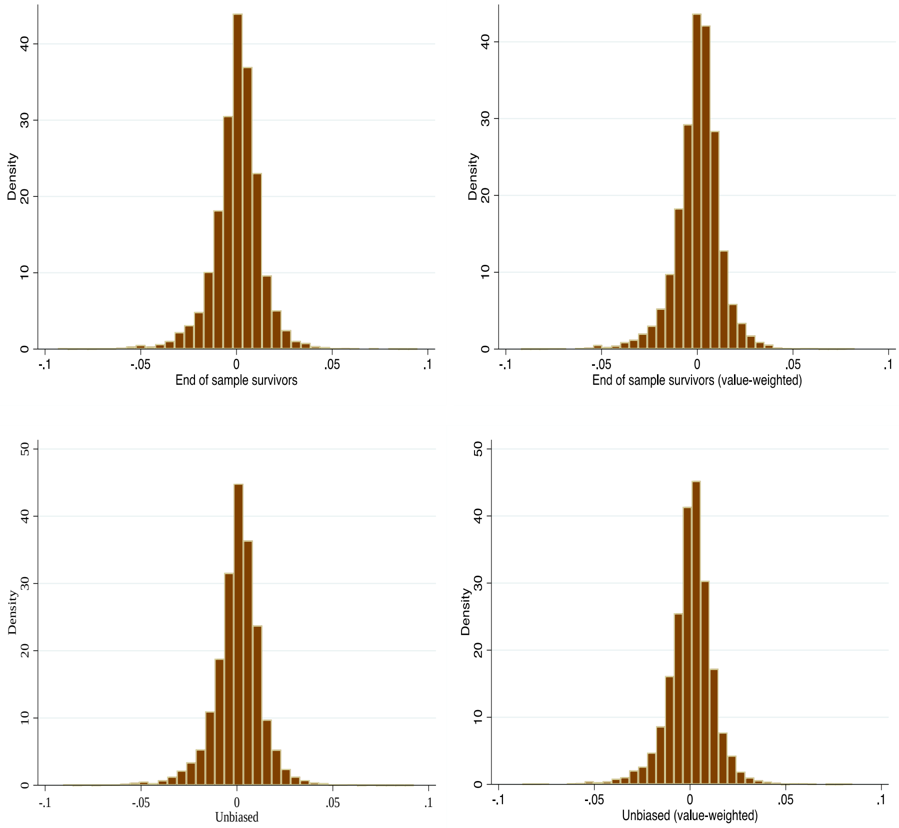

Figure 1: Portfolio Distribution. The figure shows the distribution of the equal-weighted and value-weighted unbiased and end of sample portfolios.

5.2 Performance Models

We calculate the estimates with four performance models that are commonly used in the literature (e.g. Sørensen, 2008; Rohleder et al., 2010). The simplest way to measure the survivorship bias, is to examine the excess return of each portfolio and calculate the difference as follows,

$$MER_i = \frac{1}{n}\sum_{t=1}^{T} ER_{it}$$

Whereas ER_{it} is the return of portfolio *i* in excess of the risk-free rate at day t, this will give a single measure of the mean excess return of portfolio *i*. The second model is the Jensen´s (1968) one-factor model where α_i is the performance measure for the portfolios versus the market return in excess of the risk-free rate denoted as ER_{mt}.

$$ER_{it} = \alpha_i + \beta_i ER_{mt} + \varepsilon_i$$

The third model is the Fama and French (1993) three-factor model which added the size factor SMB and the book-to-market factor HML. The α_i is the performance measure versus the market factors.

$$ER_{it} = \alpha_i + \beta_{1i}ER_{mt} + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_i$$

The final model is Carhart´s (1997) four-factor model which also includes a momentum factor which in our case is the PR1YR. α_i is the performance measure.

$$ER_{it} = \alpha_i + \beta_{1i}ER_{mt} + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}PR1YR_t + \varepsilon_i$$

5.3 Fund Characteristics and Survivorship Bias

To gain further insight into the determinants of fund disappearance and its economic relevance, we look into the relationship between fund size, performance and survival. Related literature present mixed results on the relation between fund size and performance. Grinblatt and Titman (1989) and Chen, Hong, Huang and Kubik (2004) find a negative relationship while Otten and Bams (2002) find a positive relationship. To analyse the probability of fund disappearance we follow the same approach as Chen et al. (2004) and Rohleder et al. (2010). We analyse fund disappearance in regards to fund returns and fund size. The performance of both equal-weighted and value-weighted size-quantiles are analysed by resorting funds in four rebalanced size-quantiles[15], based on yearly assets under management at the beginning of each year. Each funds asset at the beginning of the year is equivalent to the respective funds' assets at the end of the year before. Lastly, we analyse the disappearance rate of funds in each size-quantile within a one-year time period.

[15] Rohleder et al. (2010) resort their funds into size-deciles. Due to the small Norwegian sample, each decile would include very few or no funds. Although we use only four quantiles, some quantiles still contain few funds.

6 Empirical Analysis

6.1 Portfolio Performance

Table 3 and 4 presents the performance measures and factor loadings for all seven portfolios. In relation to the analysis of the survivorship bias, the first three groups are most relevant. Out of these three portfolios, the end of sample survivors shows a slightly higher mean excess return than the full data survivors, while the unbiased portfolio show the lowest mean excess return for both the equal-weighted and the value-weighted sample. In terms of performance for the equal-weighted sample, all alpha´s are negative and significantly different from zero. For the value-weighted sample, all alphas are also negative but insignificant, except for the Jensen 1-factor alpha for Non-survivors and New funds, which is also negative but significant on a 10% level. The insignificant p-values for the value-weighted sample, might be due to assets under management being rebalanced on a yearly basis, and therefore fails to capture the variation in assets throughout the year. The equal-weighted and value-weighted End of sample portfolio´s show higher alpha´s compared to the unbiased portfolio´s in all cases. The explanation for that is that the non-surviving funds in our sample period have on average lower returns than funds that are still alive at the end of the sample period, which indicate that survivorship bias is present.

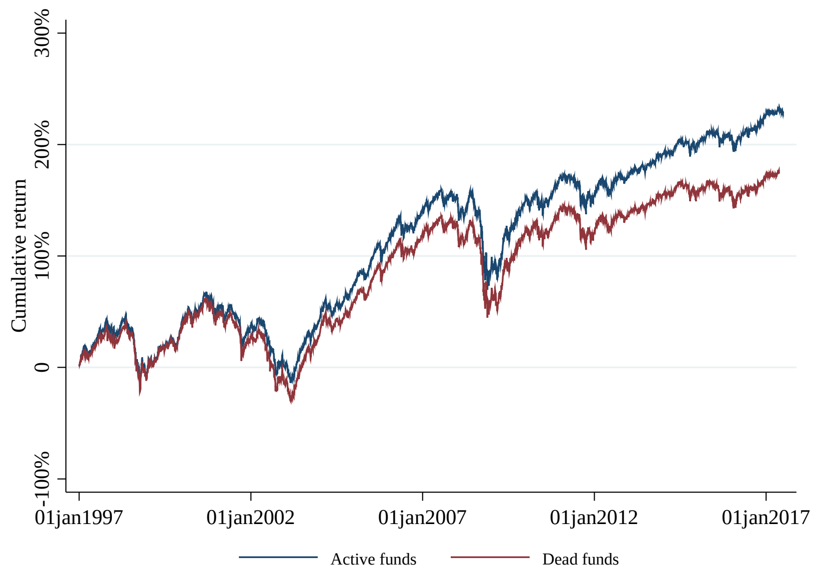

Figure 2: Active funds versus inactive funds over our sample period

A comparison of the equally-weighted and the value-weighted alpha´s for the unbiased portfolio, clearly shows that the value-weighted sample outperforms the equal-weighted sample. Equal-weighted estimates range from -0.0821% to -0.0570% (-20.7% to -14.4% annually) versus -0.0274% to -0.0193% (-6.9% to -4.9% annually) for the value-weighted estimates on a daily basis. The reason for this is that the poor performance of small non-surviving funds is overstated when they are given the same weights as bigger, better performing funds. For the biased End of sample portfolio, we find very similar results. The value-weighted sample shows performance estimates three times higher than the equal-weighted. We also find similar results for the full-data survivors. Considering results from similar studies in the US market (e.g. Rohleder et al., 2010), this is surprising, as one would think that the full-data survivors consisted mainly of a homogenous group of larger funds that were able to stay alive throughout the entire sample period. In such case, different weighting schemes should not affect the performance of the full data survivors. The reason for this could be that there are few very large funds in the Norwegian market. When we resort funds in size-quantiles (section 6.3) we find in general very few funds in the larger quantiles. The majority of our sample funds are resorted to the smaller quantiles, which implies that full data survivors is a less homogenous group in Norway than in the US and, therefore, value-weighting understates the performance of the small, poor performing funds. End of sample survivors perform better than Full data survivors when equal-weighted, while the opposite is true when value-weighted. This is consistent with the findings of Rohleder et al. (2010), who argue that the reason could be related to fund size, since Full data survivors consist mainly of larger funds. However, following our previous argument, we do not find that full data survivors includes a drastically higher number of larger funds than the End of sample survivors, although the end of sample includes a larger number of small funds. This might explain the small performance difference between the two portfolios as they consist of many of the same funds (Full data survivors together with Non full data survivors make out the End of Sample survivors). We analyse the relationship between fund size and performance in more detail in section 6.3.

Among the last four fund groups, Non-full data survivors outperform not only the other three fund groups, but all seven groups with a clear margin. This can also explain why the End of sample survivors outperform the Full data survivors when equal-weighted. Before making a new fund (Non-full data) publicly available, managers wish to create funds with positive return histories, while spending very little money (e.g. Deaves, 2004; Karoui and Meier, 2009; Evans, 2010). Only the funds who successfully accomplish positive returns are released onto the public, whereas unsuccessful funds are liquidated. This phenomenon is referred to as incubation bias, and it is likely that is present in our sample. Again, and in contrast to Rohleder et al. (2010), Non-full data survivors still outperform the other fund groups, except for most of the fund groups on the Jensen´s 1-factor model, when value-weighted. The performance difference between the two portfolios is still small, regardless of the weighting scheme. In resemblance to previous arguments, the reason might be that our sample of Norwegian funds includes few large funds, which means that the large funds takes up less of the total weight when value-weighted. Another explanation in relation to the previous, could be that our sample suffers from what Rohleder et al. (2010) refer to as "new-fund-survivorship bias", whereby relatively small out-performing new funds manage to survive. This might also explain the relatively good performance of the New funds portfolio when equal weighted. When value-weighted, New funds perform worse on all performance measures except for the Non-survivors, which is the worst performing fund group regardless of performance model and weighting scheme.

Further, table 3 and 4 also contains factor loadings for our portfolios. We focus on Full data survivors, Non-full data survivors and Non-survivors since these three fund groups together make up the Unbiased portfolio. Value-weighted portfolios represent the fund market more accurate than the equal-weighted portfolios. Since our value-weighted portfolios are rebalanced once a year, they fail to catch all the variation in total assets, and thereby losing valuable information, which might explain the insignificant value-weighted values. Therefore, we also focus on analysis of the equal-weighted portfolios. In general, the value-weighted portfolio´s show lower exposure to the factor loadings, except for the PR1YR factor. In terms exposure to the market, Full data survivors show the highest values in all cases, except for the value-weighted Jensen´s 1-factor model. All three portfolios show a negative and significant exposure to SMB when equal-weighted and a negative but insignificant exposure when value-weighted. HML show mixed results. When equal-weighted, all portfolios show a positive and insignificant exposure to HML, except for Non-full data survivors, which is significant on a 10% level. The value-weighted Full-data and Non survivors show a small, negative and insignificant exposure to HML, while Non-full data survivors show a small positive and insignificant exposure. Equal-weighted Full data survivors and Non-full data survivors show a negative and insignificant exposure to PR1YR and Non-survivors show a negative exposure which is significant at a 5% level. The value-weighted portfolio´s show a negative insignificant exposure to PR1YR, with the exception of Non-full data survivors which is significant at a 10% level. Sørensen (2008) find similar results for the Norwegian fund market. In contrast to the US market, HML and PR1YR seem to be less important for understanding the Norwegian fund market. While different survivor groups practice different investment styles, all funds groups have by far the highest loadings on ER_m. Choosing the appropriate model specifications that coincide with the market environment, can therefore further reduce the survivorship bias.

Table 3: Performance Measures of Different Portfolio´s (equal-weighted)

This table shows the performance measures of the five different fund portfolios measured by daily percentage in excess of the risk free rate in the sample period 1997-2017. All measures are based on daily return calculated from daily prices of each fund. The unbiased portfolio is all the funds that have been alive at some point during our sample period. End of sample survivors are all funds active at the end of our sample (41 funds). Full data survivors are the funds that have survived entire sample period (23 funds). Non-full data survivors are the funds that came to life during our sample period. Full data survivors and Non-full data survivors make up the End of Sample survivor portfolio. Non-Survivors are the funds that have discontinued operations at some point during our sample period. P-values are listed in parentheses. The R-squared of our regression estimates range from 0,76 (Non-full data, Jensen's one factor model) to 0,87 (Unbiased portfolio, both Fama & French and Carhart).

	Excess return	Jensen's 1-factor		Fama & French 3-factors				Carhart 4-factor				
Equal-weighted	MER (%)	α	ER_m	α	ER_m	SMB	HML	α	ER_m	SMB	HML	PR1YR
Unbiased Portfolio	0.0274	-0.0821	1.3236	-0.0572	1.1894	-0.2918	0.0677	-0.0570	1.1893	-0.2915	0.0677	-0.0064
	(0.138)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.155)	(0.000)	(0.000)	(0.000)	(0.157)	(0.359)
End of Sample Survivors	0.0302	-0.0801	1.3329	-0.0548	1.1968	-0.2959	0.0685	-0.0546	1.1967	-0.2957	0.0684	-0.0044
	(0.103)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.157)	(0.000)	(0.000)	(0.000)	(0.159)	(0.573)
Full Data Survivors	0.0301	-0.0811	1.3437	-0.0555	1.2064	-0.2964	0.0650	-0.0554	1.2064	-0.2962	0.0650	-0.0028
	(0.107)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.190)	(0.000)	(0.000)	(0.000)	(0.193)	(0.729)
Non-Full Data Survivors	0.0283	-0.0788	1.3258	-0.0527	1.1778	-0.3049	0.0805	-0.0524	1.1774	-0.3046	0.0804	-0.0075
	(0.138)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.089)	(0.000)	(0.000)	(0.000)	(0.090)	(0.288)
Non-Survivors	0.0209	-0.0878	1.3111	-0.0637	1.1808	-0.2830	0.0659	-0.0633	1.1806	-0.2826	0.0657	-0.0093
	(0.253)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.152)	(0.000)	(0.000)	(0.000)	(0.155)	(0.084)
New funds	0.0255	-0.0783	1.2928	-0.0553	1.1646	-0.2755	0.0639	-0.0550	1.1644	-0.2751	0.0638	-0.0080
	(0.158)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.157)	(0.000)	(0.000)	(0.000)	(0.159)	(0.213)
Initial funds	0.0281	-0.0833	1.3469	-0.0568	1.2045	-0.3097	0.0719	-0.0566	1.2044	-0.3094	0.0718	-0.0048
	(0.135)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.156)	(0.000)	(0.000)	(0.000)	(0.158)	(0.519)

Table 4: Performance Measures of Different Portfolio´s (value-weighted)

The table shows the performance measures of the seven different fund portfolios measured by daily percentage in excess of the risk free rate in the sample period 1997-2017. All measures are based on daily return calculated from daily prices of each fund. The unbiased portfolio is all the funds that have been alive at some point during our sample period. End of sample survivors are all funds active at the end of our sample. Full data survivors are the funds that have survived entire sample period. Non-full data survivors are the funds that came to life during our sample period. Full data survivors and Non-full data survivors make up the End of Sample survivor portfolio. Non-Survivors are the funds that have discontinued operations at some point during our sample period. New funds and initial funds are funds that have begun operations during our sample period and funds that was operative at the start of our sample, respectively. p-values are listed in parentheses. The R-squared of our regression estimates range from 0,72 (New funds, Jensen's one factor model) to 0,81 (Unbiased and Initial funds portfolios, Carhart).

	Excess return	Jensen's 1-factor		Fama & French 3-factors				Carhart 4-factor				
Value-weighted	MER (%)	α	ER_m	α	ER_m	SMB	HML	α	ER_m	SMB	HML	PR1YR
Unbiased Portfolio	0.0243	-0.0274	0.7395	-0.0193	0.6942	-0.0886	0.0005	-0.0193	0.7523	0.0469	-0.0081	-0.0081
	(0.138)	(0.111)	(0.000)	(0.446)	(0.000)	(0.412)	(0.989)	(0.323)	(0.000)	(0.469)	(0.726)	(0.114)
End of Sample Survivors	0.0263	-0.0248	0.7310	-0.0176	0.6912	-0.0769	-0.0028	-0.0177	0.7485	0.0357	-0.0113	-0.1395
	(0.136)	(0.152)	(0.000)	(0.487)	(0.000)	(0.473)	(0.929)	(0.365)	(0.000)	(0.578)	(0.603)	(0.117)
Full Data Survivors	0.0263	-0.0243	0.7244	-0.0175	0.6871	-0.0715	-0.0050	-0.0175	0.7431	0.0313	-0.0132	-0.1364
	(0.133)	(0.163)	(0.000)	(0.488)	(0.000)	(0.501)	(0.874)	(0.366)	(0.000)	(0.625)	(0.538)	(0.122)
Non-Full Data Survivors	0.0228	-0.0275	0.7205	-0.0173	0.6613	-0.1216	0.0206	-0.0174	0.7206	0.0790	0.0119	-0.1447
	(0.198)	(0.119)	(0.000)	(0.479)	(0.000)	(0.243)	(0.544)	(0.362)	(0.000)	(0.201)	(0.622)	(0.095)
Non-Survivors	0.0173	-0.0337	0.7299	-0.0238	0.6750	-0.1072	-0.0006	-0.0239	0.7309	0.0670	-0.0088	-0.1362
	(0.335)	(0.060)	(0.000)	(0.338)	(0.000)	(0.314)	(0.988)	(0.219)	(0.000)	(0.302)	(0.745)	(0.117)
New funds	0.0192	-0.0297	0.7010	-0.0211	0.6527	-0.0941	-0.0008	-0.0211	0.7090	0.0536	-0.0091	-0.1373
	(0.262)	(0.080)	(0.000)	(0.376)	(0.000)	(0.353)	(0.980)	(0.250)	(0.000)	(0.377)	(0.704)	(0.102)
Initial funds	0.0249	-0.0273	0.7467	-0.0189	0.6998	-0.0922	0.0014	-0.0189	0.7577	0.0505	-0.0071	-0.1412
	(0.165)	(0.123)	(0.000)	(0.460)	(0.000)	(0.398)	(0.968)	(0.339)	(0.000)	(0.441)	(0.765)	(0.118)

6.2 Survivorship bias

The main results of this thesis is presented in table 5. We present estimates from the two most important fund groups, the end of sample- and Full data survivors. All survivorship bias estimates are positive, regardless of performance model and weighting scheme used. The equal-weighted End of sample survivors are significantly different from zero on the 1% level for all performance models, except the Jensen 1-factor model which is significant on the 5% level. The value-weighted sample are significantly different from zero on the 5% level for MER and Jensen 1-factor and on the 10% level for Fama & French 3-factor and Carhart 4-factor. Equal-weighted Full data survivors are significantly different from zero on the 1% level for MER. The Jensen 1-factor model, Fama & French and Carhart are insignificant. Value-weighted, the Jensen 1-factor is the only model that is significantly different from zero (5% level). Again, this might be due to the yearly rebalancing of assets under management. In general, our findings seem to confirm previous findings, that the presence of the survivorship bias leads to overstating the performance of fund portfolios. The statistically significant results range from 0.0017 to 0.0028 percent on a daily basis, which adds up to annual estimates of 0.42 and 0.71 percent, respectively[16]. The annualized results are comparable to the results found by Brown and Goetzmann (1995) in the US market, Dahlquist et al. (2000) in the Swedish market and Sørensen (2008) in the Norwegian market, who find survivorship bias estimates of 0.8%, 0.7% and 0.84%, respectively.

Concerning different weighting schemes for the End of sample survivors, equal-weighting yields the highest estimates (except for Jensen 1-Factor) and are significantly different from zero on the 1% level in all cases. The equal-weighted estimates range from 0,0021 to 0.0028 percent daily (0.52 to 0.71 annually) and value-weighted estimates range from 0.0017 to 0.0026 (0.43 to 0.66 annualized). For the Full data survivors, the results are less clear. In most cases value-weighting yields higher estimates, but are also statistically insignificant. Consequently, we cannot conclude either way in terms of which weighting scheme that yields the higher survivorship bias estimates for the Full data

[16] $SB_{annual} = (1+SB_{daily})^{252} - 1$, (Rohleder et al., 2010; and Deaves, 2004)

survivors. Regarding the different performance models, there is no model clearly outperforming the other. For example, the Jensen 1-factor show the highest survivorship bias estimates when value-weighted and the lowest estimates when equal-weighted for both End of sample and Full data survivors. Further, MER show the highest estimates when equal-weighted and the second highest when value-weighted for both fund groups. Fama & French 3-factor and Carhart 4-factor performs better compared to the other models when equal-weighted and a lot worse when value-weighted for the End of sample survivors. Again, there is little consistency to be found. In terms of different methodical combinations, the equal-weighted End of sample portfolio yields, in general, the highest bias estimates with daily estimates ranging from 0.0021% to 0.0028% (0.52 to 0.71 percent annually). The value-weighted End of sample survivorship biases are the lowest, with estimates ranging from 0.0017% to 0.0026% on a daily basis (0.42 to 0.65 annualized). Rohleder et al. (2010) find similar results.

Table 5: Survivorship Bias Estimates

This table shows the survivorship bias estimates (α) for the entire sample period. The estimates are calculated based on the differences in average between the biased portfolios and the unbiased one. All the bias estimates are in daily percentages. P-values are listed from two-sided t-test for means and two-sided t-test for regression estimates. P-values for regression coefficients are calculated with HAC-consistent variances (Newey and West, 1987)

	End of Sample		Full Data	
Equal weighted	α	p-value	α	p-value
MER	0,0028	0,0002	0,0027	0,0081
Jensen 1-factor	0,0021	0,0150	0,0011	0,3280
Fama & French 3-factor	0,0024	0,0040	0,0017	0,1220
Carhart 4-factor	0,0023	0,0050	0,0015	0,1240
Value-weighted				
MER	0,0020	0,0267	0,0020	0,1596
Jensen 1-factor	0,0026	0,0120	0,0031	0,0240
Fama & French 3-factor	0,0017	0,0670	0,0018	0,1810
Carhart 4-factor	0,0017	0,0850	0,0018	0,1710

6.3 Fund Size, Performance and Disappearance

Table 6 present the mean yearly asset under management (MYAM) and the alpha´s of our four performance models; MER, the Jensen 1-factor, the Fama & French 3-factor and the Carhart 4-factor. We analyse the relationship between fund size, performance and fund disappearance by resorting funds in four size-quantile portfolios which are rebalanced once a year. All performance measures are statistically significantly different from zero using both weighting schemes, with the exception of mean excess return. When equal-weighted, we find that the largest 25% of funds perform best in all cases (except for MER, which is insignificant). Interestingly, we find that the smallest 25% of funds perform second best out of the four quantiles, which points slightly towards a negative relationship. Previous research (e.g. Grinblatt and Titman, 1989; Chen et al., 2004) explain that such a negative relationship between fund size and performance with liquidity disadvantages. Cremers and Petajisto (2009) explains a negative relationship with smaller funds being more active while larger funds tend towards indexing strategies. This also support our own previous arguments, in that the smaller funds in many cases outperform the bigger funds, and might be explained by a potential presence of incubation bias in our data. A possible explanation could be that when relatively small funds start operating with positive return histories (incubation bias), they attract customers and start to grow. Eventually, they outgrow the smallest size-quantile and, since it is difficult to maintain positive return histories over time, their performance stagnates. This could also explain why the two middle size-quantiles are the worst, in terms of performance. When value-weighted, we also find that the largest 25% of funds outperforms the other fund groups on all performance measures, except for MER. Further, value-weighting seem to reduce the good performance of the smallest 25% of funds, which are outperformed by the second largest quantile of funds for the Fama & French 3-factor model and the Carhart 4-factor model. Our results are mixed, but in general, they point towards a positive relationship between fund size and performance. Related literature (e.g. Indro, Jiang, Hu and Lee, 1999) usually explain such a positive relationship between funds size and performance with economies of scale.

Table 6 also present the disappearance rates of funds in each size-quantile within a one-year period. Apart from the largest size-quantile[17], the disappearance rates of funds increase with decreasing funds size and are

Table 6: Fund size and performance

The table shows statistics on size-quantile portfolios in the period 1997-2017 (30.06). The portfolios are created by rebalancing yearly assets under management (YAM) at the beginning of the year. The first quantile includes the largest 25% of funds, and the last quantile includes the smallest 25% of funds. Mean YAM (MYAM) represent the mean of the aggregated YAM time series of the portfolios in million NOK. The disappearance rate is the average percentage of funds dying within our sample period per quantile. The performance measures are constructed using daily return data. The value-weighted returns are based on YAM at the beginning of each year. p-values are computed using a two-sided t-test for means and regression coefficients. p-values for the regression coefficients are based on Newey and West HAC-consistent covariances (1987). p-values are reported in parentheses.

	Size-quantile			
	1 (Large)	2	3	4 (Small)
MYAM (Mill. NOK)	4431.7	2893.8	1732.9	349.9
Disappearance rate (%)	1.25	0.88	1.00	2.18
Equal-weighted performance (%)				
MER	0.0234	0.0204	0.0224	0.0284
	(0.145)	(0.312)	(0.241)	(0.127)
Jensen-Alpha	-0.0717	-0.0893	-0.0897	-0.0815
	(0.000)	(0.000)	(0.000)	(0.000)
Fama & French-Alpha	-0.0551	-0.0592	-0.0622	-0.0566
	(0.000)	(0.000)	(0.000)	(0.000)
Carhart-Alpha	-0.0548	-0.0587	-0.0619	-0.0563
	(0.000)	(0.000)	(0.000)	(0.000)
Value-Weighted performance (%)				
MER	0.0230	0.0187	0.0230	0.0258
	(0.152)	(0.327)	(0.227)	(0.155)
Jensen-Alpha	-0.0718	-0.0873	-0.0882	-0.0826
	(0.000)	(0.000)	(0.000)	(0.000)
Fama & French-Alpha	-0.0553	-0.0570	-0.0606	-0.0584
	(0.000)	(0.000)	(0.000)	(0.000)
Carhart-Alpha	-0.0550	-0.0564	-0.0602	-0.0583
	(0.000)	(0.000)	(0.000)	(0.000)

accelerating as the funds get smaller. The smallest 25% of funds have a disappearance rate that is more than twice as high as the second smallest quantile. A probable explanation for this pattern could be that fund managers

[17] The average disappearance rate for the entire sample is calculated by dividing the number of funds that disappeared by the total number of funds at the beginning of the period for each quantile. Only two funds died in the largest quantile, however, since the largest quantile only includes a total of 8 funds throughout the entire sample period, the impact of fund disappearances is much greater in this quantile. Hence, the disappearance rate for quantile 1 is most likely not representative for the largest funds in the Norwegian market.

seek to maximize profits. Therefore, maintaining large underperforming funds makes sense in order to retain the fund's assets. On the contrary, retaining the assets of small funds make little sense, as they only contribute to a small part of the funds revenues. Large funds simply seem too be too big to die.

7 Conclusion

We analyse the survivorship bias for Norwegian domestic equity mutual fund data by applying various methodical approaches onto a uniform dataset. Previous studies have been inconsistent with the methods and definitions applied, and therefore they are difficult to compare. We found that the most common methodical differences lie in the definition of survivors and the weighting scheme used for aggregating fund returns. Comparing different method combinations allows us to better understand the impact on the magnitude of the survivorship bias, and how to interpret the results of other studies using different methodical approaches.

For the End of sample survivors, we find positive and statistically significant survivorship bias estimates, regardless of the method applied. The Full data survivors also present positive estimates of the survivorship bias, however, in most cases the result are statistically insignificant. Further, we find that the choice of method matter and that the differences between the methodologies are consistent. Annualized survivorship bias estimates range from 0.27% to 0.78% depending on the method applied. In terms of weighting schemes, equal-weighting yields the highest survivorship bias estimates for the End of sample survivors with estimates ranging from 0.52% to 0.71% per year versus 0.42% to 0.65% for the value-weighted. For the Full data survivors, we are unable to conclude either way, as value-weighting yields higher bias estimates but are also insignificant. Concerning performance models, we cannot find one model consistently outperforming the others across combinations. We do, however, find that the factors HML and particularly PR1YR (momentum) are less important in order to understand returns in the Norwegian market compared to the US. Thus, choosing the appropriate model in relation to the market environment can help reduce the survivorship bias further.

Regarding different survivor definitions, the three most important survivor groups in relation to survivorship bias (Unbiased, End of sample and Full data) show value-weighted alphas three times higher than when equal-weighted. This can be explained by the poor performance of small funds that is overemphasized when equal-weighted. Additionally, End of sample survivors outperform the unbiased portfolio on all measures, confirming that alphas are overstated in the presence of survivorship bias. Furthermore, End of sample survivors show higher survivorship bias estimates than the Full data survivors when equal-weighted and lower estimates when value-weighted. This pattern can partly be explained by the practice of incubating new funds, before they are made available to the public, since this practice have a greater effect on the equally-weighted End of sample survivors than on Full data survivors. Also related to this pattern, we found that the Full data survivors are a less homogenous group of funds in terms of size in the Norwegian market compared to other bigger countries, particularly the US. This also helps explain the small performance difference between the two fund groups.

Analysing the relationship between fund size and performance, we find somewhat mixed results. The largest 25% of funds perform best on all measures, regardless of model and weighting scheme. Interestingly, we find that the smallest 25% of funds are second best in terms of performance, which further amplifies existing evidence that the Full data survivors consist of a larger number of relatively small funds in the Norwegian market than in the US. However, value-weighting reduces the good performance of the small funds. In general, our findings point toward a positive relationship between fund size and performance. Related to the relationship between fund size and performance, we find that small, poor performing funds disappear more frequently than larger, better performing funds. The smallest 25% of funds have a disappearance rate which is more than twice as high as the second smallest 25% of fund. This pattern can be explained by managers who seek to maximize profits, large under-performing funds are kept alive, while smaller under-performing funds are liquidated.

Regarding future research, we suggest looking into other biases that might be present in the Norwegian mutual fund data (including our own dataset), such as incubation bias. Additionally, Linnainmaa (2013) show that studies on survivorship bias tend to understate funds´ estimated alphas relative to their true alphas, since they don´t account for poor performance caused by negative idiosyncratic shocks, and is referred to as “reversed survivorship bias”. In order to get a more complete picture of the most important drivers of survivorship, it is important that we understand other implications that arise when correcting for survivorship bias.

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9 Appendices

A The Norwegian Mutual Fund Industry (Total)

Table 7: Descriptive Statistics of the Norwegian Mutual Fund Industry in Total Numbers

The table shows descriptive statistics per year for the Norwegian equity mutual funds in the sample as defined by the Norwegian Mutual Fund Association (VFF). Column two shows the number of funds included in the sample at the end of each year. Column three shows the total number of customers each year. Column four shows assets under management in total in million NOK for each year. Column five through seven shows total inflows, outflows and net flows in million NOK each year.

Year	Funds included	Total Number of Customers	Assets under management in total	Total Inflow	Total outflow	Total Net inflow
1997	52	700549	32238	15665	7237	8428
1998	62	808953	22196	7216	7573	-357
1999	60	859381	34299	6671	5984	687
2000	68	813188	31448	7734	10157	-2423
2001	67	819195	25924	5601	6473	-872
2002	67	711899	16014	5159	6038	-879
2003	67	667288	23746	4093	4254	-161
2004	66	599806	28237	6650	10393	-3744
2005	70	520167	35486	11548	16102	-4554
2006	75	496550	48344	16047	14380	1667
2007	66	477503	50468	12248	14517	-2269
2008	64	466432	24377	13715	13630	85
2009	64	481158	55582	20616	9938	10678
2010	67	458502	75143	23305	18948	4357
2011	67	439236	58584	15695	17178	-1483
2012	63	412679	57707	20993	19483	1510
2013	68	347421	79642	16299	16886	-587
2014	71	322567	83168	26416	28135	-1719
2015	68	301877	84615	21782	25812	-4030
2016	66	311323	104677	23009	16512	6497
2017	66	289683	127959	29614	24800	4814

B Data processing

The data retrieved from VFF consists of 20 yearly excel-reports from 1997-2017 (June, 30), each divided in separate sheets for every individual fund manager. From these reports, excluding pension funds and sector funds, we extracted all equity mutual funds with a Norwegian mandate, which resulted in a total of 224 individual fund entries. Out of the 224 funds, a total of 109 funds have been subject to name changes, mergers and, acquisitions. Name changes and acquisitions are pooled in single time-series and given the name of the fund to which it was last registered. Table 8 includes name changes and acquisitions. Merging funds are kept separate until the time of the merger. After resolving name changes, mergers and acquisitions to the best of our ability, the resulting sample consists of 114 individual funds, which make up the basis for gathering daily return from Oslo Stock Exchange and Bloomberg Financial and monthly assets under management from VFF. In addition to the 114 funds in the final sample, we failed to acquire return data for 12 funds. Table 9 present the excluded funds and the rationale for exclusion.

Remarks:

- In some rare cases, funds that do not meet the selection criteria have merged with funds that fulfil the selection criteria and vice versa. In these cases, return data has been partially excluded for periods of time were the respective fund did not meet the selection criteria.
- DNB´s fund portfolios have been particularly difficult to resolve due to many name changes, mergers, and acquisitions. We were unable to resolve the DNB merger of Skandia Norge and Skandia Norge II.

Table 8: Name changes and acquisitions

The table presents the resolved name changes and acquisitions for the 114 Norwegian Equity Mutual Funds included in the sample.

No.	Included Funds	Name Changes and Acquisitions
1	ABIF Norge ++	Industrifinans Aksje Norge Storkunde II
2	ABN AMRO Indeks	Alfred Berg OBX; ABIF OBX
3	Alfred Berg Aksjespar	;;;
4	Alfred Berg Aktiv	Industrifinans Aktiv; ABIF Aktiv; ABN AMRO Aktiv
5	Alfred Berg Aktiv II	Gambak Kapital; ABIF Kapital; ABN AMRO Kapital
6	Alfred Berg Gambak	Gambak
7	Alfred Berg Humanfond	Banco Humanfond; Humanfond Aksje
8	Alfred Berg Indeks	ABIF Indeks +; ABN AMRO Indeks +
9	Alfred Berg Indeks Classic	;;;
10	Alfred Berg Norge +	Industrifinans Aksje Norge Storkunde; ABIF Norge +; ABN AMRO Norge +
11	Alfred Berg Norge Classic	Industrifinans Aksje Norge; ABIF Norge; ABN AMRO Norge; Alfred Berg Norge
12	Alfred Berg Norge Etisk	Banco Norge
13	Alfred Berg Norge Instutisjon	;;;
14	Alfred Berg Vekst	;;;
15	Atlas Norge	Kaupthing Norge; Tyren Norge
16	Avanse OBX Indeks	Gjensidige OBX Indeks
17	C WorldWide Norge	Carnegie Aksje Norge
18	Carnegie Norge Indeks	Carnegie OBX
19	Danske Fund Aktiv Formuesforvaltning Aksjer	;;;
20	Danske Invest Norge I	Fokus Norge AMS; Fokus Norge; Firstnordic Norge I; Danske Fund Norge I
21	Danske Invest Norge II	Fokus Norge II; Firstnordic Norge II; Danske Fund Norge II
22	Danske Invest Norge Vekst	Fokus SMB; Firstnordic Norge Vekst; Danske Fund Norge Vekst
23	Danske Invest Norske Aksjer Institusjon I	Fokus Norge III; Firstnordic Norge III; Danske Fund Norske Aksjer Institusjon I
24	Danske Invest Norske Aksjer Institusjon II	Danske Fund Norske Aksjer Institusjon II
25	Delphi Norge	;;;
26	Delphi Vekst	;;;
27	Diversifiserte Norske Aksjer	Navigator Aksje Norge
28	DnB Norge	Postbanken Aksjespar; Postbanken Norge
29	DNB Norge Avanse I	Avanse; Avanse Norge; Avanse Norge I
30	DNB Norge Avanse II	Avanse Markedsverdi; Avanse Norge Aktiv; Avanse Norge II
31	DNB Norge I	DnB NOR Norge; DnB NOR Norge I; DnB Real-Invest;
32	DNB Norge III	DnB NOR Norge III; DnB NOR Norge II; DnB Norge II
33	DNB Norge IV	DnB Norge III; DnB NOR Norge IV
34	DNB Norge Selektiv	DnB NOR 20; DnB 20; DNB Norge Selektiv; DnB NOR Norge Selektiv I
35	DnB Norge Selektiv II	GNKF Norske Aksjer; DnB NOR Norge Selektiv II
36	DNB Norge Selektiv III	G-kapital; Gjensidige kapital; Avanse Norge Aktiv II
37	DNB OBX	DnB NOR OBX
38	DNB Real-vekst	;;;
39	DNB SMB	DnB NOR SMB
40	Eika Norge	Sundal Collier Norge Verdi; WarrenWicklund Norge Verdi; WarrenWicklund Norge
41	Eika SMB	NB Plussfond; Terra SMB
42	F-OBX	;;;
43	First Generator S	First Generator; Swedbank Generator
44	First Norge Verdi	First Aksjer Norge
45	Fondsfinans Aktiv II	;;;
46	Fondsfinans Norge	Fondfinans Spar
47	Forte Norge	;;;
48	Forte Trønder	;;;
49	Gambak Oppkjøp	;;;
50	Gjensidige AksjeSpar	G-Aksjespar
51	Gjensidige Invest	G-Invest
52	Globus Aktiv	Sundal Collier aktiv
53	Globus Norge	Globus TV-Fond
54	Globus Norge II	Sundal Collier Norge; Sundal Collier Spar
55	Handelsbanken Norge	Aksjefondet Handelsbanken
56	Holberg Norge	;;;
57	K-IPA Aksjefond	;;;
58	KLP Aksjeinvest	NKB Aksjeinvest
59	KLP AksjeNorge	;;;
60	KLP AksjeNorge Indeks	;;;

Table 8: (continued)

No.	Included Funds	Name Changes and Acquisitions
61	KLP AksjeNorge Indeks II	;;;
62	Landkreditt Norge	;;;
63	Landkreditt Utbytte	;;;
64	NB Aksjefond	;;;
65	Nordea Avkastning	K-Avkastning
66	Nordea Kapital	K-Kapital
67	Nordea Kapital II	K-Kapital II
68	Nordea Kapital III	K-Kapital III
69	Nordea Norge Pluss	;;;
70	Nordea Norge Verdi	Nordea Aksjepensjon
71	Nordea Norwegian Equity Market	;;;
72	Nordea SMB	K-SMB
73	Nordea SMB II	K-SMB II
74	Nordea Vekst	K-Vekst
75	ODIN Norge A	;;;
76	ODIN Norge B	;;;
77	ODIN Norge C	Odin Norge
78	ODIN Norge II	;;;
79	Orkla Finans 30	Omega AMS
80	Pareto Aksje Norge A	Pareto Aktiv
81	Pareto Aksje Norge B	Pareto Verdi
82	Pareto Aksje Norge C	;;;
83	Pareto Aksje Norge D	;;;
84	Pareto Aksje Norge I	Pareto Aksje Norge
85	Pareto Investment Fund A	Orkla Finans Investment Fund; Omega Investment Fund
86	Pareto Investment Fund B	;;;
87	Pareto Investment Fund C	;;;
88	Pluss Aksje	;;;
89	Pluss Indeks	Pluss OBX-Indeks
90	Pluss Markedsverdi	Pluss Indeks
91	Postbanken Aksjevekst	;;;
92	RF Aksjefond	;;;
93	Romsdal Fellesbank Plussfond	;;;
94	Sbanken Fremgang Sammen	;;;
95	Storebrand Aksje Innland	;;;
96	Storebrand Indeks Norge	;;;
97	Storebrand Norge	;;;
98	Storebrand Norge A	;;;
99	Storebrand Norge Fossilfri	Storebrand Norge Pluss
100	Storebrand Norge H	;;;
101	Storebrand Norge I	;;;
102	Storebrand Norge Instutisjon	;;;
103	Storebrand Optima Norge	;;;
104	Storebrand Vekst	Storebrand SMB
105	Storebrand Verdi	;;;
106	Terra Norge	;;;
107	Terra Vekst	;;;
108	Skandia SMB Norge	Vesta AMS
109	Skandia Horisont	Vesta Horisont
110	Skandia Indeks Norge	Vesta Indeks Norge; Vesta Aksjefond Norge
111	VÅR Aksjefond	;;;
112	WarrenWicklund Indeks+	Sundal Collier Indeks +
113	WarrenWicklund Alpha	;;;
114	XACT OBX	;;;

Table 9: Excluded funds

The table present the 27 funds that have been excluded from the sample and the rationale for exclusion. Funds labelled with * are only partially excluded from the sample due to unresolved name changes, mergers and acquisitions or changes in the fund's investment universe.

No.	Fund Name	Rationale	Comment
1	Atlas Norge*	International mandate	Changed to international focus 18.05.2017.
2	Odin Avkastning	International mandate	
3	Omega Etisk	International mandate	
4	Skagen Vekst	International mandate	
5	Storebrand Aksjespar*	International mandate	Changed to international focus in 2001.
6	Terra vekst*	International mandate	Changed to international focus in 2001.
7	Banco Norge +	NA returns	
8	C WorldWide Norge III	NA returns	
9	C WorldWide Norge IV	NA returns	
10	Carnegie Aksje Norge II	NA returns	
11	Carnegie Aksje Norge V	NA returns	
12	DnB Norge Indeks	NA returns	
13	ESG Norske Aksjer	NA returns	
14	Gjensidige OBX index	NA returns	
15	K-Barnespar	NA returns	
16	Odin Norge D	NA returns	
17	Statoil Aksjer Norge	NA returns	
18	Storebrand Saldo Finans	NA returns	
19	Alfred Berg Norge Pensjon	Pension fund	
20	DNB Aksje Pensjon	Pension fund	
21	DnB Norge Pensjon	Pension fund	
22	K-Aksjepensjon	Pension fund	
23	Nordea Aksjepensjon*	Pension fund	Restructured 2006 to Nordea Norge Verdi. Excluded prior to 2006.
24	Fokus Barnespar	Savings scheme	
25	Nordea Barnespar	Savings scheme	
26	Skandia Norge	Unresolved merger	DNB
27	Skandia Norge II	Unresolved merger	DNB

C **Summary Statistics Sample Funds**

Table 10: Summary Statistics

This table shows some summary statistics for our sampled funds. First column the number of observations, second column show the number of missing values whilst third column show the percentage of missing values for each fund. The fourth column show the average annual assets under management in thousands.

Fund	Observations	Missing values	% missing	AYAM
Alfred Berg Aktiv	5 159	11	0,21 %	159 316
ABIF Norge ++	1 169	3	0,26 %	90 802
ABN AMRO Indeks	2 755	4	0,15 %	382 717
Alfred Berg Aksjespar	691	3	0,43 %	541 467
Alfred Berg Aktiv II	3 789	30	0,79 %	60 478
Alfred Berg Gambak	5 159	39	0,76 %	940 262
Alfred Berg Humanfond	4 409	12	0,27 %	76 334
Alfred Berg Indeks	3 200	11	0,34 %	379 833
Alfred Berg Indeks Classic	847	6	0,71 %	130 975
Alfred Berg Norge +	4 122	9	0,22 %	698 756
Alfred Berg Norge Classic	5 159	19	0,37 %	752 734
Alfred Berg Norge Etisk	3 047	9	0,30 %	63 377
Alfred Berg Norge Institusjon	793	4	0,50 %	1 934 189
Alfred Berg Vekst	1 234	6	0,49 %	229 767
Atlas Norge	4 842	123	2,54 %	24 874
Avanse OBX Indeks	1 997	23	1,15 %	150 856
C WorldWide Norge	5 159	61	1,18 %	433 816
Carnegie Norge Indeks	4 998	61	1,22 %	16 926
Danske Fund Aktiv Formuesforvaltning	415	3	0,72 %	123 723
Danske Invest Norge I	5 159	34	0,66 %	1 435 278
Danske Invest Norge II	5 159	33	0,64 %	3 204 362
Danske Invest Norge Vekst	5 159	33	0,64 %	386 500
Danske Invest Norske Aksjer Institusjon I	4 330	29	0,67 %	447 526
Danske Invest Norske Aksjer Institusjon II	2 665	11	0,41 %	468 083
Delphi Norge	5 158	22	0,43 %	664 090
Delphi Vekst	4 035	29	0,72 %	176 164
Diversifiserte Norske Aksjer	2 661	15	0,56 %	936 808
DNB Norge	5 159	28	0,54 %	3 055 309
DNB Norge Avanse I	4 337	26	0,60 %	2 439 636
DNB Norge Avanse II	4 486	26	0,58 %	261 203
DNB Norge I	4 337	20	0,46 %	2 199 620
DNB Norge III	5 159	22	0,43 %	195 690
DNB Norge IV	3 676	24	0,65 %	731 782
DNB Norge Selektiv	5 159	22	0,43 %	625 811
DNB Norge Selektiv II	3 903	23	0,59 %	176 935
DNB Norge Selektiv III	5 159	43	0,83 %	772 483
DNB OBX	3 103	1	0,03 %	857 129
DNB Real-vekst	1 473	1	0,07 %	1 646 186
DNB SMB	4 099	29	0,71 %	705 477
Eika Norge	3 482	6	0,17 %	620 037
Eika SMB	3 916	9	0,23 %	41 215
F-OBX	998	16	1,60 %	24 013
First Generator S	1 719	11	0,64 %	720 582
First Verdi Norge	2 368	338	14,27 %	123 930
Fondsfinans Aktiv II	988	5	0,51 %	5 409
Fondsfinans Norge	3 661	11	0,30 %	167 825
Forte Norge	1 590	12	0,75 %	827 848
Forte Trønder	1 064	4	0,38 %	90 634
Gambak Oppkjøp	367	8	2,18 %	138 613
Gjensidige Aksje Spar	661	12	1,82 %	18 217
GJENSIDIGE Invest	949	18	1,90 %	902 541
Globus Aktiv	1 862	27	1,45 %	609 386
Globus Norge	2 192	45	2,05 %	85 595
Globus Norge II	2 009	27	1,34 %	54 881
Handelsbanken Norge	5 159	49	0,95 %	38 727
Holberg Norge	4 154	12	0,29 %	1 121 530
K-IPA Aksjefond	762	16	2,10 %	884 393
KLP Aksje Norge	4 605	38	0,83 %	17 135
KLP Aksje Norge Indeks	2 962	22	0,74 %	2 592 979
KLP Aksje Norge Indeks II	2 220	7	0,32 %	4 534 083
KLP Aksjeinvest	1 665	29	1,74 %	878 506
Landkreditt Norge	2 521	3	0,12 %	89 090
Landkreditt Utbytte	1 088	2	0,18 %	108 889
NB Aksjefond	423	9	2,13 %	173 438
Nordea Avkastning	5 159	30	0,58 %	1 983 697
Nordea Kapital	5 159	30	0,58 %	1 527 886
Nordea Kapital II	1 734	27	1,56 %	49 005
Nordea Kapital III	1 453	11	0,76 %	76 436
Nordea Norge Pluss	1 554	6	0,39 %	174 007
Nordea Norge Verdi	5 159	2	0,04 %	955 059
Nordea Norwegian Equity Market	2 966	4	0,13 %	164 166
Nordea SMB	4 459	29	0,65 %	198 806
Nordea SMB II	1 447	26	1,80 %	11 386
Nordea Vekst	4 552	29	0,64 %	890 789
ODIN Norge A	399	3	0,75 %	17 027
ODIN Norge B	399	4	1,00 %	14 270
ODIN Norge C	5 159	21	0,41 %	3 992 765
ODIN Norge II	2 915	14	0,48 %	114 687
Orkla Finans 30	2 383	19	0,80 %	113 918
Pareto Aksje Norge A	373	16	4,29 %	708 441
Pareto Aksje Norge B	2 895	9	0,31 %	387 613
Pareto Aksje Norge C	498	0	0,00 %	32 924
Pareto Aksje Norge D	498	0	0,00 %	26 939
Pareto Aksje Norge I	3 982	14	0,35 %	2 537 585
Pareto Investment Fund A	5 159	21	0,41 %	583 452
Pareto Investment Fund B	880	1	0,11 %	403 605
Pareto Investment Fund C	880	1	0,11 %	568 692
Pluss Aksje	5 159	32	0,62 %	176 487
Pluss Indeks	5 159	29	0,56 %	60 998
Pluss Markedsverdi	5 159	29	0,56 %	110 089
Postbanken Aksjevekst	2 012	9	0,45 %	416 253
RF Aksjefond	2 406	7	0,29 %	58 579
Romsdal Fellesbank Plussfond	1 114	2	0,18 %	649
Sbanken Fremgang Sammen	364	11	3,02 %	29 741
Storebrand Aksje Innland	5 159	10	0,19 %	846 436
Storebrand Indeks Norge	829	4	0,48 %	3 562 535

Storebrand Norge	5 159	10	0,19 %	350 542
Storebrand Norge A	893	0	0,00 %	374 489
Storebrand Norge Fossilfri	42	1	2,38 %	891 315
Storebrand Norge H	974	13	1,33 %	438 782
Storebrand Norge I	4 336	6	0,14 %	1 723 501
Storebrand Norge Instutisjon	809	8	0,99 %	1 058 880
Storebrand Optima Norge	4 153	6	0,14 %	209 213
Storebrand Vekst	5 159	10	0,19 %	305 584
Storebrand Verdi	4 912	10	0,20 %	755 484
Terra Norge	3 915	49	1,25 %	371 073
Terra Vekst	896	19	2,12 %	330 993
Vesta AMS	1 473	1	0,07 %	267 449
Vesta Horisont	1 473	1	0,07 %	209 815
Vesta Indeks Norge	1 473	1	0,07 %	214 359
VÅR Aksjefond	798	14	1,75 %	251 884
WarrenWicklund Alpha	1 753	4	0,23 %	57 829
WarrenWicklund Indeks	1 687	7	0,41 %	14 153
XACT OBX	3 083	29	0,94 %	454 460
Total	328 515	2297	0,70 %	72 521 499
Average	5 664	40	0,85 %	1 250 371

D Test Results

Table 11: Shapiro-Francia test results

This table report the p-values for all portfolios of Shapiro-Francia test for normality.

	Equal-weighted	Value-weighted
End of sample survivors	0.00001	0.0000
Full data survivors	0.00001	0.0000
Non-full data survivors	0.00001	0.0000
Non-survivors	0.00001	0.0000
New funds	0.00001	0.0000
Unbiased	0.00001	0.0000

Table 12: Test results for heteroscedasticity and autocorrelation

This table report the p-values of Breusch-Pagan and White tests for heteroscedasticity and Breusch-Godfrey test of serial correlation. The tests is conducted for all our portfolios towards Jensen, Fama & French and Carhart performance models.

	Equal-weighted			Value-Weighted		
Unbiased	Jensen	Fama & French	Carhart	Jensen	Fama & French	Carhart
Breusch-Pagan	0.644	0.778	0.760	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.002	0.017	0.268
End of sample						
Breusch-Pagan	0.715	0.859	0.847	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.002	0.002	0.086
Full data survivors						
Breusch-Pagan	0.617	0.575	0.568	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.007	0.007	0.253
Non-full data survivors						
Breusch-Pagan	0.091	0.938	0.959	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.274	0.120	0.474
Non-survivors						
Breusch-Pagan	0.477	0.662	0.634	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.783	0.545	0.953
New funds						
Breusch-Pagan	0.727	0.705	0.680	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.036	0.013	0.172
Initial funds						
Breusch-Pagan	0.610	0.852	0.840	0.000	0.000	0.000
White	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Godfrey	0.000	0.000	0.000	0.065	0.059	0.587

E Robustness check

Table 13: Survivorship bias estimates without filling gaps

This table shows the survivorship bias estimates (a) for the entire sample period without filling gaps. The estimates are calculated based on the differences in average between the biased portfolios and the unbiased one. All the bias estimates are in daily percentages. P-values are listed from two-sided t-test for means and two-sided Wald-test for regression estimates. P-values for regression coefficients are caclulated with HAC-consistent variances (Newey and West, 1987)

	End of Sample		Full Data	
Equal weighted	α	p-value	α	p-value
MER	0,0030	0,0001	0,0027	0,0095
Jensen 1-factor	0,0022	0,0100	0,0012	0,2760
Fama & French 3-factor	0,0029	0.0010	0,0023	0,0320
Carhart 4-factor	0,0026	0.0020	0,0019	0,0730
Value-weighted	□		□	
MER	0,0021	0,0222	0,0015	0,3144
Jensen 1-factor	0,0028	0,0080	0,0030	0,0380
Fama & French 3-factor	0,0013	0,2040	0,0008	0,5340
Carhart 4-factor	0,0012	0,2030	0,0005	0,7000

F Figures

Figure 3: The figure shows the distribution of the equal-weighted and value-weighted portfolios; Full data survivors, Non-full data survivors, Non-survivors, New funds and Initial funds.

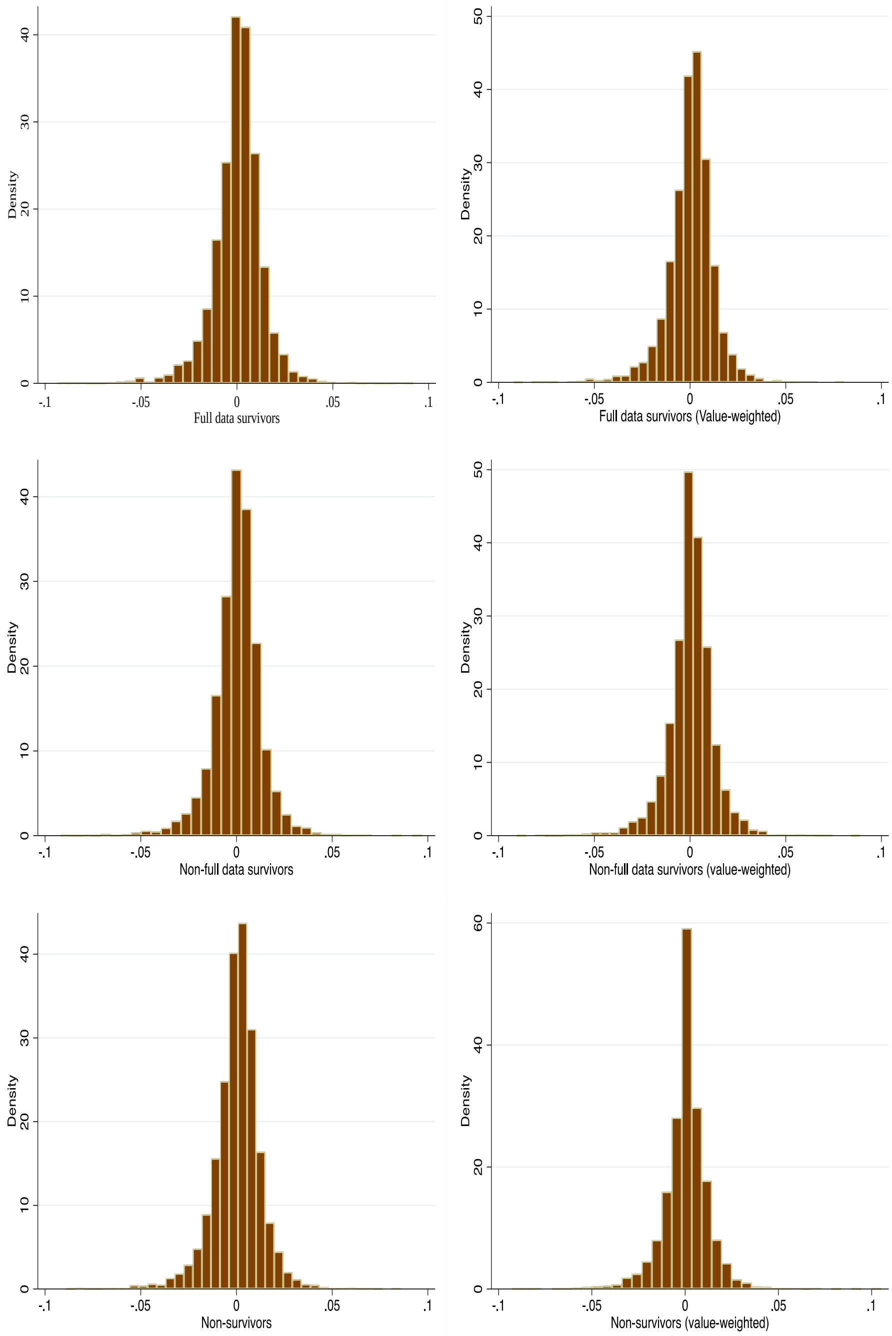

Figure 3: (continued)