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PERFORMANCE OF EMERGING HEDGE FUNDS

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Abstract

The aim of this master's thesis is to provide further evidence on the performance of emerging hedge funds and on the differences, they may have compared with the older and larger hedge funds. We study the style-adjusted alphas of emerging hedge funds relative to similar hedge funds that employ the same strategies. We also inspect the associated performance persistence, size effects and strategy differences within our emerging hedge fund population. The prior literature on the performance of emerging hedge fund suggests that emerging funds are able to provide significant alpha during their early operational life's when compared with the more established hedge funds. Existing literature has associated emerging hedge funds with characteristics of being nimbler in their investment strategies and fee structures.

In this thesis, we have collected our data from two commercial hedge fund databases. These databases were Lipper TASS and HFR, where we collected all the fund related data from 1996 until 2011 in TASS and from 1996 until 2017 in HFR. Based on these two databases we have formed a combined data sample, where we have all the unique funds from both databases. The main analysis of the thesis is based on style-adjusted alphas and we employ two types of time alignment methods, where the first one is based on the event time and the second one is based on cohorts formed by the calendar years.

Our first evidence suggests that findings of prior literature on performance of emerging hedge funds have deteriorated in magnitude. We find that style-adjusted performance of emerging funds is substantially lower than previous literature has suggested. In our cohort analysis, we noticed that emerging hedge funds are subject to over time deteriorating performance and they were only able to provide positive style-adjusted alpha during the first year of their operations. In our data, the mid-sized funds performed the best during the launch instead of the larger funds that usually have been seen to perform the best during the initial launch. Our second finding indicates that the emerging hedge funds have not been able to provide a positive style-adjusted alpha after the financial crisis of 2008. Thirdly, we find evidence that when dividing emerging hedge funds into broad strategy classifications, the directional traders classification was the only strategy classification among emerging hedge funds that were able to deliver positive average alpha during our time series. This finding suggests that the positive style-adjusted performance that we saw for our whole emerging hedge fund return series is driven to a great extent by this sub-sample of emerging hedge funds and do not represent the whole industry of emerging funds.

Based on the findings of this thesis, investors who allocate capital towards emerging funds and managers, would be able to achieve higher relative returns and diversification benefits compared with the more established hedge funds, if they focus on investing in emerging hedge funds that belong to directional traders broad strategy classification, as the whole emerging hedge funds industry has not been able to deliver relative alpha. Therefore, allocating capital broadly towards emerging hedge funds is not a valid investment strategy to diversify existing hedge fund portfolio unlike prior literature may have suggested.

Keywords
alternative investment, financial crisis, performance persistency, style-adjusted performance

Additional information

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1 INTRODUCTION

The hedge fund industry has seen substantial growth through the years and prior to the 1980s it was worth almost nothing. Although, recently the phase of growth in the industry has somewhat slowed down, nevertheless the industry still continues to grow. During the financial crisis of 2007 and 2008, the hedge fund industry experienced heavy fund outflows, but they were able to recover from this crash surprisingly fast and hedge funds quickly surpassed the assets under management (AUM) level of the industry before the crisis. It has been tough to pinpoint the exact size of the hedge fund industry as the funds usually are quite secretive to release information about their operations and since the U.S. Securities and Exchange Commission (SEC) imposes restrictions on advertising in the industry. Nevertheless, according to the HFR (2008) survey the assets under management had increased from an estimated $39 billion in 1990 to $1.8 trillion in 2007. Whereas the most recent numbers according to the survey conducted by Preqin (2017) concluded that the AUM had increased by $70 billion from December 2015 to $3.22 trillion as of November 2016. Therefore, it shouldn’t be a surprising that the industry has been attracting several new fund operators and the number of hedge funds operating within the industry has grown substantially. Although to some extent this growth can be credited to the value that has been created by the hedge funds. It has been estimated that the total number of active hedge funds in 1990 was roughly 600, whereas in 2015 it was over 10,000. A study conducted by Cao, Liang, Lo and Petrasek (2014) found that the holdings of hedge funds in publicly traded stocks were around 3% at the beginning of the 21st century, but during the financial crises it had already risen to 9%. (Aggarwal & Jorion 2010, 238; Cao, Farnsworth & Zhang 2016, 1; Agarwal, Mullally & Naik 2015, 3.)

Due to the influence that the hedge funds have had on the financial markets, it is vital to researchers to gather and study the information that is available on the hedge funds. However, gathering data from hedge funds has been harder than it has been in other financial markets or products, this is due to the loosely regulated and secretive nature of the hedge fund industry. The inflows to the existing funds and the inception of new hedge funds have both had an important impact on the growth of the industry, but the prior literature on the industry has mostly been focusing on relation between the fund performance and the following fund flows into these funds, whereas the literature that has focused on the inception is still relatively scarce. Despite the limited available data on the hedge fund industry, the academic research has been able to keep up with the growth of the industry. Before the year 2005 there was only 16 hedge fund related papers published in the major financial journals like the Journal of Finance or the Journal of Financial economics, whereas there have been 105 papers published in these major financial journals on hedge funds after 2005. In brief, the prior literature has concluded that mutual funds and certain asset classes have underperformed relative to hedge funds, this underperformance exists even if we take into consideration the documented biases in the hedge fund databases. As the industry has experienced high growth in the assets under management and in the number of funds, it is important that we take a further look at the funds inception and the subsequent returns. The main question in this thesis is that, can the new managers and funds generate alpha and is there a difference in performance between the new and the old hedge funds or in the returns of emerging hedge funds in the different time periods, such as before and after the financial crises of 2008. (Agarwal, Mullally & Naik 2015, 3, 7.)

Critics of the hedge fund industry usually depict hedge funds as a greedy, corrupt and overly compensated speculators who can cause severe market disruptions in the financial markets. Furthermore, some corporations don’t like some of the overly aggressive hedge funds’ such as the notorious activist fund Pershing Square that is managed by Bill Ackman, as they can be a quite demanding to change corporate policies that they deem as a value destroying. In a contrast, the supporters of the hedge fund industry see hedge funds as informed traders that can make the markets more efficient and hedge funds support corporate governance that values the interest of the investors. Despite the divide on people’s opinions on the hedge fund industry and the fact that there have been substantial inflows of new managerial skills and funds to the hedge fund industry, there have also been substantial outflows of capital from the industry. Barton Biggs (2006, 49) quite jokingly stated that the hedge funds and their managers have a career expectancy of your typical rock stars. A fund that generates performance that is worth a top 20 of all funds based on AUM has a less than 50% chance to remain within that top 20 group for the next three years. Whereas the average life expectancy of a hedge fund is only four years, therefore it is not a surprise that, on average, each year about a thousand hedge funds will close down their operations. Most of these hedge funds will close down due to a weak performance and the inability to attract sufficient capital to maintain the fund running, for example in 2004 a thousand new hedge funds were formed and around a thousand funds closed down. Randy (2008) state that often those funds that are unable to raise enough capital to sustain their business operations are usually funds that do not have institutional support. If these funds were backed by an institution, they would have an easier time to raise and attract capital from other institutional investors. (Agarwal, Mullally & Naik 2015, 3; Biggs 2006, 49−50.)

There has been quite a shift in the hedge fund industry regarding the average investors who operate in the industry. In the early years of the hedge fund industry, most of the investors were high net-worth individuals, whereas today the largest investors in the industry are the institutional investors such as pension funds. In the early 1990s, a typical individual investor with a high net-worth would usually invest his assets in the highly leveraged macro funds that mostly invested their capital in currencies and other assets. To the contrast when we look at the early individual investors and compare them with today's typical institutional investors, the common investment vehicles are completely different. Today the institutional investors mostly invest their capital in the hedge funds to achieve diversification benefits by searching investment vehicles that have a low correlation with the other asset classes such as equities. According to McCrary (2005) today the most common investors in the hedge fund industry are foundations, family offices, endowments, pension funds, corporations, insurance companies, the fund of hedge funds and consultants. Furthermore, investing in the hedge fund industry in general differs quite heavily from investing for example in the equities. Joenväärä and Kahra (2010) state that a typical fund of hedge funds portfolio may include investments in 20 or up to 50 different hedge funds, whereas there can be over thousand different stocks owned within a well-diversified equity portfolio. Hedge funds in general may also impose share restrictions on investor's redemptions and usually it is not possible to take short positions on hedge funds, which is known as selling short. Joenväärä and Tolonen (2010) notice that the typical hedge fund manager can often impose a lockup period of one-year to its investors, whereas the notice period is usually around 30-days regarding the quarterly redemptions from the hedge fund. In their research, they also found that the younger emerging hedge funds were more likely to impose lockup provisions for their investors than the older funds. (Agarwal & Naik 2005, 1−2.)

The vast majority of hedge fund firms are private companies that mostly are owned by the firms' founders, general partners and managing members, which usually is depends whether the company is structured as a limited liability corporation (LLC) or as a limited partnership (LP). According to Torrey (2009) most hedge funds are typically structured as LP or LLC and they usually operated in a manner that enables the hedge fund and its advisers to avoid certain federal securities laws and regulations that would apply to other investment vehicles such as mutual funds. These operating manners and structures that hedge funds use, usually involve offshore corporations as according to Clifford, Ellis and Gerken (2017) nearly 70% of hedge fund assets are held by offshore holding companies located in countries like the Cayman Islands, Bermuda and British Virgin Islands. Although in most cases these offshore funds are often managed by the U.S.-based hedge fund advisers. Hedge funds are often located in these tax haven nations so that the investors of these funds could receive more favorable tax treatment and possible enhanced privacy. Hedge funds usually have also in the beginning a situation that the founding members of the hedge fund management company will own all the shares of the company in the beginning. However, as the managers have a tendency to sell some of the shares of their equity in exchange for the early stage capital, their ownership over the fund management company usually gets smaller as the fund grows older. The hedge fund management company's equity is usually valued based on the profits from the management and incentive fees that the fund is able to collect over the firm's operational costs. On average, 15% of the fund firms tend to sell the stakes of their equity to outside owners, whom often are well-known financial institutions or investors who can bring more creditability for the funds that the hedge fund has. (Mullally 2016, 2.)

The aim of this thesis is to study emerging hedge funds and their possible capabilities to outperform the more established funds. Prior papers from researchers such as Aggarwal and Jorion (2010) find that the emerging funds had a tendency to add value in their early years, especially during their first two years of operations. Aggarwal and Jorion (2010) also find that at the startup the larger funds that were managed by the management companies that were managing more than one hedge fund (multi-fund) performed better than the management companies that were managing only one fund (single-fund). Multi-fund management companies have two options when they notice a high demand for their funds. Their first option is to allow the investors to invest into their existing funds and the second one is to create a new fund with similar investment objectives although the new fund that they create may differ from the existing fund in a fee structure, share restrictions or in currency. Randy (2008) found that the funds that launched from multi-fund management companies had an easier time to attract capital for their funds, therefore they were also more likely to be able to sustain themselves than the funds that launched from single-fund management companies. The consensus currently on the performance of start-up hedge funds has been that the emerging funds are able to deliver alpha and they are influenced by the strong incentive effects. Furthermore, emerging funds that initially will launch with a larger pool of capital or with an existing organizational infrastructure are able to generate better performance than the smaller emerging funds are capable. (Aggarwal & Jorion 2010, 238; Agarwal & Naik 2005, 28–29; Cao, Farnsworth & Zhang 2016, 8.)

It is important to study emerging hedge funds and their performance, because during the last couple of years there has been a growing interest towards the emerging funds and the diversification benefits that they provide. According to the Credit Suisse survey, the number of investors allocating capital in to the newly launched hedge funds increased by 20% in 2017 from 2016. The survey also notes that 63% of institutional investors were allocating capital towards newly established managers in 2017, whereas it was only 43% in 2016. Another survey conducted by Ernst and Young (2015) found that in 2015 an 54% of institutional investors were considering to allocate capital towards emerging hedge funds specifically. The most active investors in the emerging managers have been the fund of hedge funds from which 80% have allocated capital toward these managers. For example, Canada Pension Plan Investment Board (CPPIB) has invested in total $1.250 million in startup and young hedge funds in its Emerging Managers Program since October 2015. While the pension fund has allocated capital to external hedge funds for more than a decade before they started this program, but they rarely invested any capital in managers that had less than a year of track record. Nonetheless the capital that they have allocated to Emerging Managers Program is still quite miniscule when compared with all assets in the CPPIB ($261 billion). This move still shows that the institutional investors are starting to realize that smaller managers can access different investment opportunities than the larger funds and at the same time be more flexible on their terms and fees. One of the fund managers in CPPIB stated that early stage managers have a different return profile that may diversify their investment portfolio that has mostly investments in the mature funds. CPPIB typically invests in its Emerging Managers Program from $150 million to $250 million as a seed capital to each hedge fund startup for two to three years. For their investment, they will take a cut of the funds fee revenue and the option to invest more in the fund during the later stage. The CPPIB also participates in the so-called acceleration deals, where it provides a similar amount of capital for managers that have been operating for less than three years and have less than a $250 million in assets under management. (Berrospi 2018, 1–3; Hu 2018, 1–2.)

Starting a new hedge fund can be a desperate, even frantic adventure. There is a lot of anxiety involved in this process as generally the founders must first spend their own capital to acquire office space, create the administrative, trading, accounting and legal infrastructure of the business. Founders may also need to hire employees like analysts and traders, while at the same time try to meet prospective investors to raise capital. The founders and managers of the Hedge fund are usually compensated through two types of fees. First one of these is a fixed management fee that is a fixed percentage amount from the AUM and the second one is incentive fees that are percentage amount from the profits that the hedge fund is able to generate on its AUM. The typical fee structure in hedge funds is usually according to Strachman (2009) from 1 to 2 percent management fee and the incentive fee is generally between 10 to 20 percent. These incentive fees are commonly subject to a hurdle rate and high-water mark conditions as according to Joenväärä (2010c) 64% of hedge fund managers are using a high-water mark provision. The hurdle rate means a minimum return, which manager has to achieve before they can collect any incentive fees from their investors. The high-water mark on the other hand ensures that the fund has to first recoup any losses that investors may have suffered before they have to pay incentive fees to the managers. According to Aima and GPP report in 2017, which is cited by Macdonald (2018), the average break-even point for a small and emerging fund was around $86 million in AUM. Furthermore Leitner (2018b) cites the HFM Insights report, which concluded that the emerging managers that are coming from a “brand name” hedge funds were more likely to see their AUM exceed $1 billion during their launch. Nonetheless the break-even point according to Leitner (2018a) has risen for emerging hedge funds across the board due to the increase in regulatory requirements, which were imposed after the financial crises of 2008. Emerging hedge fund’s future generally completely depends on the fund’s performance over the first couple of years. If the fund is able to do well in the beginning, they have a high chance to attract enough capital for the fund to be able to cover the operational costs of managing the fund. However, if the fund launches with a poor initial performance, most of the investors will often redeem their capital from the fund and it will become extremely hard for the fund to be able to cover its overhead costs. This will usually lead to a situation where the founders of the fund have no option but to close it down. Even HFM report, that was cited by Leitner (2018b), points out that one-fifth of the so-called star hedge fund start-ups will end up in the liquidation. In order to mitigate these problems that the new managers are facing, specific platforms have been created to help emerging managers in their incubation. For example, OP Investment Management that was founded in 2004, partners with emerging managers as a possible seed capital provider. OP Investment also consults emerging funds and provides a marketing platform for their offerings to the institutional and professional investors. (Macdonald 2018, 1; Leitner 2018a, 1–2; Leitner 2018b, 1–2; Agarwal, Mullally & Naik 2015, 29.)

Motivation for this thesis came from the analysis of research conducted by Aggarwal and Jorion (2010), which focused on emerging hedge funds. By analyzing this research paper, we came to realization that they had used in their research very limited amount of available data. In this thesis, we aim to improve their research by employing a larger data sample, which should enable us to achieve more accurate estimations on performance of emerging hedge funds. Furthermore, we aim to study a few aspects of emerging fund performance that Aggarwal and Jorion (2010) did not research. As an example, one of these aspects is that is there a difference in the emerging hedge fund returns before and after the financial crisis of 2007 and 2008. By conducting a further research on the performance of emerging hedge funds, we seek to achieve a clearer and more accurate picture on the differences of emerging fund performance when compared with more established funds. Our thesis forms around the research question that do emerging funds indeed deliver a greater alpha on average than the more established funds. Aggarwal and Jorion (2010) concluded that this seems to be true, but the problem in this phenomenon is that we can’t be totally certain how much the bias generated by self-reporting in the hedge fund databases play’s in to this greater performance. The most crucial part of this research therefore is to correctly identify the funds that should be considered as an emerging hedge fund. By using in this thesis

TASS and HFR databases, we can employ a longer time series and a greater fund quantity as we have a larger data sample than Aggarwal and Jorion (2010) had. As we employ a larger data sample, we aim to get a more accurate identification for the emerging funds and there by stronger results on the performance of these funds.

The main analysis of the thesis is based on the style adjusted alphas. These alphas measure the excess return that the emerging hedge funds are able to generate over the corresponding index portfolio, which includes all the similar hedge funds that are sorted by their employed investment strategy. This measurement will enable us to study the difference between the different investment strategies. For example, are some of the strategies used by the hedge funds easier to be employed by the emerging hedge funds than maybe others. Our empirical analysis is based on two main time alignment methods, the first one is based on the event time and the second one is based on cohorts formed by the calendar years.

In this thesis, we find that the findings of prior literature on performance of emerging hedge funds has become weaker in magnitude. We contribute this deterioration in magnitude to our use of a longer time period and larger fund sample. Secondly, we find that the emerging funds and managers no more have been able to provide alpha during their early years after the financial crises of 2008. Thirdly, when we compare the performance of different broad fund strategies in emerging hedge funds, we find that only funds that belong to one of our broad fund strategy classifications were able to provide positive alpha in our estimation period. We will go through these findings more in detail in Section 4.

The paper is structured as follows. In Section 2, we go through some basic information about hedge funds and their operational structures but also, we review relevant prior literature in a more detail. Section 3 describes the data and methodology used in this thesis. Section 4 discusses the results of our research and analyzes the explanatory power of our findings. Section 5 explores the robustness of our findings and Section 6 draws the conclusion and further research suggestions on the topic of performance of emerging hedge funds.

2 EMERGING HEDGE FUNDS AND MANAGERS

Even though hedge funds have become more publicly known as they have attracted more media attention within the last few decades, with the rise of famous hedge fund managers such as Ray Dalio and George Soros. Nonetheless, hedge funds have still existed already for more than 60 years. The first hedge fund has usually been credited to been founded by the Alfred Winslow Jones, who was a former Fortune Magazine writer. Although, according to researchers like Lhabitant (2006) there have been even earlier examples of investment vehicles that could be identified as hedge funds, one of such example was Karl Karsten, who run a hedge fund like investment company in the 1930s. Nonetheless, Jones's fund employed a simple strategy of taking long and short positions in stocks to reduce or mitigate market risks, this practice is also known as hedging. As he was using his strategy of buying undervalued assets and selling overvalued assets, his fund was able to generate 670% return between 1955 and 1965. Also, one notable industry leader was Barton Biggs who co-founded Fairfield Partners in 1965. Although Jones's original hedge fund hedged against the market risks, these days it isn't always the case as today there isn't a generally accepted definition for the hedge funds or the strategies they can employ. Currently, hedge funds are more or less a lightly regulated group of alternative investment vehicles that use performance-based compensation structures and they may impose share restrictions on investor's capital withdrawals. Furthermore, hedge funds try to generate returns for their investors who are not highly correlated with returns of other asset classes, such as stock and bond returns. (Agarwal & Naik 2010, 2; Biggs 2006, 85; Joenväärä 2010a, 11; McCrary 2005, 1.)

The prior literature has studied some of the traits associated with the performance of emerging hedge funds. For example, Aggarwal and Jorion (2010, 238) find that each additional year of fund age decreases the fund performance by 42 basis points on average although they find that this relation was not linear. Aggarwal and Jorion (2010) focus in their studies mainly on the age and size factors of the hedge funds, whereas Cao, Farnsworth and Zhang (2016) focus mostly in their research to study the inceptions of new funds. Still most of the prior literature just like Aggarwal and Jorion (2010) that have conducted studies on the emerging funds have been mostly focusing on fund performance and the subsequent fund flows from these hedge funds.

Cao, Farnsworth and Zhang (2016, 2) state in their research that the new fund creation is mostly driven by the two economic factors, which are the investors demand for existing investment opportunities (demand-driven) and the supply of new managerial skills (supply-driven). Although they acknowledge that the creation of new funds can also be motivated by the investors' excess demand for investment opportunities. Based on the results that Cao, Farnsworth and Zhang's (2016) received in their research, it seems that the supply-driven inceptions tend to outperform the demand-driven inceptions when they compared the performance of these two type of fund launches. Cao, Farnsworth and Zhang (2016, 2) also state in their research that due to diseconomies of scale, identified by prior researchers such as Goetzmann, Ingersoll & Ross (2003), Getmansky, Lo & Makarov (2004), Fung, Hsiesh, Naik & Ramadorai (2008) and by Teo (2009), that the existing funds that will grow too large may experience worse performance than the smaller and newer funds. Furthermore, Joenväärä and Kahra (2010) find that when they select the hedge funds based on their characteristics-based allocation strategy, they noticed that the strategy allocated more capital towards smaller funds with better managerial incentives and with longer notice periods. Their findings support the notion that the increase in AUM size may affect the funds' performance negatively.

There have also been opposite opinions on the effects of hedge fund's size, and by the size we mean the AUM size of the fund. For example, Liang (1999) in his research find that the coefficient on assets under management was significantly positive with the performance of the fund. This finding would indicate that the larger funds should have a better performance than the smaller ones. Liang (1999) argue in his research that this could be because the larger funds are achieving economies of scale benefits, or it is easier for these larger funds to attract more capital, than it is for the smaller ones. Also, it can be that the funds, that are able to generate better performance than other funds will grew larger as the investors want to invest their capital into these funds. Besides Liang (1999), also Koh, Koh and Teo (2003) document in their research a positive relationship in a univariate setting between the firm size and the fund returns. These findings strengthen the argument for the positive effects of the economies of scale in fund returns. Furthermore, Gregoriou (2006) find that when looking at the fund of fund returns, he noticed a clear excess performance in the larger fund of funds compared with the smaller fund of funds. Although these results could be possible explained and be driven by the operational differences between the fund of funds and the actual hedge funds. Therefore, his results don't directly indicate that the actual hedge funds are enjoying economies of scale benefits.

When it comes into the effects of fund age, Liang (1999) makes a similar finding with the Aggarwal and Jorion (2010), as they both make the same conclusion that the fund age has a negative correlation with the average fund performance. One explanation for this effect, that they provide, is that the managers in the younger funds have a greater incentive to work hard in order to build up their reputation. Whereas the managers in the older funds are keener to focus on raising more capital than to focus on the performance. Because in older and larger funds, the managers receive most of their annual compensations from the fixed fees charged based on the AUM rather than from the fees based on the funds' performance and therefore increasing their AUM compensates them more than trying to improve their performance. Boyson (2005) also supports this finding in her studies on the relationship between hedge fund manager's tenure and performance. On top of that, when Boyson (2008) looked at the fund's past performance she did not find any performance persistence when the funds were selected purely based on their past performance. Although, when the funds were selected based on their performance and manager tenure, she found that managers with a less experience that were able to outperform their peers continued to do so in a quarterly horizon.

Next, when we look at the management effects on the hedge fund performance, Mullally (2016) makes the conclusion that, the younger funds are more likely to sell stakes from their fund management company to strategic growth partners. The value of attracting a strategic growth partner by selling them a stake from the fund management company is higher for the younger funds as they are not that well known for the investors. Outside owners are especially beneficial for the new funds, because according to Mullally (2016) the outside owners provide capital, infrastructure or expertise that is necessary for the fund management company in order to attract capital from other investors. These outside owners also may help the management company to launch a new fund or to expand their existing fund's portfolio into new investment strategies. The second reason, why an outside owner can be beneficial for the inside owners of the small fund, is that outsider's decision of purchasing a stake in the fund management company can give it creditability in the eyes of other investors. This can improve the funds quality and thus help it to attract higher fund flows. This arraignment is beneficial for the outside and the inside owners as they both have an incentive to increase the size of the business due to the fact that their stakes in the management company increase in value with the fund’s size. Furthermore, Brown, Goetzmann and Liang (2008) found that the problem funds that had for example a higher risk to try to defraud their investors had a higher likelihood to have an owner with the ownership of greater than 75%, and a more indirect ownership structure. Therefore, having a more diversified owner structure with an outside owner in the fund management company also reduces the risk of fraud for the investors. (Mullally 2016, 2–4.)

Although the prior academic research specifically on the emerging hedge funds is still quite scarce, nonetheless there is a lot of previous literature that is related to this subject. For example, size factors, managers' incentives and hedge fund reporting-related biases in the hedge fund databases will also affect emerging hedge funds. These subjects are well studied by the prior literature and they are also relevant to this thesis. For example, Agarwal, Fos and Jiang (2013) find in their research that funds’ that self-report their performance, see significantly deteriorating performance after the reporting initiation and the termination dates. According to Agarwal, Fos and Jiang (2013) this is the reason, why funds try to strategically initiate self-reporting after they have had a run of exceptional performance. Therefore, if we would use the reporting initiation and registration dates as our selection criteria for the emerging hedge funds, we would receive results that would indicate that our emerging hedge funds are able to generate higher returns than other funds. These results would lead us to think that emerging hedge funds can generate substantial alpha over the other funds although in fact these results would be mostly explained and driven by the bias created by the self-reporting. Therefore, in this thesis we use the same approach that Aggarwal and Jorion (2010) use to identify the funds that should be considered as emerging hedge funds. By doing this, we try to mitigate the effects of self-reporting bias. We will go through these approaches more in detail in Chapter 3.

3 DATA AND SETUP

3.1 Database

The data samples we will employ in our research have been gathered from two data services, which are Lipper TASS (TASS) and Hedge Fund Research (HFR). Using at least two different databases is necessary as only very few of the hedge funds report their returns to multiple commercial databases. For example, Fung and Hsieh (2009) emphasize the importance to use multiple databases as the funds that will stop reporting to another database would be classified as a dead fund in this database, but these funds could still be reporting to other databases and in these databases, they would still be classified as an active fund. This problem was also identified by researchers such as Agarwal, Daniel & Naik (2009) and Joenväärä, Kosowski & Tolonen (2012). Additionally, Lhabitant (2006) states that existing hedge fund databases and their hedge fund indices are not necessarily representative of the industry as each database and index is built by using different funds or even some cases different methods. This can cause a large variation between different databases and the results that are based on one individual database can be subject to several biases and inaccuracies. Furthermore, we are going to employ these two databases, because we need to have the date when the hedge fund was added to the database and both of these databases that we are going to use, will provide us that specific date. We will go through the reasons why we need the date added to the database variable more in detail later in this section. The Lipper TASS database has been used in most of the prior research on the emerging hedge funds, for example Cao, Farnsworth & Zhang (2016) and Aggarwal & Jorion (2010) used this exact database. Furthermore, by including also HFR database in our thesis, we are able to achieve a much larger sample size than previous papers employed. Therefore, we can achieve more accurate results on the performance of the emerging funds. Although, Joenväärä, Kosowski and Tolonen (2016) state that researchers could, based on their research, only use a one of the more complete databases such as Lipper TASS and receive a similar conclusion that they would receive by using an aggregate data sample. They also note that they receive higher alphas from the TASS database than from the other four different databases, that they studied in their research paper.

We will form a combined dataset from the TASS and HFR databases, where we have all the unique funds from both of these databases. This way we don't have any duplicate funds in our combined dataset. We will take the return history for the funds that are in both databases from that database where it has a longer performance history or a higher asset under management amount during the funds launch. Our data is gathered from the year 1996 until the year 2011 in TASS and in HFR we have a data from the year 1996 until the beginning of the year 2017. In our combined dataset that was gathered from the TASS and HFR the data sample is therefore from 1996 to 2017., We will collect all of the usable information from the TASS and HFR, such as the fund strategy and used investment vehicles. Nevertheless, the main values for this thesis are the total monthly returns net of management and incentive fees and the assets under management. In our analysis, we will use all the data that is available and for which there is a sufficient number of funds that are not backfilled. We are going to use in our analysis, the data selection method that was defined by the Aggarwal and Jorion (2010). This selection method will be disclosed next in a more detail.

Most databases have two separate datasets, one with still active funds and another with the dead funds. This dataset that has also the dead funds includes all the funds that have existed in the database at some point of time. The funds that will become dead funds will usually stop reporting to the database due to liquidation or they are closing the fund from the new investments. In our TASS dataset, we include the dead funds to minimize survivorship biases in our datasets, but we will remove from our datasets the funds that are classified as fund of funds or CTAs. In our combined dataset that is formed from TASS and HFR data, we in addition remove duplicate classes from the same fund families. Additionally, in these both datasets, we only keep the funds that provide returns nominated in the United States dollar and net of fees. This way we can eliminate situations where the same fund would appear multiple times in our dataset, but it would be nominated in a different currency. Although we can't mitigate all of these duplicate cases in our data. This is because two hedge funds, that are run by the same manager, can still exist in the dataset with an almost identical name. This is caused by the fact that these funds can have added designations "offshore" or "onshore". Also, two funds may have the same manager and the name, but the other fund is a LP (limited partnership) and the other fund is named as a limited, investment company or the abbreviation has just been written open. These situations are not that uncommon in the hedge fund industry as most of the fund companies are usually set up with a master and feeder fund structure. In this specific structure it is common that multiple feeder funds are channeling capital to one master fund and the feeders have quite similar names but are registered to different countries or have a different fee and currency structure. However, as we only look at the funds that are nominated in the US dollars, at least the feeder funds that are in different currencies are therefore removed.

Next, we will explain the fund selection criteria that we will use in our combined dataset. Firstly, if two funds from the same management company have identical returns for the months when both funds have reported their returns and one of these funds has started to report their returns later than the other one, then we will keep the older fund or the fund with the longer period of reported returns. Secondly, if two funds have identical return series when both funds have reported them and one of these funds will stop reporting before the other, we will again keep the fund that has a longer return history. In a scenario where we have two funds that have the same return history for the same months that they have reported, then we are going to keep the fund that is larger based on the initial AUM during the launch of the fund. In order to us to prevent the double-counting of assets, we are only going to retain the assets under management for the fund which return data we are going to use in our dataset. We will do this because the smaller fund is usually a feeder fund for the larger master fund. This means that the feeder fund’s AUM is already included in the master fund’s AUM. By doing these adjustments for our combined dataset set, we aim to achieve a more reliable data sample for our analysis. For example, Joenväärä and Kauppila (2016) state that by doing these adjustments for our dataset, our analysis should be based on a wider cross-section of hedge funds. This will enable us to achieve more reliable results from our analysis. Additionally, there is also a decrease in the possibility that some of our documented results wouldn’t be driven by our whole hedge fund sample, but instead by a small sub-sample of hedge funds within our whole dataset.

3.2 Constructing emerging fund returns

To construct our emerging fund returns from our datasets, we must first identify which funds we should consider as emerging hedge funds. Therefore, we need to create the parameters that will work as indicators to identify these emerging hedge funds. We are going use similar parameters that Aggarwal and Jorion (2010, 241) used in their research paper. Furthermore, when it comes to evaluating the initial performance of these emerging funds, mitigating the effects of backfill bias is a top priority. This is because, according to Joenväärä (2010b, 16; 2010c, 10) and Gregoriou (2006, 5) most of the hedge fund databases tend to suffer from multiple biases such as survivorship, self-reporting, multiperiod sampling and backfilling biases. Survivorship bias is usually caused when a database does not include the performance of funds that cease operating during the sample period. Self-reporting bias is created by the fact that hedge funds can strategically start their reporting after a period of exceptional returns. Multiperiod sampling bias is often generated when the analysis is restricted to funds that have a minimum amount of history available. Lastly backfilling bias created as funds that are starting to report to the database are allowed to backfill their prior results. Also, researchers like Cao, Farnsworth & Zhang (2016, 24) and Agarwal, Daniel & Naik (2011) note that since reporting to these databases like the TASS and HFR is in the end completely voluntary for the hedge funds, the potential for the data to be biased is significant. This is mainly because hedge funds have an incentive to try to flatter their performance history or inflate the values of their less liquid investments in order to charge bigger incentive and management fees. Due to these reasons, the main concern for researchers using these commercial databases in their studies on hedge fund performance is the possibility of backfilling bias influencing their results. Most of the funds, as the reporting is optional, tend to start to report their performance only after they have been operating for a while. This is because the managers want to portray their funds as successful and they may decide to start to report to these databases after a good historical performance, whereas after the period of substandard performance, that they may have, they can choose not to start to report their performance at all.

The widespread practice in the academic research on the hedge fund industry is to filter the first 12 months or more from the funds return data to control for the effects of backfilling bias. This method was even used by Fung and Hsieh (2000) in their report when they conclude that the median backfill period in the commercial databases was in around 12 months for the hedge funds. Whereas, according to Aggarwal and Jorion (2010, 242) there is a better method available for controlling the backfill bias than this common practice used by the likes of Fung and Hsieh (2000). Aggarwal and Jorion (2010) argue that because in this usual method we remove the funds first year worth of performance and if this fund would have had a little to no backfill bias in its first-year performance then we would have only destroyed valid information about the fund's performance. Furthermore, the funds that would have longer than 12 months' worth of backfill would still suffer from the backfill bias after this adjustment. Therefore, Aggarwal and Jorion (2010, 242) state that "A better method of controlling the backfill bias is to minimize the period between the inception of the fund and the first entry date into the database". If we try to control the backfilling bias this way, we are immediately focusing our attention towards the emerging hedge funds that have a very little to no backfill bias. Although, according to Fung and Hsieh (2000) the performance numbers from the early lives of the funds are more likely to subject to an upward bias, this is something that we need to acknowledge in our research. Because we are taking the returns from the start of the funds life and therefore we possible include some of this bias in our datasets, even though we will try to mitigate this included bias with our selection criteria for the emerging hedge funds.

The databases that we use in this thesis will provide us three different dates that we need for our emerging hedge fund selection criteria, these dates are an "inception date," a "performance start date," and "date added to database" variables. The inception date stands for the establishment date of the legal fund structure, but it does not mean the start of actual investing nor performance of the fund. The performance start date is the date when the fund reports its first monthly return. The date added to the database is the date when the fund decides to start reporting to this specific database. Usually funds inception date is going to be prior to the performance start date, and the performance start date is going to be before the date added to the database variable. As stated previously, we will use these variables in our selection criteria to identify the emerging hedge funds and therefore these variables are essential for this thesis. However, because all of the commercial hedge fund databases do not provide these values it restricts which databases we can employ in this paper and therefore we have settled to use only TASS and HFR. (Aggarwal & Jorion 2010, 242.)

Backfill bias in the hedge fund databases is usually created when the performance start date is before the date when the fund was actually added to the database. The time difference between these two dates is the period of backfill according to the Aggarwal and Jorion (2010, 242). In their research, they find that the backfill period in the TASS database was on median 480 days. In addition to this, 37% of the funds had a backfill period longer than two years and 25% of the funds had a backfill period longer than 3 years. They also note that a major concern is the previously stated problem in Section 3 that the funds only choose to report to databases if their past performance has been good enough and then this exceptional performance can be backfilled into the database. In order to mitigate this problem, we will separate the hedge fund data that we have into the non-backfilled and backfilled data sample. Our definition for the fund to be considered as non-backfilled fund is that the period between the inception date and the date added to the database has to be below 180 days. This is the same criteria that Aggarwal and Jorion (2010, 242) use in their research to identify non-backfilled funds from the backfilled funds. As we focus our attention towards the difference between the inception date and the date added to the database, we try to minimize the backfill bias and the possible omitted performance in the TASS and HFR databases. Aggarwal and Jorion (2010, 242) state in their research that we can accept this difference between these two dates to be a maximum of 180 days, because only a few of the funds will start to report to the databases immediately at the inception. This is not a surprise since most of the funds can't start to report their performance at the inception as they may still be gathering assets from the investors rather than actually investing their assets. Therefore, using a maximum lag of 180 days as our criteria we do not disqualify legitimate funds from our dataset and we can have a larger quantity of valid emerging hedge funds to base our analysis. (Aggarwal & Jorion 2010, 242.)

3.3 Time alignment

In this thesis, we will imitate two types of analysis that were conducted by Aggarwal and Jorion (2010, 242). First one of these analyses is based on event time whereas the second one is based on cohorts formed by calendar years. The first type of analysis is formed by Aggarwal and Jorion (2010, 242), as follow "We form an equally weighted portfolio of funds aligned in the first month of reported performance. Equal-weighting generates the expected return from a strategy of picking all managers meeting the relevant characteristics." Yearly returns in our analysis are formed by cumulating the first 12 months of performance, which is named as year 1, the next 12 months is then named as year 2, and so on. In our TASS data, which is from the year 1996 to the year 2011, we can have a maximum of 192 months in the event time. In order to fund to achieve this full event time it must start at the beginning of the year 1996 and survive through the years up to the end of the year 2011. In our TASS data sample we have only a few funds that have been able to do so. Whereas in our combined data the sample period is going to be from the year 1996 until the beginning of 2017, and we can have a maximum amount of 264 months in the event time.

Table 1. Emerging funds in our datasets sorted by the launch year and database

This table presents the number of funds that meet our emerging hedge funds selection criteria, which is that period between the inception date and the date added to the database is below 180 days. The emerging funds are sorted by their launch year and we report the emerging funds separately for the TASS and combined dataset. Our sample period is in TASS from 1996 to 2011, and in combined data it is from 1996 to 2017.

Year	TASS	Combined
1996	54	106
1997	49	86
1998	84	101
1999	71	78
2000	49	79
2001	92	98
2002	98	112
2003	98	130
2004	133	176
2005	212	236
2006	130	242
2007	108	212
2008	190	210
2009	150	170
2010	229	262
2011	23	132
2012		143
2013		157
2014		172
2015		105
2016		102
2017		8

As we can see from the table 1, majority of our emerging funds in this research are going to be in our combined data sample. We can see this in the combined column as it has more emerging hedge funds than the TASS column has. This will mean that the results from the combined dataset can be slightly more reliable than the results from the TASS dataset alone. From the table 1, we can also note that most of the observations in TASS and combined data are more concentrated at the end of the dataset. In TASS, most of the observations are from the year 2004 to 2010, whereas in combined dataset they are from the year 2004 to 2016.

Next in the table 2, we will report the raw returns for our emerging hedge funds portfolios. In table 2 we have two panels, which are panel A and B. The panel A shows our results from the TASS dataset, whereas in panel B we have the same calculations for our combined dataset. In our TASS data there is a 1728 backfill bias free individual funds that have started their operations within our sample period of 1996 to 2011. At the beginning of second event year in TASS, there are 1597 funds left and the number falls to 1124 during the third year. When we look at our emerging funds in the combined dataset, in the beginning we have 3094 emerging hedge funds, but the number drops to 2746 in second year and to 2071 during the third year. This fast deterioration in the numbers of funds in the beginning confirms us that the common notion that the typical hedge fund has a life expectancy of around four years is a quite accurate statement.

In table 2, where we calculate the simple raw returns for our TASS and combined datasets, we will only look the first nine cohort years in our datasets. This is because we are more interested looking at the early returns of emerging hedge funds than their returns in later fund life. Also, we have the largest sample size at the beginning of the time series and as the number of funds deteriorates the results are based on fewer number of observations and therefore their reliability weakens. We see our nine first cohort years in the panels A and B, and as we have the same amount of cohort years, we can compare our results from the TASS and combined dataset to each other. In these calculations, we will do a simple adjustment for the outliers in the data, this way we can mitigate the effects that can be caused by these few outliers to the whole dataset. In our simple adjustment, we remove the best and the worst 1% performers from the fund return data. When it comes to the backfilled data in the table 3, we will do a simple survivorship bias mitigation by filtering from the performance data the returns that are backfilled in to the databases before the funds inception. The number of funds is excepted to fall as the event years go by, due to fund closing down as well as to the funds deciding to stop reporting to the databases. Furthermore, funds that have launched later in our data sample can't have a longer period of returns, for example in our TASS dataset, funds that launched in the year 2011 can't have more than the 1-year worth of performance data. In our last event, which is 16 year, which is the longest possible time series in our TASS dataset, there are only four funds left in our TASS portfolio. Results that would be based on this last year of fund performance would be highly unreliable and therefore we focus our attention on findings on the yearly returns of our emerging hedge funds data.

Our selection process of emerging hedge funds leads to a situation, where the largest number of funds is during the first event year as every fund, that does not have backfill bias, will have the at least one-year worth of return data. The first-year performance for our funds is substantially higher than the performance for the later years of funds lives. In the table 2 at panel A we see that the average raw return in TASS for the first year is 11.37% and return falls to 5.81% during the second year. Whereas in our combined dataset in panel B we have an average raw return of 10.16% during the first year and after that it drops to 5.54% for the second year. This substantial excess performance in our datasets during the first year of funds lives would indicate that, emerging managers provide significant returns almost exclusively during their first operational year. This better performance during the launch year could indicate that the funds try to launch during the years when the markets are doing extremely well, or they will only start to report to databases if their performance is great during the launch of the fund. We can't really see any outperformance during the later years for our funds that are not backfilled. Although the excess returns are much more prominent in our backfilled fund sample in the table 3. This we can see in the panels A and B at the table 3, where we have done the similar calculation that we did for the backfill bias free emerging hedge funds, but now for the backfilled funds that do not satisfy our criteria of emerging hedge fund. We have done these calculations for the backfilled funds in both TASS and combined dataset.

Table 2. Raw returns for the emerging hedge funds

These two panels present the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Portfolios are constructed as the equal-weighted averages of fund raw returns during each month. Returns are then grouped by the year, i.e., first 12 months' worth of performance for year 1 and so on. Average of fund volatility is the cross-sectional average of annualized volatility for each fund over 12 months. Average of Sharpe ratio is calculated based on our average annualized raw returns from which we have deducted the risk-free rate and then this value is divided by our portfolios annualized standard deviation. Average fund AUM is the average of our emerging funds AUM at the start of each cohort year, whereas the number of funds is also estimated at the start of each cohort year. Panel A presents results for the emerging hedge funds, i.e., with the inception date very close to the date first reported to the TASS database. Panel B presents our results for the emerging hedge funds, i.e., with the inception date very close to the date first reported to our combined dataset. Our sample periods were in TASS from 1996 to 2011 and in combined dataset the sample period is from 1996 to 2017.

Panel A: Raw returns for the emerging hedge funds in TASS

Cohort year	Raw returns (annual)	Average fund volatility	Average Sharpe ratio	Average fund AUM ($ Millions)	Number of funds
1	11.37 %	15.56 %	0.73	28.94	1728
2	5.81 %	15.48 %	0.38	58.85	1597
3	5.92 %	15.36 %	0.39	94.23	1124
4	4.85 %	16.03 %	0.30	124.88	774
5	3.25 %	16.08 %	0.20	136.72	556
6	6.20 %	15.39 %	0.40	152.48	400
7	5.43 %	14.60 %	0.37	208.13	269
8	3.29 %	15.26 %	0.22	202.80	196
9	5.54 %	14.86 %	0.37	193.10	137

Panel B: Raw returns for the emerging hedge funds in combined dataset

Cohort year	Raw returns (annual)	Average fund volatility	Average Sharpe ratio	Average fund AUM ($ Millions)	Number of funds
1	10.16 %	14.68 %	0.69	32.47	3094
2	5.54 %	15.12 %	0.37	56.31	2746
3	4.43 %	14.82 %	0.30	84.39	2071
4	4.55 %	15.08 %	0.30	117.45	1501
5	3.43 %	15.05 %	0.23	149.63	1090
6	2.01 %	15.03 %	0.13	159.39	795
7	6.04 %	15.13 %	0.40	184.44	625
8	4.65 %	14.80 %	0.31	214.05	438
9	3.09 %	14.54 %	0.21	210.08	336

Table 3. Raw returns for the funds after inception

These two panels present the performance after the inception of our fund portfolios aligned by event time, which is the first month of reported performance. Portfolios are constructed as the equal-weighted averages of fund raw returns during each month. Returns are then grouped by the year, i.e., first 12 months' worth of performance for year 1 and so on. Average of fund volatility is the cross-sectional average of annualized volatility for each fund over 12 months. Average of Sharpe ratio is calculated based on our average annualized raw returns from which we have deducted the risk-free rate and then this value is divided by our portfolios annualized standard deviation. Average fund AUM is the average of our funds AUM at the start of each cohort year, whereas the number of funds is also estimated at the start of each cohort year. Panel A presents results for the funds in TASS, i.e., these funds do not satisfy our criteria of emerging hedge funds, which was that the inception date had to be very close to the date first reported to the database. Panel B presents our results for the funds in combined dataset, i.e., which do not either satisfy the previous definition. Our sample periods were in TASS from 1996 to 2011 and in combined dataset the sample period is from 1996 to 2017.

Panel A: Raw returns for the funds after inception in TASS

Cohort year	Raw returns (annual)	Average fund volatility	Average Sharpe ratio	Average fund AUM ($ Millions)	Number of funds
1	16.01 %	15.36 %	1.04	39.85	6444
2	12.77 %	15.64 %	0.82	65.83	6208
3	9.81 %	15.69 %	0.63	103.76	6057
4	7.99 %	15.98 %	0.50	113.57	5119
5	6.45 %	15.87 %	0.41	122.67	4151
6	6.18 %	15.75 %	0.39	140.19	3187
7	7.23 %	15.29 %	0.47	170.50	2397
8	6.18 %	15.29 %	0.40	180.40	1772
9	6.08 %	15.35 %	0.40	200.56	1272

Panel B: Raw returns for the funds after inception in combined dataset

Cohort year	Raw returns (annual)	Average fund volatility	Average Sharpe ratio	Average fund AUM ($ Millions)	Number of funds
1	14.67 %	15.45 %	0.95	39.56	9136
2	12.79 %	15.49 %	0.83	68.44	9121
3	9.66 %	15.36 %	0.63	106.64	8566
4	7.94 %	15.37 %	0.52	134.18	7587
5	6.76 %	15.11 %	0.45	157.42	6550
6	5.82 %	14.96 %	0.39	184.46	5586
7	5.46 %	14.86 %	0.37	212.44	4632
8	5.57 %	14.85 %	0.38	250.38	3820
9	4.43 %	15.30 %	0.29	275.68	3098

As we can see from the table 2 and 3, there is a much higher number of other funds in our data than we have funds that qualify as emerging hedge fund. Initially there is in TASS in table 3, in total 6444 biased hedge funds compared with 1728 emerging funds in TASS in table 2. Whereas at panel B of table 3, which shows our values for combined dataset, there are 9136 biased-funds compared with 3094 emerging hedge funds in panel B at table 2. Biased-funds in the table 3 seem to have much higher returns for the first four years compared with the non-backfilled funds in the table 2. This would indicate that the backfill bias is a substantial source of the excess performance for these four first years in our data. When comparing our results from the table 2 and 3, we see that during the first year the backfill bias is 4.64% in TASS and 4.51% in combined dataset. This bias seems to persist for the first four years and it seems to be the strongest during the second year. The amount of bias is for the next three years in TASS 6.96%, 3.89% and 3.14%. Whereas the same values are in combined dataset 7.25%, 5.23% and 3.39%. These strong excess returns on the biased data compared with the returns of emerging hedge funds would indicate that higher performance we see during the first year by the emerging managers can be influenced by the backfill biases in the data rather than by the actual capability of emerging managers to generate substantial alpha. We can't still make definitive conclusions just by inspecting funds raw returns, so a further inspection on the fund performance is necessary.

In our second type of analysis, we are going to group our funds based on the calendar year, when the fund has launched. A group of funds that starts to report during the same year, between the years 1996 to the 2011 in TASS and between the years 1996 and 2017 in combined dataset are defined as a cohort. For example, as our second performance year starts in TASS in the year 1997 we have 49 non-backfill biased funds in TASS with inception and performance date starting during that specific year. We will construct an equally weighted portfolio of returns across all the funds in this analysis for each individual month for which we have the data to get the average performance for each cohort. In our TASS and combined data, the starting size of each cohort seems to grow when we come from the past towards the current year. However, the individual cohort's size will shrink as the years go by, as we have stated one of the reasons is that for an example some of the funds will stop reporting to the databases. (Aggarwal & Jorion 2010, 243.) To get the average return for the first year of our 16 cohorts in TASS and for 22 cohorts in combined dataset, we are going to use the formula 1, which is shown next:

$$\overline{\overline{R_1}} = \frac{1}{X}(\overline{R_x} + \overline{R_{x+1}} + \cdots + \overline{R_{x+\infty}}) \quad (1)$$

In the formula 1 the R_x stands for the average fund return of the funds in cohort year x. Aggarwal and Jorion (2010, 243) form these cohorts in their research so that the average return for the second year of our cohorts is the average return of the second year of our funds operations ($\overline{R_{cohortyear2}}$). This compiling process is done for all the years in our dataset up to 16 and 22 years from 1996 until 2011 in TASS and from 1996 until 2017 in combined dataset. This cohort calendar time analysis will give us an alternative method of classifying funds. This type of analysis enables us to sort the funds by size on an annual basis, which according to Aggarwal and Jorion (2010, 244) "provides a more natural sorting for size than does the event time analysis." The results from using this analysis method can be seen in more detail in Chapter 4.

3.4 Performance measures

We will use in this thesis a similar performance measures to estimate fund's alpha and returns that Aggarwal and Jorion (2010, 244) use in their research paper. The first performance measure was the raw return data that we did in Chapter 3.3 and the advantage of using raw return data was that we do not have to do any estimations of parameters, however this method does not control for market movements or risk. In the second type of measure we use the databases fund strategy classifications. In both databases, funds are divided into 11 or 12 different strategies and in our data after we remove two fund strategies that are CTA's and Fund of Funds. The remaining 9 different main strategy sectors are in TASS as followed: Emerging markets, event driven, global macro, long/short, market neutral, multi-strategy, others, relative value and short bias. In our combined dataset, we have 10 strategy classifications instead of 9 we had in TASS, which are combined with the classifications in HFR database, these main strategies are the following: Emerging markets, event driven, global macro, long/short, market neutral, multi-strategy, others, relative value, sector and short bias. In their study Aggarwal and Jorion (2010) are comparing each sector with its available corresponding index from CSFB, this gave them the asset-weighted portfolio returns of funds selected from the databases such as TASS. These CSFB provided corresponding indexes include funds with at least one-year worth of track record, with at least minimum AUM of $10 million and audited financial statements are required to fund to be included in these indexes. Nevertheless, because we don’t have these indexes available for us, we will build our own indexes separately for our TASS and combined datasets based on the classifications used in these CSFB indexes. To create our own benchmark index that we can use to compare our emerging hedge funds returns, we will compound all our funds sorted by the employed main strategy in the corresponding database together. We will filter from this data all the funds that do not meet the criteria of minimum AUM of $10 million dollars and at least 1-year worth of track record. Because we couldn’t accurately identify which funds have audited financial statements, we have to drop this specific criterion from our own benchmark indexes. Now as we have created our own strategy benchmarks, we will use them in similar fashion that Aggarwal and Jorion (2010) used their CSFB benchmark indexes.

We are going to use these sector returns to adjust the individual fund’s returns to sector effects, basically we use these sector indexes as benchmarks for our hedge funds. The formula we use to measure abnormal style-adjusted returns is replicated from Aggarwal and Jorion’s (2010, 244) research paper, where they measure these returns by using the formula 2, which is detailed below:

$$AR_{it}^{S} = R_{it} - \beta_{it} R_{St} \quad (2)$$

In this formula 2 the R_{it} is the return on the fund i at the time t. R_{St} is the return on the corresponding strategy index S to which the fund i is going to be benchmarked at. β_{it} is the actual sector exposure of the individual fund i, averaged over two calendar years, but in some cases this period can be shorter, as for an example if the fund only has a one-year worth of performance data and therefore the time series which determines the funds strategy exposure will be shorter. To describe this method of calculating the individual funds strategy exposure more precisely, the exposure β_{it} for years 1 and 2 is calculated by using all the fund i’s return data from the years 1 and 2. After this β_{it} is going to be calculated by using return data from the years t_x and t_{x-1}.

The benefit of using this particular approach is according to the Aggarwal and Jorion (2010, 244) that “it is simple to implement. It controls for sector effects, which is appropriate when comparing performance across funds. It also adjusts for general movements in fund returns, such as the period of negative returns experienced during the third quarter of 1998, at the time of the Long-Term Capital Management hedge fund crisis." The result from this approach is that we can achieve a lower variance of abnormal returns than we would receive if we only would use raw returns data. This will increase the statistical significance of our analysis in this thesis. Furthermore, by using this method, we can simultaneously control the risk which is taken as factor exposure. For example, as we keep the correlation fixed the result should be that the fund that employs higher amount of leverage should have a higher volatility and beta in our data samples. (Aggarwal & Jorion 2010, 244.)

Our classifications of funds into previously mentioned nine different strategy sectors in TASS and into ten different sectors in our combined dataset may end up to be quite arbitrary. The problem in this can be that the funds are using multiple strategies, or the funds are changing their main investment strategies over time. Therefore, this approach is going to only provide us with a measure of relative performance compared with the other funds with the same investment style. Because hedge funds are not in our analysis compared with the other asset classes, this means that if the fund has a negative alpha it doesn't necessary mean that fund has a mediocre performance in the absolute returns if we would compare it with the other asset classes. Another concern that rises from this approach is that we must estimate in-sample abnormal returns and betas, this will cause a situation where there isn't a predictive period after our estimation period. As we focus in this research towards the emerging hedge funds and managers, who by definition do not have a past returns and the concern of missing a predictive period should be considered as a cost for the adjustment of risk. In general terms, our approach is quite similar to Aggarwal and Jorion (2010) and to those that are commonly used in most hedge fund performance related research papers that focus on a short-time period, series-based performance and performance persistence. (Aggarwal & Jorion 2010, 244.)

4 EMPIRICAL RESULTS

4.1 Style-adjusted performance using event time

In this chapter, we will first present style-adjusted returns for our event-time portfolios. In the panel 4 we present our alphas by age for the first nine years after funds inception for our emerging hedge funds. In the panel A, we have our results for the TASS dataset and in the panel B for the combined dataset, whereas panel C shows our regression results for these datasets.

Table 4. Style-adjusted performance of the emerging hedge funds

These two panels present the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. Panel A presents emerging hedge fund portfolio alphas in TASS, whereas B shows our results for the combined dataset. Panel C presents our regressions for portfolio alphas for our data samples. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Number of funds is estimated at the start of each cohort year. Our sample is in TASS from 1996 to 2011 and in combined dataset from 1996 to 2017.

Panel A: Style-adjusted performance of emerging hedge funds in TASS

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	1.55 %	0.561	2.34 %		1728
2	1.05 %	0.575	2.21 %	4.71*	1597
3	0.81 %	0.583	2.00 %	1.90	1124
4	0.33 %	0.611	1.88 %	4.65*	774
5	-0.23 %	0.653	1.76 %	4.88*	556
6	0.52 %	0.682	1.62 %	-6.65	400
7	0.35 %	0.716	1.40 %	1.61	269
8	0.20 %	0.641	1.49 %	0.76	196

Panel B: Style-adjusted performance of emerging hedge funds in combined dataset

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	0.20 %	0.656	2.64 %		3094
2	-0.59 %	0.687	2.41 %	5.02*	2746
3	-0.50 %	0.695	2.06 %	-0.51	2071
4	-0.12 %	0.691	1.74 %	-2.30	1501
5	-0.65 %	0.686	1.53 %	1.51	1090
6	-0.38 %	0.676	1.48 %	-1.93	795
7	-0.08 %	0.672	1.42 %	-1.75	625
8	-0.19 %	0.676	1.34 %	1.23	438

Panel C: Regression of portfolio alphas on age (annual) in TASS and Combined

	TASS	Combined
Independent variables:		
Constant	0.0130*	-0.0027
	(0.0433)	(0.0125)
Ln(Age)	-0.0017*	-0.0005*
	(0.0026)	(0.0049)
Adj. R-squared	0.5063	-0.1651
Number of observations	96	96

In the table 4 at panel A, we can see that first-year alphas in TASS are 1.55% and they fall to 1.05% in second year, whereas in combined dataset at panel B, the first-year alpha is only 0.20% and it falls to -0.59% in second year. It seems that after the first year in combined dataset the alpha is remaining in the negative values and there doesn't seem to be any alpha generated by the emerging hedge funds after the first initial launch year. Whereas in panel A, we can see some level of alpha generated during the first 3 operational years. When looking at the average alpha during the first four years in panel A in TASS dataset, we have an average alpha of around 0.94% per year and for the next four years we have an average alpha of 0.21%. Whereas in combined dataset in panel B we have an average alpha of -0.25% during the first four years and -0.33% for the next four-year period. The typical fund betas, taken as the arithmetic average for our funds in the emerging hedge funds portfolios seem to be on average around 0.63 in TASS and 0.68 in our combined dataset relative to our constructed style indexes. These betas differ from unity as typical fund may not be closely correlated with our style factors. The reason for this is that managers may have new investment ideas, different amount of leverage or have different volatility than our average constructed from all the funds in the data grouped by their main strategies. The results that we receive in the table 4 seem to be quite in line with the results that we receive from our raw returns for the emerging hedge funds in table 2. In the table 2, we saw that the emerging funds were generating the most significant outperformance almost exclusively on their first operational year. Also, TASS seems to have greater returns for the emerging hedge funds both in raw returns and in alphas. Excess performance seems to last longer, around three first year, for emerging hedge funds in TASS than it does in combined dataset, where it only seems to exist during the initial launch year. When we compare the raw returns and alphas we can see that in size the raw returns are much greater during the launch year in table 2, whereas alphas are not that significant in table 4. We can also see that alphas in table 4 get weaker in a much slower phase than raw returns in table 2. This would suggest to us that newest and emerging hedge funds tend to and try to launch during times when the markets are already performing extremely well. From the panel C in the table 4, we can see that the fund age has a greater effect on funds performance in TASS than it has in the combined dataset and both of these findings are statistically significant.

Next, we aim to check if there is a difference between the emerging hedge funds returns before and after the financial crises of 2008. We are going to study this phenomenon by using our combined dataset as in TASS dataset we do not have enough years after the financial crises. We show our results for style-adjusted performance of our funds before and after the financial crises in the table 5. We can see the difference between these two periods by dividing our combined dataset into two sub-sets. These sub-sets are the set from 1996 to 2008, which is the pre-financial crises set in the panel A. The other set is from 2009 to 2017, which is named as the after financial crises set, which is the panel B. In panel C of table 5 we can see our regressions for our portfolios of panel A and B.

Table 5. Style-adjusted performance before and after financial crises

These two panels present the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. Panel A presents emerging hedge fund portfolio alphas before the financial crises in combined dataset, whereas B shows our results for after the financial crises. Panel C presents our regressions for portfolio alphas for our data samples. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Number of funds is estimated at the start of each cohort year. Our sample is in before financial crises set from 1996 to 20008 and in after financial crises dataset from 2009 to 2017.

Panel A: Style-adjusted performance before financial crises in combined dataset

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	0.54 %	0.641	2.96 %		1860
2	0.01 %	0.683	2.55 %	4.34*	1631
3	-0.56 %	0.690	2.44 %	0.56	1196
4	-0.31 %	0.761	2.09 %	-2.35	849
5	-0.83 %	0.727	1.64 %	1.78	624
6	-0.21 %	0.702	1.50 %	-1.50	463
7	0.04 %	0.701	1.53 %	-0.75	356
8	-0.45 %	0.693	1.38 %	0.06	275

Panel B: Style-adjusted performance after financial crises in combined dataset

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	-0.31 %	0.679	2.53 %		1234
2	-1.47 %	0.692	1.60 %	9.81*	1115
3	-0.42 %	0.702	1.55 %	2.16	875
4	0.12 %	0.720	1.10 %	-7.29	652
5	-0.43 %	0.631	0.97 %	0.64	466
6	-0.62 %	0.640	0.95 %	1.20	332
7	-0.24 %	0.634	0.86 %	-4.30	269
8	0.25 %	0.648	0.65 %	-2.59	163

Panel C: Regression of portfolio alphas on age (annual) for our sub-samples

	Before financial crises	After financial crises
Independent variables:		
Constant	0.0011	-0.0087
	(0.0032)	(0.0038)
Ln(Age)	-0.0007*	0.0011
	(0.0006)	(0.0008)
Adj. R-squared	0.0509	0.1211
Number of observations	96	96

In the table 5, we can see that the alphas in the panel A, before financial crises, were significantly better than after the financial crises in panel B. Before the financial crises it seems that the emerging hedge funds were able to provide alpha during their first operational year. However, after the financial crises the emerging hedge funds do not seem to be able to generate any alpha based on our style-adjusted performance. In panel C, the regression shows that before the financial crises the fund age has a negative effect on fund performance, but after the financial crises the age actually has a positive effect. Although this positive effect after financial crises is not statistically significant. The reasons, why the emerging hedge funds have performed so poorly after the financial crises, can't be exactly explained, but we can theories that it can be associated with the increased competitiveness of the industry and with the increased regulatory pressure and requirements that came with the aftermath of the financial crises. This wouldn't be out of the realm of possibility as Strachman (2009) notes that congress and the federal government were keen on attempting to further regulate the hedge fund industry even before the 2008 market crash began, which manifested in 2006 as SEC passed the most aggressive regulative ruling against hedge funds, although it was later reversed by the U.S. Court of Appeals. We go through these details and changes more in detail in our explanations and conclusion in Chapter 6.

In the hedge funds industry, the hedge funds can differ notably in their organizational structures from each other's. The common types of structures are that hedge funds are run by large multi-product fund management companies, whereas others are run by a single-fund management company. Prior literatures suggest that the single-fund management companies may enjoy higher incentives to succeed as the managers don't have to divide their focus between multiple funds. Instead they can completely concentrate on managing a single fund. Furthermore, managers in multi-product fund management companies, due to reputational spillover reasons, may have a strong incentive to reduce and hide poorly performing funds. This may cause them to shut down their underperforming hedge funds. (Aggarwal & Jorion 2010, 245.) Next in table 6 and 7, we will examine whether differences in fund management organization structures have effect on the funds style-adjusted performance in TASS and in our combined datasets.

Table 6. Style-adjusted performance of the multi- and single-funds in TASS

These two panels present the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. In this table, we split the sample into funds from management companies with multiple and single funds. Panel A presents emerging hedge fund portfolio alphas for single-fund companies in TASS, whereas panel B presents our emerging hedge fund portfolio alphas for multi-fund companies in TASS. Panel C presents our regression on portfolio alphas divided into single- and multi-funds. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Number of funds is estimated at the start of each cohort year. In our sample, we have 1719 emerging hedge funds instead 1728 as nine funds do not have firm id and therefore can't be classified as single- or multi-fund company. Our sample is in TASS from 1996 to 2011.

Panel A: Abnormal performance of single-fund companies in TASS

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	1.27 %	0.607	2.53 %		653
2	1.25 %	0.691	2.32 %	5.41*	604
3	0.89 %	0.638	2.08 %	-4.06	423
4	0.44 %	0.701	2.12 %	4.20*	287
5	0.56 %	0.743	2.16 %	-2.86	198
6	0.82 %	0.803	1.82 %	-2.16	147
7	-0.24 %	0.816	1.64 %	0.77	99
8	0.71 %	0.672	1.58 %	-3.23	74

Panel B: Abnormal performance of multi-fund companies in TASS

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	1.74 %	0.535	1.85 %		1066
2	0.92 %	0.506	1.92 %	6.30*	983
3	0.77 %	0.552	1.61 %	0.17	693
4	0.23 %	0.539	1.64 %	4.42*	483
5	-0.66 %	0.604	1.77 %	-3.68	354
6	0.31 %	0.611	1.50 %	-2.59	251
7	0.69 %	0.658	1.42 %	1.85	168
8	-0.14 %	0.620	1.54 %	3.26*	122

Panel C: Regression of portfolio alphas on age (annual) divided in single- and multi-funds in TASS

	Single-fund	Multi-fund
Independent variables:		
Constant	0.0136*	0.0144*
	(0.0139)	(0.0146)
Ln(Age)	-0.0014*	-0.0020*
	(0.0026)	(0.0019)
Adj. R-squared	0.3871	0.3518
Number of observations	96	96

Table 7. Style-adjusted performance of the multi- and single-funds in Combined data

These two panels present the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. In this table, we split the sample into funds from management companies with multiple and single funds. Panel A presents emerging hedge fund portfolio alphas for single-fund companies in combined dataset, whereas panel B presents our emerging hedge fund portfolio alphas for multi-fund companies in combined dataset. Panel C presents our regression on portfolio alphas divided into single- and multi-funds. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Number of funds is estimated at the start of each cohort year. Our sample is in combined dataset from 1996 to 2017.

Panel A: Style-adjusted performance of single-fund companies in Combined data

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	-0.29 %	0.715	2.80 %		1471
2	-0.23 %	0.746	2.79 %	-1.81	1296
3	-0.64 %	0.732	2.53 %	2.78*	968
4	0.11 %	0.725	1.97 %	-3.96	713
5	-0.62 %	0.723	1.90 %	4.30*	500
6	-0.28 %	0.704	1.87 %	-1.56	370
7	0.22 %	0.736	2.08 %	-1.43	290
8	0.23 %	0.714	1.88 %	-0.03	216

Panel B: Style-adjusted performance of multi-fund companies in Combined data

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	0.65 %	0.602	3.48 %		1623
2	-0.91 %	0.634	2.87 %	7.21*	1450
3	-0.38 %	0.663	2.09 %	-0.43	1103
4	-0.33 %	0.660	2.04 %	-2.55	788
5	-0.68 %	0.655	1.70 %	1.99	590
6	-0.46 %	0.652	1.73 %	0.77	425
7	-0.34 %	0.617	1.63 %	-0.56	335
8	-0.60 %	0.639	1.76 %	0.20	222

Panel C: Regression of portfolio alphas on age (annual) divided in single- and multi-funds

	Single-fund	Multi-fund
Independent variables:		
Constant	-0.0092*	-0.0103
	(0.0125)	(0.0095)
Ln(Age)	0.0007	-0.0008*
	(0.0049)	(0.0027)
Adj. R-squared	0.1556	0.0300
Number of observations	96	96

The panel A shows us the alphas for the single-fund companies in table 6 and 7, whereas the panel B shows us the alphas for the multi-fund companies at these tables. As we can see, most funds belong to multi-fund companies in these datasets. In TASS, 1066 out of 1719 funds belong to multi-fund, whereas we see quite equal distribution in the combined dataset as there is only 1623 multi-funds compared with 1471 single-fund companies. In tables 6 and 7, we see that in our datasets the returns for our funds from both types of organizations are quite similar, but the multi-fund companies have significantly better performance during the initial launch year compared with single-fund companies. Whereas single-fund companies seem to have slightly better alphas during the following second and third year. Our abnormal performance results for these datasets are quite similar to results that Aggarwal and Jorion (2010) receive. Our results are also consistent with the findings of Chen, Hong, Huang and Kubik (2004) in regards that mutual funds tend to have slightly increases in performance when the fund was managed by multi-fund corporation. They credited this faintly improved performance to the economies of scale in trading commissions and marketing costs.

When we look at our beta's at these tables, we can see that the funds run by multi-fund companies have systematically lower betas in TASS and combined dataset when compared with single-fund companies. Nevertheless, when we compare our combined dataset results for the alphas in tables 7 to the TASS alphas of table 6 for the multi- and single-fund companies, we see that our received alphas seem to be messier in combined dataset than the alphas in TASS. There doesn't seem to be a clear pattern in these alphas in combined dataset unlike in TASS. Although, overall our findings from TASS that funds run by multi-fund companies tended have better launch year than single-funds, whereas the single-funds had better alpha during second and third years than multi-funds, this is also true in combined dataset. However, as the alphas in the table 7 vary so heavily from year to year, we can't really feel confident to make any clear predictions based on these alphas. One concern that is raised from these results was that maybe our selection criteria won't work properly in combined dataset when it does in TASS. However, as we can clearly see a similar pattern in single-fund and multi-fund betas in both databases and in the number of funds, it seems that the selection parameter works properly. Other concerns are that the benchmarking isn't working, but as it works in table 4 and the results in the table 7 are in line with the results from the table 4 when you cumulate all these emerging funds back together. Therefore, we must conclude that our received alphas are correctly estimated. Due to the messiness of the received alphas in combined dataset, we could make a hypothesis that based on these results overall there isn't really a difference between these fund companies as the cumulated alphas are pretty much identical when we look at the whole 8-years period.

Next, we are going to look more in detail, how the style-adjusted alphas are dividing on the level of individual months during the first three operational years. Table 8 shows us these style-adjusted alphas for the first 36 months in the combined dataset. When we look at our alphas in the table 8, we see that during the first year the positive alphas come between the 4 and 12 months. As it comes to years two and three, there is no months with the positive alphas. During the first 3 months the negative alphas possible can be caused by the fact that the funds are just starting up their operations. This can cause the fund to incur more costs and less time is focused on investing their assets during the first couple months, which can also lead to poorer performance for the fund. All in all, there is not much you can tell based purely on these values, but they give us once again more evidence that the core of the alpha generated by emerging hedge funds is mostly produced during the first operational year.

Table 8. Style-adjusted performance of first 36 months in Combined data

This panel presents the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. In this panel, we present the emerging hedge fund portfolio alphas for the first 36 months in combined dataset. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. Our sample is in combined dataset from 1996 to 2017.

	Year	1		2		3
Month	α	Ste	α	Ste	α	Ste
1	-0.31 %	2.41 %	-0.51 %	2.67 %	-0.50 %	2.15 %
2	-0.03 %	2.35 %	-0.56 %	2.21 %	-0.55 %	2.08 %
3	-0.18 %	2.49 %	-0.49 %	2.38 %	-0.42 %	2.02 %
4	0.26 %	2.74 %	-0.55 %	2.29 %	-0.49 %	2.05 %
5	0.43 %	2.77 %	-0.66 %	2.45 %	-0.47 %	1.99 %
6	0.37 %	2.70 %	-0.61 %	2.52 %	-0.54 %	2.11 %
7	0.26 %	2.68 %	-0.70 %	2.37 %	-0.48 %	2.04 %
8	0.33 %	2.79 %	-0.63 %	2.33 %	-0.56 %	2.07 %
9	0.27 %	2.44 %	-0.68 %	2.38 %	-0.51 %	2.12 %
10	0.25 %	2.73 %	-0.57 %	2.35 %	-0.49 %	1.96 %
11	0.39 %	2.78 %	-0.54 %	2.51 %	-0.47 %	1.92 %
12	0.35 %	2.80 %	-0.60 %	2.45 %	-0.53 %	2.09 %
Total	0.20 %	2.64 %	-0.59 %	2.41 %	-0.50 %	2.06 %

4.2 Backfilled vs. non-backfilled funds

In this chapter, we are going to show our alphas in event time for the backfilled funds in our TASS and combined datasets. To identify how much of this performance is created by the firms backfilling positive returns to the databases, we are going to re-create our backfilled sample by removing all monthly return observations prior to the fund starting to report performance to the database. Since we have the date added to database variable available in our data, we can treat all monthly return observations prior to this date as backfilled. Therefore, we can remove them from the data. Next, we calculate alphas for the remaining non-backfilled observations in event time, where the date added to the database is the beginning of event time. We can see these results for the backfilled funds in panel A and for the non-backfilled funds in panel B, whereas in panel C we have regressions for these alphas. In table 9 we show our results for the TASS and in table 10 for the combined dataset.

Table 9. Backfilled vs. non-backfilled fund alphas in TASS

These two panels present the performance of our portfolios aligned by event time, which is the first month of reported performance. Funds are backfilled. In panel A, the event time starts with the first month of reported performance after inception. In panel B, the event time starts with the first month of reported performance after the fund starts reporting to the TASS database. Panel C shows our regressions on portfolio alphas on age divided based on backfill in TASS. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level is indicated by *. Average of fund beta is the cross-sectional average of beta for each fund. Our sample is in TASS from 1996 to 2011.

Panel A: Style-adjusted performance from inception in TASS

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	4.09 %	0.775	2.24 %		6444
2	3.42 %	0.780	2.08 %	0.29	6208
3	2.87 %	0.787	2.05 %	-0.37	6057
4	2.61 %	0.813	1.83 %	-0.34	5119
5	2.16 %	0.847	1.79 %	-0.42	4151
6	1.77 %	0.793	1.62 %	4.25*	3187
7	1.55 %	0.875	1.61 %	2.20	2397
8	1.67 %	0.804	1.68 %	-0.71	1772

Panel B: Style-adjusted performance from date added to database in TASS

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	2.60 %	0.686	1.92 %		5989
2	2.12 %	0.702	1.67 %	0.31	5777
3	1.66 %	0.710	1.75 %	-0.38	5498
4	1.33 %	0.777	1.69 %	-0.31	4729
5	0.89 %	0.757	1.24 %	-0.47	3876
6	0.66 %	0.784	0.99 %	4.40*	2995
7	0.45 %	0.768	1.43 %	2.80*	2264
8	0.76 %	0.814	1.77 %	-0.84	1685

Panel C: Regression of portfolio alphas on age (annual) divided based on backfill in TASS

	Backfilled	Non-backfilled
Independent variables:		
Constant	0.0413*	0.0263*
	(0.0320)	(0.0222)
Ln(Age)	-0.0036*	-0.0029*
	(0.0039)	(0.0043)
Adj. R-squared	0.9215	0.8682
Number of observations	96	96

Table 10. Backfilled vs. non-backfilled fund alphas in combined dataset

These two panels present the performance of our portfolios aligned by event time, which is the first month of reported performance. Funds are backfilled. In panel A, the event time starts with the first month of reported performance after inception. In panel B, the event time starts with the first month of reported performance after the fund starts reporting to our combined dataset. Panel C shows our regressions on portfolio alphas on age divided based on backfill in combined dataset. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level is indicated by *. Average of fund beta is the cross-sectional average of beta for each fund. Our sample is in combined data from 1996 to 2017.

Panel A: Style-adjusted performance from inception in combined dataset

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	2.48 %	0.800	1.94 %		9136
2	2.02 %	0.808	2.07 %	0.48	9121
3	1.58 %	0.815	1.58 %	0.41	8566
4	1.55 %	0.817	1.55 %	0.30	7587
5	1.45 %	0.819	1.45 %	0.29	6550
6	1.21 %	0.827	1.21 %	5.40*	5586
7	0.96 %	0.838	0.96 %	1.90	4632
8	0.95 %	0.844	1.65 %	0.09	3820

Panel B: Style-adjusted performance from date added to database in combined dataset

Year	Alpha (Annual)	Average of fund beta	Standard error	T-statistic of Equal Alpha	Number of funds
1	1.92 %	0.797	2.25 %		8246
2	1.65 %	0.804	1.25 %	0.47	8132
3	1.22 %	0.811	1.73 %	0.40	7777
4	1.20 %	0.815	1.26 %	0.30	7010
5	1.00 %	0.817	1.47 %	0.29	6130
6	1.01 %	0.826	1.32 %	5.50*	5272
7	0.65 %	0.838	0.97 %	2.19	4391
8	0.61 %	0.843	1.28 %	0.17	3653

Panel C: Regression of portfolio alphas on age (annual) divided based on backfill

	Backfilled	Non-backfilled
Independent variables:		
Constant	0.0245*	0.0196*
	(0.0212)	(0.180)
Ln(Age)	-0.0021*	-0.0018*
	(0.0015)	(0.0012)
Adj. R-squared	0.9089	0.9233
Number of observations	96	96

As we can see in tables 9 and 10 the alphas are higher in these datasets for the funds when we calculate them from the inception rather than from the date added to the database. This difference can be easily seen in tables 9 and 10 as the alphas get weaker as we move from the inception in panel A to date added to the database in panel B. This would suggest that during the first few years of a fund's life there are important return effects that can be missed if we simply remove all backfilled returns. These findings are in line with the findings of Aggarwal and Jorion (2010) although the differences between our alphas from inception in panel A and the alphas from the date added to the database in panel B of the table 9 and 10 are much smaller than they are in their research. This could indicate that the backfill bias is not that heavy in our data sample than it was in the dataset that they employ in their research. We can also note that it seems that age has stronger effect on backfilled hedge funds than it has on non-backfilled funds.

4.3 Performance persistence

Based on our results it seems that the emerging funds and managers tend to on average perform better during their earlier years, especially during their first year of operations. Next, we will look more in detail if this over-performance is created by specific fund or by a sub-sample of funds within our data sample. To identify whether specific funds that have performed well continue to perform well, we will use the same method that Aggarwal and Jorion (2010, 250) use in their paper as we examine whether performance is persistent in the cross-section of emerging funds or not. Our methodology is based on Carpenter and Lynch (1999) as they suggest that you would form the portfolios of funds based on performance deciles if there is little to none survivorship bias in the data that is being employed. However, as the number of hedge funds is smaller than the number of mutual funds in their research, the Aggarwal and Jorion (2010) suggest that we should form quintiles from our funds instead of deciles.

We will rank our emerging hedge funds based on the first-year performance in the quintiles. The lowest average alphas are in Q1 and the highest average alphas are in Q5 portfolio. During each year, we calculate the average annual alpha for each of the portfolio quintiles. The funds will stay in the same quintile as they were ranked in the first-year. Lastly, we measure the difference between the average annual alpha of Q5 and Q1. The results for the performance persistence of our fund portfolios in TASS and combined datasets can be seen table 11. In table 11, the panel A show our results for the TASS datasets and the panel B shows the results for our combined dataset.

Table 11. Performance persistence in event time: Non-backfilled hedge funds

Panel A and B will present our results for differences in performance between top and bottom portfolio quintiles sorted by prior performance. We sort our hedge funds into five portfolios by alpha (α) quintiles in year t – 1 (the ranking period); after this the performance is measured from the annualized average portfolio alpha (α) in year t (the evaluation period). Funds may have partial observations during the evaluation period, this way there isn't a look ahead period. During the evaluation periods, each quintile's alpha is reported with standard errors (Ste) and average fund betas (β). The "difference" column reports the difference in annual alpha between the top quintile (Q5) portfolio and the bottom quintile (Q1) portfolio.

Panel A: Alphas sorted by year of inception, then by size quintile in TASS

		Year							
Alpha quintile		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Q1 (bottom)	α	-8.42 %	-6.54 %	-5.41 %	-3.81 %	0.16 %	0.96 %	-1.71 %	0.52 %
	Ste	5.55 %	5.40 %	4.84 %	5.61 %	4.96 %	4.46 %	5.08 %	4.55 %
	β	0.966	0.931	0.922	0.845	0.825	0.886	0.826	0.712
Q2	α	-0.59 %	-1.19 %	-1.08 %	-0.79 %	-0.21 %	-0.70 %	-0.69 %	0.25 %
	Ste	3.01 %	3.12 %	2.91 %	3.22 %	2.85 %	2.72 %	3.46 %	2.71 %
	β	0.614	0.662	0.675	0.703	0.769	0.839	0.781	0.714
Q3	α	3.84 %	2.03 %	1.94 %	1.55 %	-0.80 %	0.79 %	1.17 %	0.81 %
	Ste	2.55 %	2.74 %	2.63 %	2.84 %	2.45 %	2.41 %	2.79 %	2.67 %
	β	0.390	0.441	0.446	0.509	0.516	0.506	0.625	0.587
Q4	α	5.03 %	3.56 %	2.96 %	1.95 %	-0.73 %	1.24 %	0.78 %	-0.04 %
	Ste	2.50 %	2.90 %	2.94 %	3.28 %	2.78 %	2.65 %	3.02 %	2.60 %
	β	0.372	0.384	0.409	0.489	0.520	0.550	0.600	0.567
Q5 (top)	α	7.87 %	7.39 %	5.90 %	2.73 %	0.55 %	0.50 %	2.19 %	-0.54 %
	Ste	4.54 %	4.33 %	4.30 %	4.52 %	4.05 %	4.07 %	4.45 %	3.54 %
	β	0.480	0.466	0.482	0.553	0.631	0.661	0.747	0.626
Difference Q5 – Q1	α	16.29 %	13.93 %	11.31 %	6.54 %	0.39 %	-0.46 %	3.90 %	-1.06 %

Panel B: Alphas sorted by year of inception, then by size quintile in combined dataset

		Year							
Alpha quintile		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Q1 (bottom)	α	-7.62 %	-6.94 %	-5.76 %	-3.57 %	-2.28 %	0.29 %	-1.87 %	0.67 %
	Ste	5.36 %	5.02 %	5.08 %	5.06 %	4.60 %	4.71 %	4.47 %	4.43 %
	β	0.931	0.912	0.951	0.965	0.837	0.812	0.842	0.829
Q2	α	-1.54 %	-1.67 %	-1.62 %	-0.77 %	-0.68 %	0.12 %	-2.34 %	-1.41 %
	Ste	2.87 %	2.90 %	2.91 %	3.05 %	2.53 %	2.66 %	2.93 %	2.79 %
	β	0.724	0.768	0.771	0.767	0.713	0.733	0.717	0.730
Q3	α	1.54 %	0.96 %	1.05 %	0.62 %	-0.86 %	-0.97 %	0.98 %	0.36 %
	Ste	2.36 %	2.19 %	2.37 %	2.37 %	2.29 %	2.23 %	2.46 %	2.49 %
	β	0.540	0.597	0.583	0.582	0.646	0.605	0.631	0.628
Q4	α	3.15 %	1.84 %	1.78 %	1.43 %	0.42 %	-0.71 %	2.14 %	-0.79 %
	Ste	2.23 %	2.45 %	2.60 %	2.41 %	2.46 %	2.26 %	2.64 %	2.77 %
	β	0.520	0.517	0.537	0.521	0.560	0.578	0.556	0.533
Q5 (top)	α	5.52 %	2.95 %	2.06 %	1.68 %	0.16 %	-0.65 %	0.71 %	0.98 %
	Ste	4.48 %	4.22 %	4.29 %	3.91 %	3.85 %	3.58 %	4.08 %	3.55 %
	β	0.572	0.638	0.634	0.615	0.677	0.657	0.614	0.667
Difference Q5 – Q1	α	13.14 %	9.89 %	7.82 %	5.25 %	2.24 %	-0.94 %	2.58 %	0.31 %

When we look at the results which we get from the table 11, we notice that there is a clear difference between the Q1 and Q5 in both datasets in panel A and B during the first four years. In TASS, the difference is during these initial four years 16.29%, 13.93%, 11.31% and 6.54%. Whereas, the difference in combined dataset is a little bit lower as it is during four first years 13.14%, 9.89%, 7.82% and 5.25%. Our results are in-line with the results of Aggarwal and Jorion (2010) and with the prior literature such as Kosowski, Naik, and Teo (2007). Although Aggarwal and Jorion (2010) find clear performance persistency for the funds during the first 5 years for the top quintile and for the first 6 years for the bottom quintile. Whereas we can only see performance persistency for the top quintile during the first four years. For the bottom quintile we also see persistence for the first four years in TASS, but for the first five years in combined dataset. On average we see performance persistency for the first four years and after that the spreads get quite messy. According to the Aggarwal and Jorion (2010) this finding is important as the performance persistence for poorly performing funds can be caused by the fact that the fund's poor performance will cause the investors to do redemptions from the fund. This can force the fund to liquidate some of their holdings so that they can meet these redemptions, which can lead even further performance deterioration. We can conclude that the specific emerging funds that perform better during the first year relative to other emerging hedge funds seem to continue to do so for the first few years. It is also true that the funds that do badly will continue to do badly for a few first years, this indicates that there is clear performance persistence in our emerging hedge funds data.

4.4 Controlling for size

The evidence we have gathered so far on the better performance of emerging hedge funds, especially in their first operational year, could be explained by the number of different factors. For example, this improvement in performance could be explained by the incentive effects of our emerging funds. Furthermore, it is possible that this outperformance is actually generated by the fund's size instead of fund's age. The size of the fund is measured in TASS and in our combined data as assets under management in US dollars for each fund. Therefore, we are able to factor in the AUM to our regressions and identify if it is the source of our emerging hedge fund outperformance. We can evaluate the fund performance by dividing the funds into size quintiles based on their AUM at the time of their inception. We are going to use once again similar method that Aggarwal and Jorion (2010) use in their paper. We will sort the funds by the year of inception rather than cumulate all these funds together. After this, we will divide them into quintiles as the average size of emerging funds has increased significantly over the years. If we would just pool all of our emerging funds to form these quintiles, the largest quintile would most likely be the latest year, which would be in TASS 2011 and in combined dataset 2017. This would mean that our largest quintile would have only couple years' worth of performance data. Therefore, we are going to form quintiles of funds beginning from 1996, then quintiles of funds in 1997 and so on until the last year in that sample.

Next, we are going to run our analysis in event time and keep each fund in the same quintile. This means that the fund may grow or shrink in size, but it will stay in the same assigned quintile it belongs to at the beginning of our analysis. The key factor in this analysis therefore is the initial beginning AUM of the fund. By using this selection or categorization criteria, we can get a clearer picture if the outperformance is generated by the funds that are initially smaller in size, or do the larger funds have a better performance. According to Aggarwal and Jorion (2010, 251) the disadvantage from using this kind of sorting method is that it does not ensure a continuously balanced allocation into quintiles. Nevertheless, this disadvantage should be seen as a necessary sacrifice in order to achieve proper sorting for our emerging hedge funds AUM.

The results we receive in table 12 are comparable to the results we received in the table 4. As we can see from the panel A and C our quintiles are not exactly equal. This is caused by the fact that the funds are divided in to five ranking portfolios based on AUM in a percentage basis. However, this shouldn't really make a noticeable difference in our results. In panels A and C, we see that the number of funds decreases sharply as we move further in the event time. Still although this decrease in our quintiles, they stay quite balanced in the number of funds relative to each other's. When we look at our alphas, we notice that in panel A in TASS data there seems to exist quite uniform size effect on the alphas. On the contrary, this does not seem to be true in panel C for the combined dataset. Our last column shows as the average alpha, beta, standard error and AUM for our quintiles over eight years. The panels B and D show our regressions to the TASS and combined dataset, where the small funds are quintiles 1 to 3 and the large funds are quintiles 4 and 5.

Table 12. Alphas sorted by year and then by size quintile

These tables present the performance of our emerging hedge fund portfolios in TASS and combined dataset aligned by event time, which is the first month of reported performance. Our funds are non-backfilled. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alphas are measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Funds are classified into size quintiles formed by assets under management (AUM) in each individual year. Panel A presents the average alpha and other statistics for the funds in TASS. Panel C presents the average alpha and other statistics for the funds in combined dataset. Panels B and D show our regressions on portfolio alphas on age and size for our datasets. Quintiles are classified by calendar year to account for the growth in assets in the hedge fund industry (after adjusting for inflation) and measured in 2011 dollars in TASS and in 2017 dollars in combined dataset. The first row presents the average annual alpha (α). The second row is the standard error (Ste). The third row reports the average fund beta (β) and the fourth row reports the average AUM in a million $ at the beginning of each year. The fifth row reports the number of funds (N) at the beginning of each year since inception. In the end, we have the average column where we have calculated the averages of our estimates for eight years. The bottom row reports the T-statistic for the test of the joint hypothesis that five quintiles have the same alpha. Statistical significance at the two-sided 95% level is indicated by *.

Panel A: Alphas sorted by year of inception, then by size quintile in TASS

Size quintile		Year 1	2	3	4	5	6	7	8	Average
Smallest	α	2.08 %	1.27 %	1.10 %	1.29 %	0.88 %	0.89 %	0.31 %	0.79 %	1.08 %
	Ste	1.93 %	1.55 %	1.26 %	1.51 %	1.57 %	1.45 %	1.73 %	1.42 %	1.55 %
	β	0.513	0.582	0.595	0.638	0.623	0.678	0.722	0.698	0.631
	AUM	0.95	1.75	2.61	3.58	3.88	4.01	5.46	5.30	3.44
	N	354	327	212	158	105	74	51	35	
2	α	1.85 %	0.78 %	0.69 %	0.81 %	-0.73 %	0.54 %	-0.03 %	1.14 %	0.63 %
	Ste	2.00 %	1.79 %	1.54 %	1.69 %	1.93 %	1.80 %	1.76 %	2.12 %	1.83 %
	β	0.546	0.591	0.602	0.609	0.669	0.694	0.693	0.603	0.626
	AUM	3.66	6.81	12.13	16.65	16.78	19.62	23.38	23.69	15.34
	N	368	342	236	163	117	81	59	45	
3	α	1.68 %	1.18 %	1.04 %	0.56 %	-0.13 %	0.81 %	0.32 %	0.94 %	0.80 %
	Ste	1.85 %	1.60 %	1.69 %	1.65 %	1.70 %	1.37 %	1.43 %	1.76 %	1.63 %
	β	0.563	0.576	0.577	0.583	0.665	0.723	0.724	0.614	0.628
	AUM	8.96	18.07	32.85	43.08	47.49	55.95	62.62	66.15	41.90
	N	374	348	244	156	120	86	60	39	
4	α	1.02 %	0.94 %	0.49 %	-0.79 %	-0.22 %	0.69 %	0.81 %	-0.72 %	0.28 %
	Ste	1.76 %	1.43 %	1.72 %	1.58 %	1.50 %	1.68 %	1.75 %	1.63 %	1.63 %
	β	0.604	0.571	0.573	0.607	0.688	0.686	0.706	0.645	0.635
	AUM	22.13	44.97	76.17	100.83	118.33	135.54	156.85	177.11	103.99
	N	361	337	228	159	114	82	52	44	
Largest	α	0.96 %	1.11 %	0.72 %	-0.33 %	-0.99 %	-0.37 %	0.41 %	-1.35 %	0.02 %
	Ste	1.57 %	1.69 %	1.41 %	1.40 %	1.64 %	1.17 %	1.09 %	1.73 %	1.46 %
	β	0.586	0.546	0.567	0.618	0.612	0.623	0.739	0.657	0.619
	AUM	106.61	217.98	335.78	455.95	498.20	548.14	793.48	741.60	462.22
	N	262	233	196	134	96	75	45	33	
F-statistic		3.43*	4.39*	-2.00	0.13	-1.61	4.10*	-0.91	1.09	
P-value		0.10	0.06	0.89	0.64	0.20	0.08	0.74	0.91	

Panel B: Regression of portfolio alphas on age (annual) and size, sorted by size in TASS

	Small	Large
Independent variables:		
Constant	0.0155*	0.0117*
	(0.0129)	(0.0137)
Ln(Age)	-0.0013*	-0.0017*
	(0.0085)	(0.0089)
Ln(Size)	-0.00005	-0.00007
	(0.0062)	(0.0084)
Adj. R-squared	0.2534	0.3147
Number of observations	288	192

Panel C: Alphas sorted by year of inception, then by size quintile in combined data

		Year								
Size quintile		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Average**
Smallest	α	0.41 %	-0.78 %	-0.59 %	-0.23 %	-0.52 %	-0.08 %	-0.57 %	-0.57 %	-0.37 %
	Ste	1.93 %	1.74 %	1.23 %	1.19 %	1.50 %	1.26 %	1.32 %	1.21 %	1.42 %
	β	0.645	0.697	0.699	0.665	0.700	0.673	0.696	0.679	0.682
	AUM	1.01	1.75	2.57	3.15	3.44	3.21	3.09	3.56	2.72
	N	636	561	366	289	218	151	118	85	
2	α	-0.03 %	-0.98 %	-0.36 %	-0.19 %	0.21 %	0.08 %	0.27 %	0.48 %	-0.07 %
	Ste	1.73 %	1.63 %	1.29 %	1.44 %	1.57 %	1.41 %	1.23 %	1.31 %	1.45 %
	β	0.668	0.704	0.695	0.677	0.678	0.696	0.664	0.706	0.686
	AUM	4.14	7.58	11.23	13.22	14.07	13.72	13.98	17.05	11.87
	N	609	571	459	323	225	163	139	92	
3	α	0.31 %	-0.13 %	-0.44 %	0.22 %	-0.86 %	-0.18 %	0.51 %	0.34 %	-0.03 %
	Ste	1.64 %	1.45 %	1.33 %	1.45 %	1.23 %	1.31 %	1.06 %	1.30 %	1.35 %
	β	0.658	0.680	0.698	0.642	0.690	0.671	0.653	0.662	0.669
	AUM	10.73	18.72	27.30	32.00	35.06	39.86	43.70	54.25	32.70
	N	689	535	478	336	243	175	140	96	
4	α	-0.12 %	-0.45 %	-0.71 %	-0.47 %	-0.95 %	-1.26 %	-0.08 %	-0.69 %	-0.59 %
	Ste	1.51 %	1.50 %	1.33 %	1.51 %	1.50 %	1.29 %	1.22 %	1.36 %	1.40 %
	β	0.667	0.678	0.693	0.651	0.691	0.684	0.697	0.694	0.682
	AUM	24.15	42.63	63.31	76.11	91.72	101.78	121.42	155.77	84.61
	N	614	582	447	319	223	172	127	90	
Largest	α	0.40 %	-0.58 %	-0.38 %	0.08 %	-1.22 %	-0.41 %	-0.81 %	-0.66 %	-0.45 %
	Ste	1.54 %	1.50 %	1.36 %	1.30 %	1.49 %	1.36 %	1.27 %	1.38 %	1.39 %
	β	0.640	0.679	0.690	0.633	0.668	0.652	0.650	0.632	0.656
	AUM	122.44	210.95	317.96	462.94	604.30	640.61	740.15	840.33	492.46
	N	546	497	321	234	181	134	101	75	
F-statistic		0.58	0.40	0.30	0.30	5.42*	1.70	0.61	2.83*	
P-value		0.37	0.81	0.51	0.17	0.05	0.90	0.74	0.11	

Panel D: Regression of portfolio alphas on age (annual) and size, sorted by size in combined data

	Small	Large
Independent variables:		
Constant	-0.00372	-0.00140*
	(0.00209)	(0.00243)
Ln(Age)	0.00019*	-0.00091*
	(0.00045)	(0.00060)
Ln(Size)	0.00084*	0.00010
	(0.00659)	(0.00477)
Adj. R-squared	0.0308	0.0825
Number of observations	288	192

Our results on the average alphas in the table 12 for our quintiles are quite different when we compare the combined data and TASS. In combined data in panel C it seems that the mid-sized funds (rank 3) have the best performance in our eight-year period. However, the smallest and largest funds (rank 1 & 5) have the best initial performance during the launch year. Whereas in TASS in panel A the smallest funds (rank 1-3) seem to have the best launch performance. When we look at the TASS results over the eight-year period, we see that smallest and mid-sized funds in the first and third quintile have the best total performance. If we combine these findings, we can conclude that the funds that will launch with around 10$ million in AUM have the best performance and these findings would align with the previous findings of Aggarwal and Jorion (2010).

The bottom two rows in our panels A and C have our results for the joint test of equality of alphas across of these five quintiles. In both panels, we have a few years, where we have to reject the hypothesis of equality of alphas, with a low P-value. These years are in panel A first, second and the sixth year and in panel C years fifth and eight. However, the main information in these tables is the variation, that we can see across the years and not the variations we can see in the quintiles. When we look at our regressions in the tables B and D, we notice that our regressions have quite different results in TASS than we have in the combined dataset. Both age and size have a negative effect on fund performance in TASS for both small and large funds. However, when we look at our results for the combined dataset in panel D, the size has a positive effect on fund performance regardless of the initial size of the fund. Whereas the age has a positive effect on smaller funds and negative for the larger funds. Nonetheless, our results indicate that picking a manager by the age of their fund would be a more informative method, than choosing them by the initial AUM size of the fund. These findings are consistent with our hypothesis that the age is the driving factor of the emerging hedge funds performance rather than the size of the funds.

Based on our TASS and combined datasets it seems that the small managers are outperforming the larger managers slightly during the first couple years of operations. This finding aligns with the hypothesis that small managers provide a slightly greater alpha than the funds that launch with a larger AUM pool. Aggarwal and Jorion (2010) end up in their research in the conclusion that the larger managers seem to do better in their first or two years of existence. However, they explain that this can be due to the small AUM sizes of their quintiles, whereas our AUM sizes in each quintile are much larger. Although, the AUM in our largest quintiles are at the inception around 110$ million, which still is a relatively small size for the hedge fund. Therefore, it is highly unlikely that our emerging hedge funds would suffer from the diseconomies of scale in a notable degree. It is actually more likely that they would benefit from it as an example, via decreased trading costs and better access to information. It is also noteworthy that smaller managers seem to close down faster from the inception than the larger managers in our data. This could indicate that funds that start with the larger initial AUM base are more capable of withstanding the variation in their performance and following possible investor's redemption requests. This would be a reasonable expectation as most of the funds that do start with the larger AUM base are funds that come from multi-fund companies. Furthermore, investors have been more tolerable towards performance variation in funds that come from multi-fund companies due to the existing reputation for these multi-fund management companies. Additionally, we expect that the multi-funds have an advantage to attract more capital for their new fund launches than the single-fund companies are capable of. Also, it can be the case that these managers, who already have been able to attract more capital during their launch phase, are enjoying greater trust effects. This can be the reason that leads into a situation, where the investors are not that sensitive to redeem their capital from these funds as they would be in the smaller funds. It is also noteworthy, that due to the fee structure of the hedge funds, the smaller emerging hedge funds are not as capable of sustaining themselves if the initial performance is poor as the larger funds are. The reason for this is that if the fund’s performance is poor, they won’t receive enough income from their fixed fees and therefore they can’t cover their overhead costs.

4.5 Performance difference between general fund strategies

Next, we are going to look more in detail if there is a difference in performance between the different fund strategies. We are going to cumulate our ten different fund strategies in combined dataset into four broad strategies that Agarwal, Daniel and Naik (2009) identify in their paper. These broad strategies are directional traders, relative value, security selection and multiprocess. The strategies that belong under the directional traders in our data are the sector, short bias, emerging markets, global macro and others. Whereas under the relative value belongs relative value and market neutral. Additionally, long/short belongs to security selection. Lastly, the multiprocess contains multi-strategy and event driven fund strategies. In table 13 we can see our results for our broad strategy classifications. The style-adjusted alphas are estimated for our strategy cohorts for the first eight operational years. In the end, we have the average alpha over these eight first years with the average standard error. The number of funds at this table are measured at the beginning of each year.

Table 13. Broad strategy alphas in combined dataset

This panel presents the performance of our emerging hedge funds portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. In this panel, we present the emerging hedge fund portfolio alphas sorted by their investment strategy into broad strategies in combined dataset. Portfolios are constructed as the equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{st}$, where R_s is the style index and beta are estimated over a two-year window. Alpha and its standard error are annualized. Average of fund beta is the cross-sectional average of beta for each fund. The N is the number of funds at the beginning of that current year. Our sample is in combined dataset from 1996 to 2017.

		Year								
Strategy		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Average**
Directional	α	1.23 %	-0.39 %	-0.45 %	0.44 %	-0.23 %	0.74 %	1.45 %	0.35 %	0.39 %
Traders	Ste	4.10 %	3.39 %	2.94 %	2.44 %	2.05 %	1.97 %	1.85 %	1.60 %	2.54 %
	N	778	710	557	407	293	219	166	98	
Relative	α	-0.09 %	-0.54 %	-1.14 %	-0.82 %	-1.14 %	-1.41 %	-1.23 %	-1.17 %	-0.94 %
Value	Ste	2.34 %	2.34 %	2.05 %	1.82 %	1.68 %	1.76 %	1.72 %	1.74 %	1.93 %
	N	613	552	422	308	227	158	123	84	
Security	α	-0.46 %	-1.04 %	-0.40 %	-0.16 %	-0.77 %	-0.34 %	-0.14 %	0.03 %	-0.41 %
Selection	Ste	2.02 %	1.93 %	1.39 %	1.15 %	0.96 %	0.81 %	0.74 %	0.72 %	1.22 %
	N	883	768	565	424	306	225	177	140	
Multi-	α	0.16 %	-0.34 %	-0.16 %	-0.11 %	-0.55 %	-0.85 %	-0.73 %	-0.21 %	-0.35 %
process	Ste	2.15 %	2.01 %	1.86 %	1.58 %	1.48 %	1.49 %	1.51 %	1.59 %	1.71 %
	N	820	716	527	362	264	193	159	116	

When we look at our results from the table 13, we notice that only directional traders are able to generate a substantial alpha during the initial launch year. We can also notice that the directional traders are the only broad strategy classification that is able to generate positive alpha on average through our time series. Although the directional traders also have the largest variation in performance within this group as their standard error is almost double to the other strategy classifications. We can hypothesize, that the difference we see between the directional traders and other broad strategies, could be explained by that the directional traders' category is not as competitive as others. Other explanation could be that these strategies are easier to employ or there are more opportunities for a small sized funds. On the other hand, relative value, security selection and multi-process can be more capital intensive or there are greater benefits for the funds to be obtained through the economies of scale.

Additionally, when we look at the table 13, we see that most strategies are experiencing their best performance during the initial launch year. For example, multi-process fund strategies only achieve average positive alpha during their launch year and relative value has the weakest negative alpha during this launch year. This ensures us that the better initial performance in our emerging hedge funds is not only driven by some sub-sample of our strategies although the actual positive alpha we see in our combined emerging hedge fund return data during the launch year is clearly driven by the funds that belong to the category of directional traders. Further research could be necessary if we would want to identify if this performance we see in directional traders is driven by a specific strategy sub-sample in this particular broad strategy classification. Although we would need a much larger data sample in order to get accurate estimates as we only have at the beginning of our time series only 778 funds in total that belong to directional traders broad strategy classification. This would mean that there would be possible less than 100 funds in these strategy sub-samples and therefore our measurements would be based on very few observations, which would make them highly unreliable. Nonetheless, based on our results from the table 13, we can confidently state that the better initial performance that emerging hedge funds are able to generate in our data are driven by the funds that belong directional traders category, these strategies were sector, short bias, emerging markets, global macro and others. Therefore, investors, that allocate capital towards emerging hedge funds, would be able to achieve greater relative returns, compared with more established hedge funds, on their investments if they would focus on investing in emerging hedge funds that belong to directional traders broad strategy classification and avoid investing in other emerging hedge funds altogether.

5 CONCERNS IN THE DATA AND RESULTS

In this chapter, we are going through a few things to address some of the empirical concerns that maybe affecting the results of this thesis.

5.1 Backfill bias

In our thesis, we use databases that have an inherent risk of having backfill biased hedge fund performance data as the reporting is voluntary in both of our employed databases, which were TASS and HFR. The backfill bias generated by the self-reporting in these commercial databases is our main concern regarding this thesis. This is because the backfill bias tends to affect most heavily early returns in the funds' life, which is the main focus of this thesis. The self-reporting may cause some backfill issues as funds can register to the database, but if their performance is not great during the fund launch, they may choose to never start reporting their performance to these databases. This can be the reason why we have a positive alpha during the initial launch year. As funds that have had great initial launch performance may start to report within our 180-days period between the date added to database and first performance reporting date. Whereas funds that have had for example, poor performance after 100 days may choose not to start to report their performance. This is normal for the fund managers that want to portray their funds as positively as possible. Therefore, they may choose not to start to report their performance if their fund's performance was not up to their standards immediately after the inception. (Cao, Farnsworth & Zhang 2016, 24–25.)

Due to these reasons, the available performance data, especially from the funds' early lives immediately after the inception, can have an upward bias. This bias may exist even after our emerging fund selection criteria, which has also been concern in prior literature like in research by Fung and Hsieh (2000). They identify that these commercial databases tend to have a backfill bias effect. This potential backfill bias is a concern in our analysis, because we compare emerging hedge funds performance after the inception to more seasoned hedge funds. Our analysis is also mostly looking at the performance of these funds during the first few operational years. We try to mitigate these problems that arise from the backfill bias by using our strict selection criteria for emerging hedge funds. However, as our emerging hedge funds tend to generate alpha pretty much exclusively during their first operational year, it can be likely that this initial alpha is mainly generated by the backfill bias. Because the backfill bias still affects the immediate performance most heavily after the funds launch. (Cao, Farnsworth & Zhang 2016, 24–25.)

5.2 Errors in the statistical models and codes

In this thesis, the harder parts have been the conduction of statistical analysis of the subject. As we have worked on large datasets that have caused a few issues and generally conducting the analysis have been tedious in coding vice. Therefore, we can't say that there couldn't be any coding errors or error in our statistical models, that may have altered our results. It can be possible that someone with a better coding and statistical skills could receive different results based on the exactly same data. These problems and errors can be hard to detect and therefore some of them may have remained in our models. We think that there is still much to learn, especially in use of statistical software's such as R, Python and SAS and in turning statistical models and calculations in to code. Coding our models has been the most time-consuming part in this thesis. It is necessary for us to recognize that these things may have indeed affected the quality of our research. Therefore, this should be recognized when estimating the validity of our results regarding the performance of emerging hedge funds.

5.3 Alternative benchmark to estimate emerging fund alphas

We could have used a different benchmark to estimate the emerging hedge fund alphas. As now we use our own constructed benchmark based on available fund performance data in our used databases TASS and HFR. We could have instead used the exact same method that Aggarwal and Jorion (2010) used by getting the CSFB indexes. Mainly, we could have tried to include the one criteria that we couldn't include in our own benchmark. This criterion was in CSFB indexes and it was the requirement that the fund had to have audited financial statements. Nevertheless, as we didn't see any easy way to include this criterion in our data, we had to leave it out from our benchmarks. Due to our use of the different benchmark and time series, our results are not directly comparable to the results that Aggarwal and Jorion (2010) receive in their research.

6 CONCLUSIONS

The prior literature has analyzed the emerging hedge funds and some of the properties that are associated with them. These properties can be for example the incentive effects that emerging funds enjoy. Prior literature find that emerging funds can be nimbler when it comes to investment strategies and fee structures. They also have a stronger financial interest to be able to deliver strong performance than the older funds do. Newer hedge funds are on average more open to new investors and may provide access to strategies that otherwise wouldn't be open for the investors. Prior literature find that the emerging hedge funds tend to provide alpha over the industry average in their early years. Our thesis provides further analysis on emerging hedge fund performance and we contribute a few new findings in the hedge fund literature.

First, we replicate the analysis conducted by Aggarwal and Jorion (2010) with the larger data sample. We did this to see if the prior findings on the emerging hedge funds have changed in magnitude. We find that the style-adjusted performance of emerging hedge funds has weakened from the findings of prior literature. Although, most of the findings that prior literature has made are still valid, but the magnitude of these findings has become much weaker. In our cohort analysis, we find that the performance of emerging funds deteriorates over time and on average they provide positive style-adjusted performance only during their initial launch year. We also find that instead of the funds that will start with a larger AUM pool, the mid-sized funds performed the best, when we are looking at the funds size effects.

Secondly, we find that after the financial crises the emerging hedge funds have not been able to deliver positive style-adjusted performance during their early years, as they did before the financial crises. This deterioration in performance after the financial crises could be explained by the increased regulatory pressure and the increased competitiveness of the industry. Furthermore, it can be the case, that before the financial crises there were more opportunities that could have been exploited by the smaller emerging hedge funds, but these opportunities were too small for the larger more established hedge funds to be worth of their capital and time. The reasons why the emerging hedge funds have lost their capability to generate alpha after the financial crises are not completely explicit and the phenomena would need a further study that we could receive definitive answers to the subject.

Thirdly, we find evidence that when comparing emerging hedge fund performance divided into broad strategy classifications, the directional traders was the only classification that was able to deliver positive alpha on average. Therefore, we have to conclude that the positive style-adjusted performance that we see in our data for the early life of the emerging hedge funds is to a great extent driven by the directional traders sub-sample. This would indicate that there is a clear performance difference between the emerging hedge funds that belong under this classification and with the emerging hedge funds that try to employ other broad strategies. Although we don't have a clear picture if this better relative performance in directional traders broad strategy classification is driven by a sub-sample strategy within this strategy group. Therefore, this question would need a further study in the future in order to achieve a better picture on the reasons that drive directional traders better relative performance. All of our findings that we have previously mentioned were found after we controlled for the backfill bias. Based on our findings in this thesis, we conclude that, only very specific group of the emerging funds and managers have been driven the earlier findings on the performance of emerging hedge funds. Furthermore, the emerging hedge funds collectively have not been able to add any value, relative to more established funds, after the financial crises.

We also have one suggestion on further research relative to the performance of emerging hedge funds besides the suggestions that we have previously mentioned in this chapter. The extent literature on hedge fund in general has focused when studying fund leverage on the determinants of fund leverage and to some extent to its impact on fund performance and systemic risk, but there is no research on fund leverage and its impact on emerging hedge fund's performance and risk. This subject could be important to receive more focus from the researchers in the future as it could give us information on how emerging hedge funds differ in leverage usage from the older more established funds. Conducting further research on this subject could give more clarity to the performance differences between the emerging hedge funds and more established hedge funds.

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