https://lib.uliege.be https://matheo.uliege.be

Do investors choose hedge funds according to their past performance ? A flow & performance analysis

Auteur : Goller, Rachel
Promoteur(s) : Lambert, Marie
Faculté : HEC-Ecole de gestion de l'Université de Liège
Diplôme : Master en sciences de gestion, à finalité spécialisée en Banking and Asset Management
Année académique : 2019-2020
URI/URL : http://hdl.handle.net/2268.2/8953

Avertissement à l'attention des usagers :

Tous les documents placés en accès ouvert sur le site le site MatheO sont protégés par le droit d'auteur. Conformément aux principes énoncés par la "Budapest Open Access Initiative"(BOAI, 2002), l'utilisateur du site peut lire, télécharger, copier, transmettre, imprimer, chercher ou faire un lien vers le texte intégral de ces documents, les disséquer pour les indexer, s'en servir de données pour un logiciel, ou s'en servir à toute autre fin légale (ou prévue par la réglementation relative au droit d'auteur). Toute utilisation du document à des fins commerciales est strictement interdite.

Par ailleurs, l'utilisateur s'engage à respecter les droits moraux de l'auteur, principalement le droit à l'intégrité de l'oeuvre et le droit de paternité et ce dans toute utilisation que l'utilisateur entreprend. Ainsi, à titre d'exemple, lorsqu'il reproduira un document par extrait ou dans son intégralité, l'utilisateur citera de manière complète les sources telles que mentionnées ci-dessus. Toute utilisation non explicitement autorisée ci-avant (telle que par exemple, la modification du document ou son résumé) nécessite l'autorisation préalable et expresse des auteurs ou de leurs ayants droit.

DO INVESTORS CHOSE HEDGE FUNDS AND LIQUID HEDGE FUNDS ACCORDING TO THEIR PAST PERFORMANCE? A FLOW & PERFORMANCE ANALYSIS

Jury :
Promoter :
Marie LAMBERT
Readers :
Andrew CONLIN
Nicolas MORENO
Philippe MACLOT

Dissertation by
Rachel GOLLER
For a Master's Degree in Management Sciences with specialization in Banking & Asset Management
Academic year 2019/2020

Acknowledgments

First, I would like to thank my promoter, Marie Lambert, for her outstanding support throughout the academic year. She helped me to materialize my ideas and was always available to answer any questions.

Secondly, I would like to thank Cedric Gillain for the help he procured while retrieving my data sample on Eurekahedge at the University's trading room.

Thirdly, I also would like to thank my reading committee, Nicolas Moreno, Philippe Maclot and Andrew Conlin, in advance for taking the time to evaluate my work and for their upcoming feedback.

Finally, I am forever grateful to my partner, Valentin Goffin, who provided me with a basic training of the software Matlab which was needed in order to perform my analysis and for the time he took in order to proof read my work. Thank you to my friend Clara Feron for taking the time to proof read my thesis.

Table of Contents

1. Introduction

Nowadays, investors can invest in different assets on their own or can choose to trust a financial intermediary to make investment decisions such as investment funds, asset managers, pension funds or even insurance companies. Such choice depends on whether the investor feels qualified enough to create value for himself. The decision of which financial intermediary to choose is then a matter of how tailored he wishes the strategy to be. Indeed, asset managers design strategies according to the investor's personal needs and preferences while investment funds provide the same service to many investors by pooling money. An infinity of possibilities can be offered as a multitude of assets exists such as equity, fixed income, real estate or even private assets and as many strategies exists. Traditional investment funds' strategies include passive strategies where the fund follows a benchmark whereas active strategies are built from scratch. Alternative strategies such as private equity, real estate and hedge funds can provide higher returns to investors which comes with other risks as well. What differentiates hedge funds and mutual funds (traditional funds) for instance, is the type of assets used which are more sophisticated for hedge funds and sometimes prohibited for mutual funds to use. Mutual funds most often follow an index and thus seek relative returns with a simple strategy while hedge funds rely on the expertise of their managers to provide absolute returns with an active strategy. A feature that is particular to the hedge fund industry is the performance fees charged to the investor which can be seen as a motivation for hedge fund managers to provide their clients with the best returns possible which is not a feature of the mutual fund industry (Agarwal & Naik, 1999). The incentive fees are one of the many hedge fund's characteristics which differentiates them from mutual funds. On top of those high fees also comes limited liquidity as hedge fund investors have lock-up periods after investing in the fund and notice periods when wanting to withdraw the invested capital. However, whether the fund is traditional or alternative, it does not prevent it from being regulated which can offer protection for the investors. Evidently, as hedge funds are less regulated, they are not required to be as transparent as mutual funds which are regulated both in Europe and in the United States.

The regulatory framework for European mutual funds 'Undertakings for Collective Investments in Transferable Securities' (UCITS) was set up in 1985 and has been launching directives ever since (Busack, Drobetz & Tille, 2017). As investors were eager to earn higher returns instead of investing in passive funds, the hedge fund industry was increasing substantially in terms of assets under management and in number of funds before the financial crisis of 2008. Due to the lack of liquidity and transparency coming from alternative funds in the aftermath of the crisis, there was a clear need for more regulation coming from the investors. This UCITS framework became more attractive in the eyes of the hedge fund managers who perceived these directives as a way to attract investors by being more transparent, regulated and liquid. Another interesting aspect of this UCITS framework for hedge fund managers is that they can attract retail investors which they are not able to do in the hedge fund industry since they are not diversified enough and are thus fitted only for accredited investors. UCITS funds implementing hedge fund-like strategies, through derivatives to replicate short selling exposures, emerged as “Newcits” and/or “Alternative UCITS” funds. However, these alternative UCITS are still regulated and thus prohibited to short sell and to invest in illiquid assets such as real estate for instance. Since these non-traditional strategies require the manager’s skill, alternative UCITS are allowed, like hedge funds, to charge performance fees which can thus enhance the performance of the fund (Busack, Drobetz & Tille, 2017). A similar phenomenon was also developed in the United States as “hedged mutual funds” emerged. Indeed, those mutual funds implement a hedge fund like strategy while complying with the SEC and the Investment Company Act of 1940 which regulates the mutual fund industry. The goal of these funds is similar to the one of the newcits funds as they both want to attract retail investors while seeking higher returns. In addition, like the alternative UCITS, hedged mutual funds have restrictions on borrowing, short positions and liquidity and also charge performance fees (Hartley, 2016).

As previously stated, investors are seeking returns and invest in funds according to their performance because they believe that performance is persistent. A previous research by Agarwal, Green & Ren (2018) shows that successful hedge funds receive capital inflows which is understandable as the outperformance is a proof of the manager’s skill which investors are looking for. This conclusion was also reached by Berk and Green (2002) who concluded that investors are looking for high performance which explains the flows to the fund. Additional research from Cao, Hsu, Xiao & Zhan (2017) proves that the fund’s performance drives the fund’s flows. Furthermore, past performance has been shown to be an indicator of managers’ abilities and thus investors’ flows will be determined by the funds’ higher expected returns (Berk and Green, 2004, cited by Huang, Wei & Yan, 2012). The relationship between the fund flows and their performance is however convex as funds with good performance can attract new investors while bad performing funds experience capital outflows coming exclusively from their investors’ base (Berk & Tonks, 2007). Literature has thus shown that performance indeed drives flows however, whether the flows between liquid hedge funds (including hedged mutual funds and newcits funds) and hedge funds are determined by their respective past performance, has not been studied yet. Alternative UCITS grew faster than hedge funds after the financial crisis and doubled their assets under management (AUM) in 2010 according to Eurekahedge's report of April 2020. As understanding what causes these capital flows is important, this paper will thus examine the performance between these two types of funds and try to provide an answer to this question. An important aspect of this research is to determine whether the regulation has any impact on the performance of the fund and thus on the flows. A focus is set on whether the regulations prevent liquid hedge funds from outperforming standard hedge funds and whether performance is the key driver of the flows.

In order to perform this analysis, with a sample of funds retrieved from Eurekahedge, the performance of funds will be computed using the Capital Asset Pricing Model and a multi-factor model which will further be used in a panel regression to deduct whether the flows between hedge funds and liquid hedge funds are due to their respective past performance. Results show that investors tend to use the Capital Asset Pricing Model as a performance evaluation tool, as previous studies also discovered (e.g., Agarwal et al., 2018, Cao et al., 2017). Previous performance indeed influences the fund flows however, the effect is more pronounced for liquid hedge funds which could be due to the increased liquidity and reporting. There is no negative effect between the hedge fund flows and the liquid hedge funds performance while hedge funds' past performance has a positive impact on liquid hedge fund flows. This finding can suggest that hedge fund investors are not influenced by the positive performance of liquid hedge funds and might prefer higher risk-adjusted returns instead of more liquidity and transparency. Indeed, as liquid hedge funds have heavy restrictions on which assets to invest in, on the liquidity they provide and on the risk they take, obtaining similar risk-adjusted returns to hedge funds is not realistic. On the other hand, liquid hedge fund investors appear to be more sensitive to the hedge funds' performance which is consistent with the current decline in popularity that liquid hedge funds are experiencing. One still has to keep in mind that the fund flows do not only depend on the past performance and are determined by other fund characteristics as it will be explained later on.

The thesis is divided as follows: section 1 will cover the literature review about the industry, the different regulations and the role of hedge funds in the financial crisis of 2008. Section 2 will discuss the methodology and thus the choice of the samples the flow and performance measures used in order to perform the panel regression. Potential biases that can occur with hedge fund databases will also be discussed. Section 3 will examine the summary statistics and the results of the performance measures and of the panel regression. Finally, the conclusion will be the last section of the thesis.

2. Literature Review

2.1. Hedge Fund's Characteristics

"Hedge" in hedge funds stands for "hedging" and thus protecting portfolios against potential losses however, it is well known that hedge fund managers seek absolute returns and use derivatives to increase the leverage of their portfolios for instance, which increases the risk (Patassi, 2015). The first hedge fund was created by Alfred Winslow Jones in 1949 and had a long short equity strategy but the particularity was that the fund charged a 20% management fee which was an innovation at the time (Goetzmann & Brown, 2003). As stated in the introduction, hedge funds implement more sophisticated strategies highly dependent on the manager's skills. In order to motive the manager to create value for its investors, hedge funds charge annual performance fees of about 20% usually (Getmansky, Lee & Lo, 2015). However, as the industry has become more fragmented, meaning a larger number of small funds are now established, the competition has increased which lead to pressure on the management fees. On top of these incentive fees, the fund also has to charge annual management fees to cover the expenses the fund occurs which are usually ranging from 1% to 2%. Even though mutual funds do not charge performance fees, fixed annual management fees are also demanded to fund their operations. Furthermore, hedge funds can implement a high-water mark system for performance fees where the fees are charged only if the previous losses are recovered the following period. In a nutshell, if the hedge fund managers suffered from a loss the previous year and earns back half of the loss the following period, he will not be able to charge incentive fees for the current year as he still has not recovered one hundred percent of the capital. This additional mechanism acts thus as an additional motivation for the managers to create value for his investors and these funds tend to perform better (Agarwal, Daniel & Naik, 2009, cited by Getmansky et al., 2015).

Another particularity of hedge funds is the lack of liquidity which investors can experience. As sophisticated strategies employed by hedge funds depend on the manager's skills, some strategies can be capacity constrained and therefore, these funds cannot welcome more than a certain number of investors as gains are limited (Getmansky et al., 2015). Lock up periods can also be set up and prevent new investors from withdrawing their capital for a pre-determined period of time which can go up to three years. If investors want to withdraw their capital at any given time, hedge funds often impose a notice period (usually 30 days) in order to inform the fund about the request and a redemption period to recover the capital. During financial crises, funds often use gates to limit withdrawals to avoid going bankrupt. Even though these mechanisms reduce the liquidity for investors, literature has shown that lock up periods can increase the excess returns of a fund (Aragon, 2007, cited by Getmansky et al., 2015). As liquidity restrictions allow hedge fund managers to invest in illiquid assets, they can thus reap an illiquidity premium and increase the returns of the fund (Aragon, 2007, cited by Joenväärä & Kosowski, 2014).

When taking a closer look at hedge fund flows, literature agrees that performance positively impacts flows (Goetzmann, Ingersoll & Ross, 2003, Baquero & Verbeek, 2009, cited by Getmansky, Lee & Lo, 2015). It is to be noted that the capital flows do not only depend on returns but also on the alpha (the manager's skills), the perception of investors, the restrictions of the fund and finally the market conditions. For instance, Aragon & Qian (2010) showed that fund flows are more impacted by the performance when the fund imposes a high-water mark system (cited by Getmansky, Lee & Lo, 2015).

In conclusion, hedge funds are particular investment vehicles with uncommon and strict features but can provide higher risk-adjusted returns to investors due to these restrictions. Traditional and passive strategies were thus traded for more exotic and return yielding strategies which hedge funds were able to provide explaining their increasing popularity before the financial crisis of 2008.

2.2. The Industry

According to Eurekahedge's October 2019 report, we can observe that the Hedge Fund industry has been steadily growing **(Figure 1)** with about 2,269.9 billion dollars of assets under management in September 2019. However, according to Eurekahedge's report of April 2020, the number of hedge fund launches has been decreasing since the crisis of 2008 (**Figure 2**) since investors had a hard time trusting hedge funds and also wanted more transparency and liquidity as it will be further discussed. However, the recent decrease in launches can be partially explained by MiFID II implemented in January 2018 which increases the pressure, the compliance costs and the reporting standards imposed upon hedge funds which act as a barrier to enter. As it can also be observed, the assets under management continue to increase, showing the investors' interest for higher risk-adjusted returns following a low-return environment, as the Eurekahedge's report of October 2019 explains. Unfortunately, this also means accrued competition within the industry which makes it hard to survive or even to enter. However, this competition means lower performance fees for investors compared to 2007 for example.

Figure 1: Hedge Fund Industry Growth

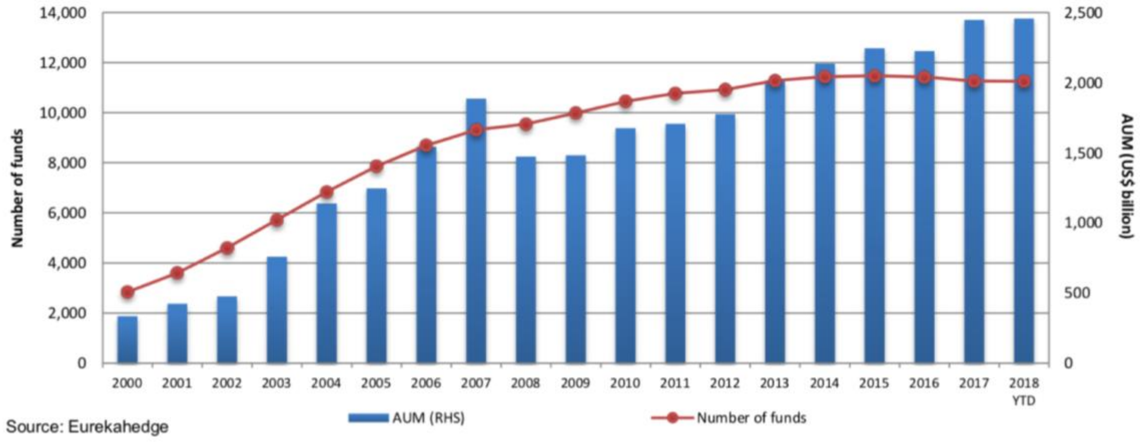
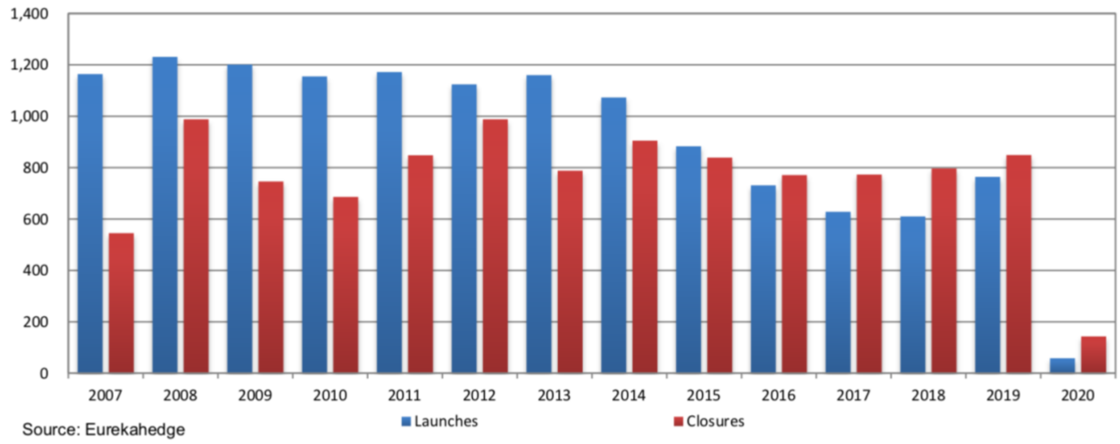


Figure 2: Annual Launches and Closures of the Global Hedge Fund Industry



The UCITS fund industry added up to 10.41 trillion of dollars in August 2019 according to EFAMA's factsheet which can be compared with its American counterparty, the mutual fund industry (Joenväärä & Kosowski, 2014). An article from Tuchschmid, Wallerstein & Zanolin (2010) states that the alternative UCITS universe had grown 500% from 2006 until 2010 while the hedge fund industry only grew 2% over the same period. According to the ESMA Economic report (2013), UCITS hedge funds' AUM increased from 20 billion euros to 85 billion euros from 2007 until the end of 2012. The reported UCITS' AUM by the end of 2012 was of 6,29 trillion euros showing that alternative UCITS represented a small proportion of the industry. As it can be seen on **Figure 3**, even though the UCITS industry remained stable over the years, the UCITS hedge funds grew over 325%. Due to the Eurozone crisis in 2011, the industry stabilized until 2013 where the AUM increased again. As for launches of European funds since 2006, an important increase in launches of UCITS hedge funds is translated by a decrease of launches for their hedge funds counterparties as shown on **Figure 4**, ending up with more than

50% of the European hedge fund launches being UCITS compliant as reported by Eurekahedge's report of April 2020.

Figure 3: Assets Under Management of UCITS

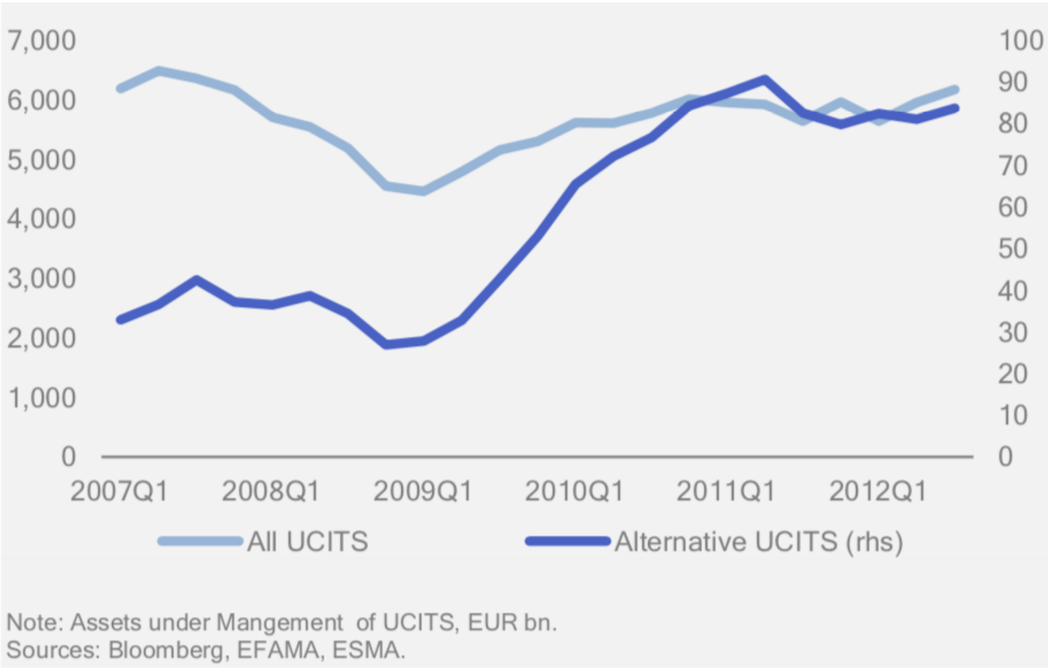
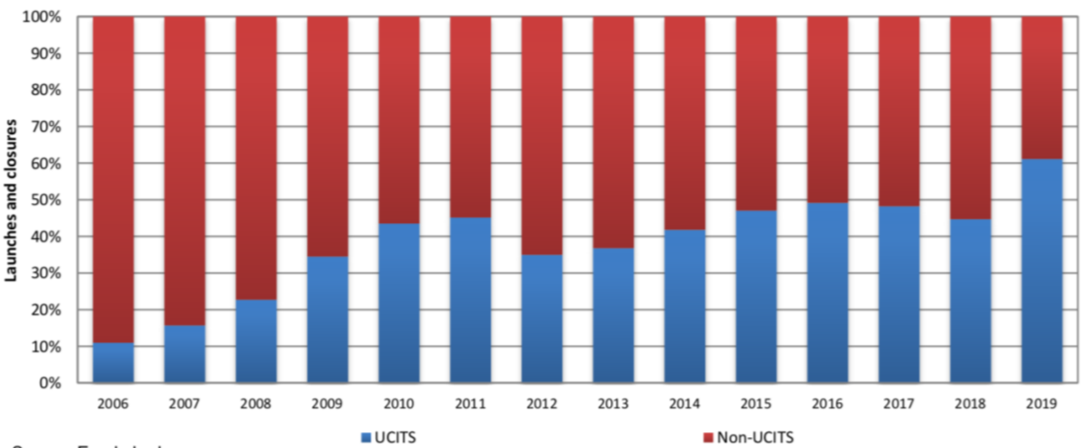


Figure 4: Percentage of UCITS and Non-UCITS European Hedge Fund Launches



Source: Eurekahedge

As for hedged mutual funds, they represented one eighteenth of the hedge fund industry in 2014 according to Forbes (Diedrich, 2014). Kanuri & McLeod (2014) also reported that in 2005 and 2009, these funds' inflows respectively represented 11% and 25% of the mutual fund industry's inflows. In 2011, hedged mutual funds' total assets under managements amounted to $132.82 billion. As liquid hedge funds are becoming more attractive to investors and managers, understanding the restrictions to which they are subject and how they affect their performance is crucial for this research.

2.3. History of the UCITS Directives

As stated in the introduction, the first ‘Undertakings for Collective Investments in Transferable Securities’ directive was launched in 1985 by the European Union (Tuchschmid & Wallerstein, 2013). The goal was to define a common legal framework for open-ended structures across Europe (Joenväärä & Kosowski, 2014). Under UCITS I, funds could only use derivatives in order to hedge and to reduce risk.

In the early 1990s, UCITS II was launched to ease the marketing of funds across countries since every country had its own laws. The marketing process was also hindered by the limitation of the securities in which funds could invest (Joenväärä & Kosowski, 2014).

As the UCITS directives created many restrictions for the fund managers, it was not until UCITS III, implemented in 2001, that hedge fund-like strategies could be replicated through the UCITS structure since it expanded the assets in which UCITS could invest (Joenväärä & Kosowski, 2014). This product directive expanded the eligible investment products beyond transferable securities, otherwise known as bonds and equities, to options, money market instruments, funds of funds, financial futures and cash deposits for instance (Dewaele, Markov, Pirotte, Tuchschmid, 2011). Investing in such assets ensures that the redemption and purchase of shares can be satisfied at any moment, by selling assets and thus insuring the liquidity but also the diversification of the fund leading to increased investor’s protection (Patassi, 2015). Furthermore, to ensure the liquidity, funds have the obligation to provide bi-monthly net asset value (NAV) for investors and 20% of this NAV should be available for redemptions at any time (Tuchschmid et al., 2010). Nevertheless, authorities have to check the NAV computation of the fund at least twice per week and investors should get the NAV computations twice per month. On top of the product directive UCITS III, the management directive introduced the obligation to publish a detailed and simplified prospectus along with a Key Investor Information Document (KIID) in order to better inform investors (Johannsen, 2011).

Even though the latest directives widened the possibilities for eligible financial instruments, heavy restrictions on leverage, concentration, diversification and liquidity remain, making it hard to exactly replicate hedge fund strategies and capture similar return levels. Indeed, as mentioned by Dewaele et al. (2011), there are non-eligible financial instruments, in which UCITS funds cannot invest more than 10% of the NAV called the trash ratio. Other assets which are totally prohibited include commodities, real estate, bank loans and private equity otherwise known as illiquid and debt securities (Johannsen, 2011). Investing in other hedge funds and commodities was then permitted by the eligible asset guideline, through financial indices provided that they are fully transparent in order to allow for constant tracking (Busack, Drobetz & Tille, 2014).

The directives also prohibit the use of short selling which can be replicated through derivatives allowing hedge funds to replicate one of their most popular strategy through the UCITS structure, the long short equity strategy. The UCITS directive thus allowed funds to hold the derivative without owning the underlying securities leading to a replication of short selling (Busack et al., 2014). In addition, the use of derivatives (listed or over-the-counter) allows managers to create more sophisticated strategies such as arbitrage (Patassi, 2015).

Diversification levels are also imposed upon UCITS structures to prevent the exposure to a concentrated number of assets (Patassi, 2015). Indeed, with the 5/10/40 rule, funds cannot invest more than 5% of its assets in a security by the same issuer which can be increased to 10% if the exposure to issuers does not excess 40% (Joenväärä & Kosowski, 2014).

Furthermore, multiple restrictions are in place in order to limit the risk of the fund such as value-at-risk (VaR) limitations and the obligation to have an independent risk management team which has to produce a daily risk report (Tuchschmid et al., 2010). UCITS funds having an index of reference cannot have a VaR that is above two times the one of the index and more sophisticated UCITS, such as Alternative UCITS, usually use an absolute measure where the VaR cannot be above a certain percentage of the NAV (Tuchschmid et al., 2010). Leverage is also prohibited unless the UCITS fund needs liquidity for redemptions and can thus not be used to enhance returns. The leverage is limited to 200% of the NAV but can be lower if the restriction for the VaR is already reached (Tuchschmid et al., 2010). Still, funds can use derivatives in order to replicate the effect of the leverage (Busack et al., 2014). These restrictions prevent alternative UCITS to use any hedge fund-like strategies relying on these specific instruments. In addition, the lack of liquidity premium, the reduced investment size and increased costs can lead to a lower performance for newcits funds compared to hedge funds (Busack et al., 2014). However, due to the increasing capabilities of the funds under the directives, hedge fund like strategies can still be implemented and therefore give a non-traditional flavour to retail investors. Even though hedge funds do not have such tight restrictions, European hedge funds still fall under the AIFM directive which will now be discussed.

2.4. The AIFM Directive

In 2011, the Alternative Investment Funds Managers Directive, also known as AIFMD, was put in place in order to regulate the European alternative fund managers who didn't fall under the regulative framework of UCITS to ensure the stability of the financial markets (Patassi, 2015). This regulation thus applies to real estate, private equity and hedge funds. Furthermore, in this new regulation, the managers are regulated unlike in the UCITS directives. However, restrictions on the fund's leverage, liquidity and risk profile are applicable through AIFMD and thus influence the fund's operations as well as the managers. With the introduction of the directive, many hedge funds moved to the European Union in order to obtain the passport which lead to an increase of hedge funds domiciled in Luxembourg and Ireland as reported by Eurekahedge's report of April 2020.

The UCITS framework is thus the regulation for funds with a less sophisticated strategy while the AIFMD regulates the alternative funds. Even though each type of fund has its own directive, hedge fund managers saw an opportunity in the UCITS directive. After the crisis, non-professional investors needed more transparency, protection and liquidity which the hedge funds were not able to previously deliver. By adopting the UCITS form, funds could also attract retail investors by replicating their strategies under certain constraints while delivering absolute returns instead of relative returns (Patassi, 2015). The increasing regulation set on European hedge funds might also be one of the drivers for the increased popularity of hedged mutual funds and alternative UCITS funds.

2.5. Hedged Mutual Funds

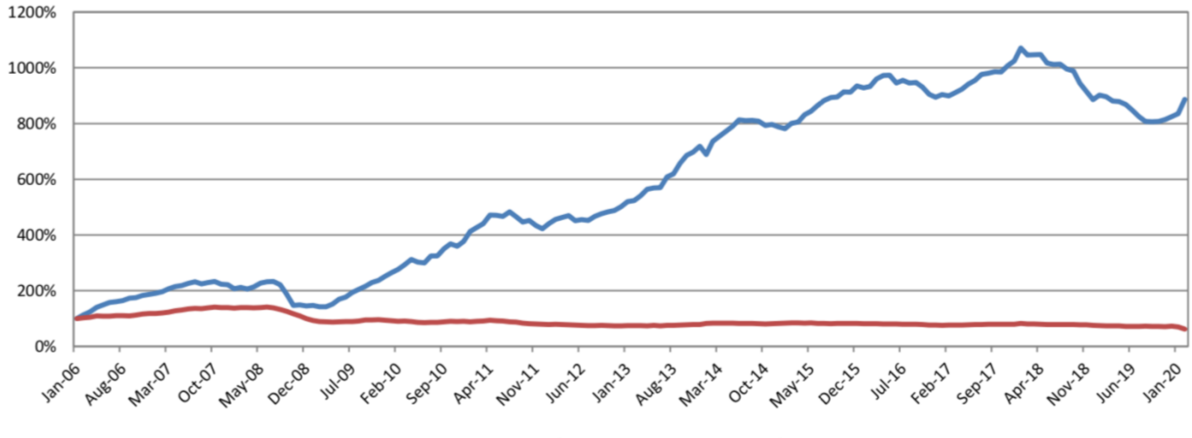
In the United States, the phenomenon of liquid hedge funds also developed itself with the arrival of the hedged mutual funds. These mutual funds comply with the SEC and the Investment Company Act of 1940 but replicate hedge funds strategies. As the UCITS directives were developed in Europe, the Investment Company Act has different rules for these hedged mutual funds but they address the same concerns that can be observed in the hedge fund industry. These liquid hedge funds have to compute daily NAVs and can borrow up to onethird of their total assets. In addition, they cannot invest more than 15% of their assets in illiquid securities which is quite similar to the UCITS directives. Finally, they have rules about covering their short positions, options, futures and forwards (Newton, 2009). Before 1997, hedged mutual funds could not invest more than 30% of their gross income in assets held for less than three months or they had to pay a 35% tax on their result (Kanuri & McLeod, 2014). The removal of this rule in 1997 allowed funds to use short term hedging products and to be able to implement market timing strategies. Of course, like the newcits funds, the hedged mutual funds have to provide daily liquidity to their shareholders who can get out on a daily basis (Agarwal, Boyson & Naik, 2006). As stated in the introduction, the hedged mutual funds and newcits funds increased in popularity and in scope as the climate post 2008 drove investors to want more transparency, liquidity and protection which hedge funds were not known for.

2.6. Hedge Funds and the Subprime Crisis

A key factor, which lead to the development and success of liquid hedge funds, is the reputation of the hedge funds following the financial crisis of 2008. According to Lysandrou (2011), even though hedge funds denied their responsibility in the subprime crisis as they were not responsible for the creation of the mortgage backed securities (MBS), the investors' demand for high yield products pushed hedge funds to pressure the banking sector which lead to the creation of toxic MBS. Of course, hedge funds were not the only intermediary to supply these products but they created a massive market for these types of securities making the problem even bigger as they held 47% of the collaterized debt obligations (CDOs) in 2006. Indeed, since hedge funds were less regulated than pension or mutual funds, buying a large proportion of these risky and not transparent securities was not forbidden. Getmansky et al. (2015) reports that a study of the Financial Crisis Inquiry Commission in 2011 showed that hedge funds bought the majority of the riskiest tranches of the CDOs while they also shorted other tranches and used credit default swaps to cover their positions. Hedge funds could thus benefit if the market crashed and if the CDOs were going to succeed after all (Getmansky et al., 2015). It is well known that hedge funds are keen on taking on more risks and are looking for new opportunities which lead them to suffer from important losses during and after the financial crisis.

Even though investors still believe that 2008 was more a banking crisis than a hedge fund crisis, hedge funds still decreased in popularity as investors wanted more transparency and liquidity. The idea of a regulated fund with daily liquidity, full transparency which still yields interesting returns was very appealing and possible under the UCITS directives when alternative UCITS emerged. As reported by Eurekahedge's report of April 2020, UCITS European hedge funds' AUM increased since 2008 at the expense of the European hedge funds' AUM growth as we can observe on **Figure 5**.

Figure 5: Relative AUM Growth of UCITS European Hedge Funds



Source: Eurekahedge

With the literature review chapter, it is now clear that there is a sharp increase in popularity of these liquid hedge fund which was driven by evolving investor's needs after the financial crisis as the industry numbers show above. Those funds differ from the regular hedge funds with their multitude of strict restrictions which can prevent them from perfectly replicating hedge funds strategies. The choice between liquid hedge funds and regular hedge funds can be seen as a trade-off between liquidity, transparency and higher risk-adjusted returns. As there is no free lunch on the financial markets, one cannot simply reap the advantages of both worlds as it will be analysed in the following chapters.

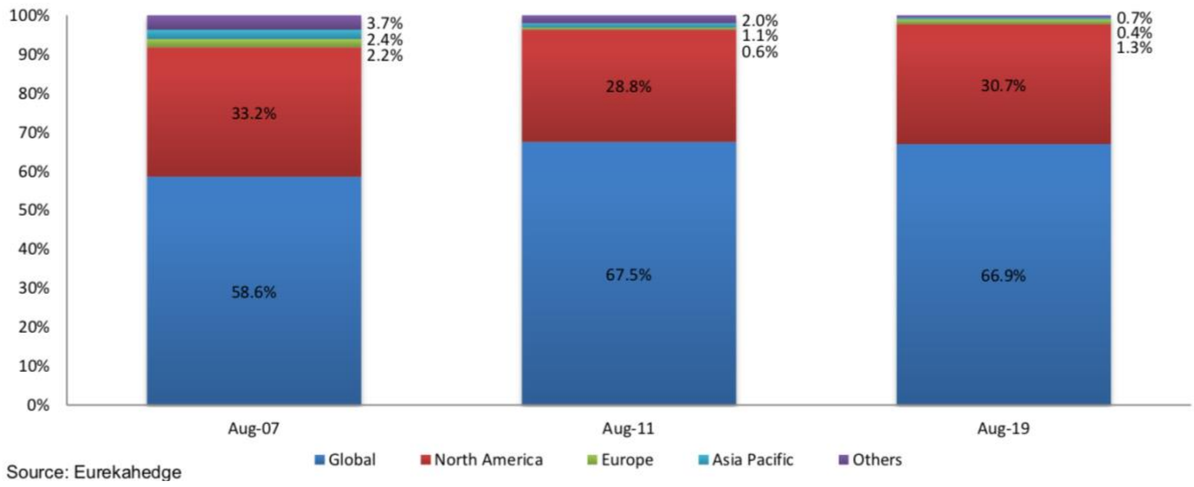
3. Data and Methodology

3.1. Data Sample

In order to further examine this topic, the North American Hedge Fund excel file was retrieved from the EurekaHedge database accessible at the trading room of the University. Eurekahedge is the largest hedge fund database in the world containing 25 765 hedge funds covering many regions and many strategies worldwide. On top of indices and various performance measures, Eurekahedge also provides monthly report about the industry with key figures and graphs. The North American hedge fund data base of Eurekahedge documents US hedge funds based in North America or investing in it, containing 12 804 funds in total with 116 data point per fund where 90% of the NAVs are updated by the end of each month, as reported on their website.

The North American hedge fund data feed was then filtered in order to retrieve the hedge funds, the newcits funds and the hedged mutual funds with an inception date starting from 2010, with a long short equity and fixed income strategy which are UCITS and non UCITS compliant, SEC registered and non-registered and who have a North American mandate and are reporting in USD. As investors still seek diversification, 66,9% of North American hedge funds have a global mandate against 30,7% for North America **(Figure 6)** as reported by Eurekahedge's report of October 2019. However, in order to compare similar funds, the data was filtered to obtain funds with a North American mandate who are reporting in USD.

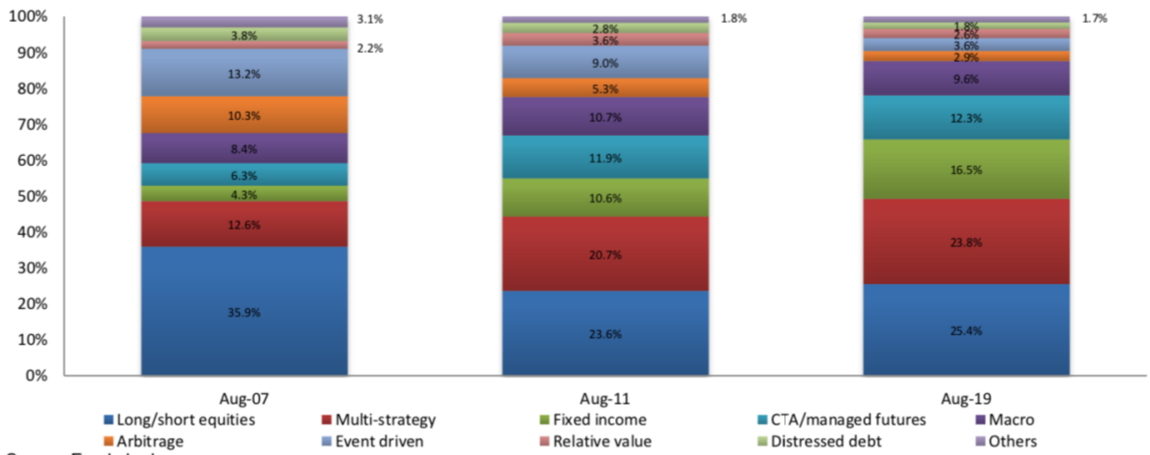
Figure 6: AUM Distribution of North American Hedge Funds by Geographic Mandate



Secondly, retrieving funds with an inception date starting from 2010 is motivated by the effect that the financial crisis had on investors who were craving more transparency and protection. Liquid hedge funds grew more rapidly than hedge funds afterwards due to these new investors' demands and thus studying the relationship between the performance and the flow is best pursued after 2010.

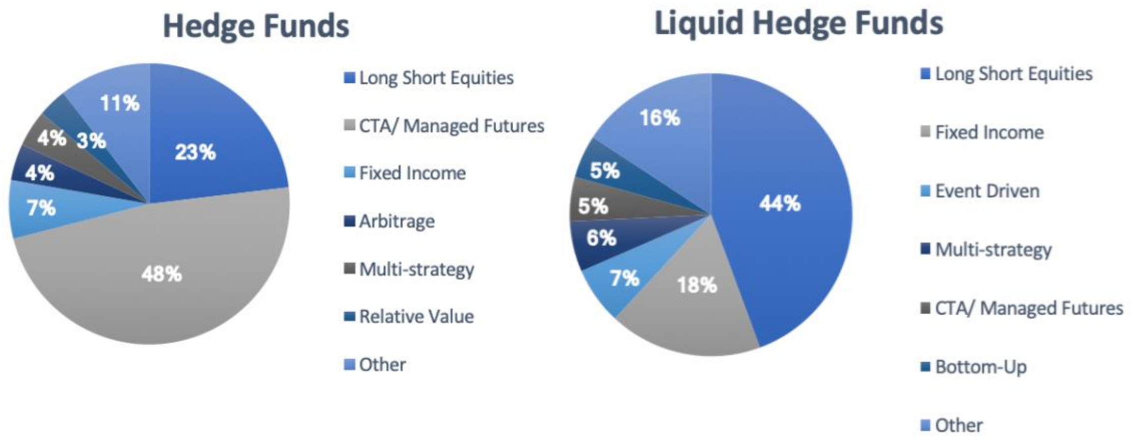
Thirdly, we can observe a decline in the popularity of the long short strategy for North American hedge funds which was previously the preferred strategy of investors as shown on **Figure 7**. This decline is due to improved investor awareness that different strategies exist with an increasing preference for arbitrage and fixed income strategies. Analyzing two different strategies allows to compare the effect of the performance on the fund flows for a strategy with a higher degree of liquidity, the **long short equity** strategy and with a lower degree of liquidity, the **fixed income** strategy. The choice of strategy is motivated by the fact that the long short strategy is still one of the most popular strategy chosen by hedge funds and is one of the easiest to replicate for liquid hedge funds as it only requires to buy undervalued security and to short overvalued ones. Liquid hedge funds can replicate the short exposures with derivatives as it is allowed by the regulations. As stated in Eurekahedge's report of April 2020, 40,9% of the alternative UCITS' AUM is managed by fixed income funds while 23,4% is managed by long short equity funds. The long short strategy accounts for 35,4% of hedge funds' AUM while the fixed income strategy accounts for 13,6%. 476 hedge funds and 730 liquid hedge funds with a North American mandate reporting in USD with an inception date starting in 2010 were retrieved and classified by strategy to discover the trend in each sample. The fixed income strategy is the second most popular strategy in our sample **(Figure 8)** and that has a lower degree of liquidity since it consists of investing in different categories of bonds which by definition are less liquid than stocks.

Figure 7: Strategic Mandates by AUM for North American Hedge Funds



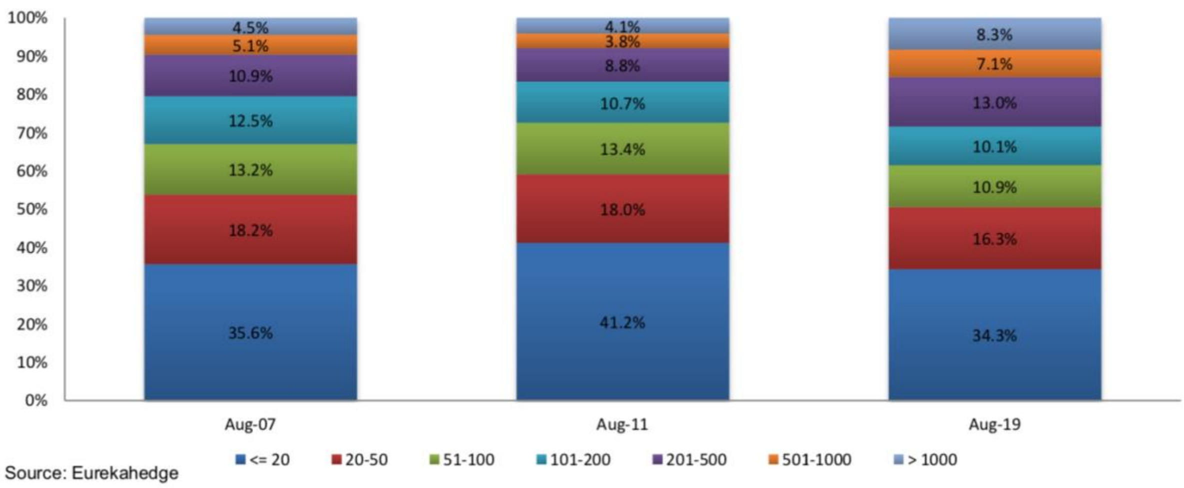
Source: Eurekahedge

Figure 8: Strategy Repartition Within the Samples



As funds with different size cannot properly be compared, two categories of funds were defined according based on Eurekahedge's classification: small funds with a fund size lower than 100 million USD and mid & large sized funds with a fund size above 100 million USD (Berger, 2009). Two categories instead of three were chosen since no hedge fund and a few liquid hedge funds had a fund size above 500 million USD. **Figure 9** shows that 61,5% of North American hedge funds in august 2019 has a fund size below 100 million USD which motivates why the majority of our sample lies in that category. This result is not surprising as the industry is highly fragmented and composed of a majority of small funds. Smaller funds' proportion has declined due to the increasing competition and thus decreasing fees and increasing compliance costs since this category is more vulnerable as reported by Eurekahedge's report of October 2019.

Figure 9: Breakdown of North American Hedge Fund Population by Size (US$ million)



Finally, funds reporting less than 24 monthly return measures were removed from the final sample as the Capital Asset Pricing Model and a multifactor model will be used to compute the performance of the fund with a rolling time window regression of 36 months. The number of funds in the final sample for both strategies and their corresponding size group can be observed in **Figure 10**.

Figure 10: Final Sample for the Long Short & Fixed Income Strategy

	Hedge Fund	Liquid Hedge Fund
Small	57	108
Mid & large	6	44

	Hedge Fund	Liquid Hedge Fund
Small	13	38
Mid & large	5	25

3.2. Potential Biases

As hedge funds are less regulated than their traditional counterparty and thus are not subject to reporting obligations, multiple biases can arise on the different available databases which can hinder the performance analysis. Funds decide whether to provide their performance to databases and usually do so when they are in search of new investors, who have to buy the information, or when their performance is good, leading to a self-selection bias. Indeed, funds with bad performance do not usually report the returns or some funds may not want to be included in an index computation that will maybe raise the level of their own benchmark. This bias is misleading for investors as hedge funds are not allowed to advertise their funds and thus depend on word-of-mouth with databases acting as distributors (Baquero, Horst & Verbeek, 2005). Mutual funds benefit from an association, the Investment Company Institute, which acts as a "central depository" which is thus not the case for hedge funds (Fung & Hsieh, 2004).

Funds reporting their performance can also smooth their returns affecting the alpha and beta computations. This phenomenon can be verified if the fund reports its returns to another database, by cross-referencing the data. In addition, funds that existed before they are added to a database, tend to backfill their previous returns creating a backfilling or instant history bias (Getmansky et al., 2015). Literature discovered that younger funds tend to exhibit higher performance which can be associated with the need of attracting new investors with good performance (Agarwal & Jorion, 2009, cited by Getmansky et al., 2015).

Evidently, as reporting to a database is not mandatory, funds can decide to remove themselves from the database at any given point. This phenomenon is usually observed because of poor performance which biases the performance upward as only the good performance of the fund remains on the database (Getmansky et al., 2015). This bias is closely linked to the survivorship bias where the database choses to remove dead funds only to keep alive funds affecting the reported performance. Indeed, as stated before, funds yielding poor performance usually stop reporting and having only alive funds can improve the overall performance of the funds on the database. In addition, as stated by Fung & Hsieh (2004), hedge fund indexes created with the data from these databases will thus be biased as well and not every index provider will try to correct these biases. This bias, however, does not seem to be present in our final sample as many dead funds are included as shown further in the summary statistics. As Eurekahedge's report of October 2019 states, 3723 North American hedge funds out of the 12 497 funds are dead while the remaining are alive. Furthermore, as reported by Busack et al. (2014), the survivorship bias for alternative UCITS is more present for data before 2009 and the sample was filtered with inception dates starting in 2010. In addition, as liquid hedge funds target retail investors, funds have thus an incentive to report to databases which should lower the bias. As for pure hedge funds, a potential solution would be to remove the data between the inception date and the added date as Agarwal et al. (2018) suggests, however, this would lead to a considerable loss of data points for this research as the sample period is of 9 years.

Finally, before the liquidation of a fund, hedge fund managers usually stop providing their performance to databases creating a delisting bias. Removing those returns can increase the performance of the fund which may deteriorate before the liquidation and thus bias the analysis.

One way to minimize all the biases mentioned above, is to merge multiple commercial databases which was performed by Joenväärä, Kosowski & Tolonen (2012). Unfortunately, this solution was not possible for this analysis as Eurekahedge was the only hedge fund database available for students. In the following sections, the methodology used to perform the analysis will be described and the results will be analysed in the next chapter.

3.3. Computing the Fund Flows

The aim of this research is to discover whether the fund flows of hedge funds and liquid hedge funds are linked to their respective past performance. In order to perform the panel regression to discover the relationship, the fund flows have to be computed.

The net of fees monthly returns (in %) and assets under management (AUM) in millions of USD of the final sample were retrieved from the North American hedge fund data feed. Monthly measures allow to best observe the dynamics between the funds when compared to annual measures as more observations are obtained.

The dollar fund flow $\mathbf{F_{pt}}$ of fund p in month t, unlike in the paper of Cao et al. (2017) and the paper from Agarwal et al. (2018) where the flows are measured in percentages, is defined as in the paper of Getmansky (2012) and of Berk & Tonks (2007):

$$F_{pt} = AUM_{pt} - \left(1 + R_{pt} \right) x \, AUM_{pt-1}$$

Where:

- $\mathbf{AUM_{pt}}$ is the assets under management of the fund p at month t
- $\mathbf{AUM_{p,\,t\text{-}1}}$ is the assets under management of the fund p at month t-1
- $\mathbf{R_{pt}}$ represents the total return of the fund p for month t

The monthly dollar flow thus measures the monthly change in assets under management subtracting the appreciation as defined by Del Guercio & Tkac (2002). Computing the dollar flow instead of the flow in percentages allows to better see what drives the investor's investments which is the goal of this research (Del Guercio & Tkac, 2002).

An important proportion of funds in the sample are dead funds but these were not removed in order not to bias the research. However, as stated before, funds reporting less than 24 monthly returns were removed from the samples. As funds have different lifespan, each fund does not report the flows for the same period and thus only the reporting period is taken into account. After computing the flows, the performance using different asset pricing model has to be calculated in order to complete the final step of this research, the panel regression.

3.4. Computing the Fund's Performance

Hedge funds usually offer superior performance and as stated in the literature review, charge performance fees for their skills. It is thus important for the investors to be able to measure the manager's skills, through alpha, which reflects the outperformance relative to a passive benchmark. As stated by Cao et al. (2017), alpha is the risk-adjusted return of a fund which is considered as abnormal performance. Returns also depend on various factors but investors should focus on alpha and choose their funds accordingly. If most of the fund's returns can be reaped with a passive investment, investors do not have any incentive to pay high fees, to have a lack of transparency or liquidity restrictions imposed by hedge funds.

Many models have been developed over the years adding new risk factors trying to best explain the return the funds. Previous research by Agarwal et al. (2018) studied which asset pricing model best explains the relationship between risk-adjusted performance and the hedge fund flows. According to their research, the CAPM alpha best explains the hedge fund flows which is surprising as hedge fund investors are considered accredited and thus should rely on more complicated multifactor models. Furthermore, hedge funds are usually exposed to other sources of risks which the CAPM does not take into account.

Research by Cao et al. (2017), Barber et al (2016) and Berk & van Binsbergen (2015) show that mutual fund flows depend more on the CAPM than the multi-factor models' alphas. This result is driven by the fact that mutual fund investors find the risk factors of multifactor models more complicated to understand and thus prefer simpler models such as the CAPM.

However, both research stated above also discover that investors prefer exotic risk factors compared to traditional risk factors. This result is consistent with the fact that investors cannot easily access exotic risk exposure compared to traditional market risk. According to Cao et al. (2017), as time goes by, investors learn about new risk factors and move from the CAPM to more complicated models. Agarwal et al. (2018) finds that the same conclusion applies to hedge funds as investors prefer returns coming from exotic factors. Cao et al. (2017) also concluded that as there are less funds tracking these exotic risks factors, investors tend to prefer the CAPM over more complicated models.

The choice of the model depends on which one the investors use when making investment decisions which means that if an investor puts more emphasis on the market risk, the CAPM alpha will have a greater impact on the fund flows (Agarwal et al., 2018). Additionally, to the CAPM, the Fama & French 3 factor model with two additional factors is also computed to best capture the two types of risk exposure faced by liquid hedge funds and hedge funds but also to best capture the model preferences of investors. The model was developed in 1993 is widely used to measure the performance of portfolios and explains about 90% of the returns (Kanuri & McLeod, 2014). As the fixed income strategy is analysed, two additional factors are added to take into account the credit risk premium and the liquidity risk premium. In the following section, the two models will be computed and the results will be analysed in the following chapter.

3.4.1. Capital Asset Pricing Model Alpha

The Capital Asset Pricing Model (CAPM) is an asset pricing model where the excess return of the fund over the risk-free rate depends on alpha (the manager's skills) and the difference between the market return and the risk-free rate called the risk premium:

$$Rp_t - Rf_t = \alpha p_t + \beta p_t \, (Rm_t - Rf_t)$$

Where

- $\boldsymbol{Rp_t}$ is the return of the fund p at month t, in %
- $\boldsymbol{Rf_t}$ is the risk-free rate at month t, in %
- $\boldsymbol{\alpha p_t}$ is the intercept at month t which measures the fund's p manager's skills
- $\boldsymbol{\beta p_t}$ is the volatility of fund p with regards to the market at month t
- $\boldsymbol{Rm_t - Rf_t}$ is the risk premium at month t, in %

The monthly market's returns and the risk-free rates are retrieved from the Fama-French factors 'website [1] in order to have the same components for the CAPM and the Fama & French 3 factor model which will be computed in the next section. The fund's alpha for each month will be estimated using a rolling window of 36 months on Matlab and thus requiring a minimum of 24 monthly reported returns to be in the sample as stated before. The Matlab code can be consulted in **appendix A** and the results of the regression will be discussed in the next chapter.

3.4.2. The Multifactor Model Alpha

The Fama-French 3 Factor Model (FF3) is an asset pricing model where the excess return of the fund over the risk-free rate depends on alpha (the manager's skills), the difference between the market's return and the risk-free rate (risk premium), a size premium and a value premium. Two additional factors were added to best capture the origin of the fixed income strategy's returns. Indeed, fixed income hedge funds' returns depend on the credit spread as they can buy bonds with a low credit quality and low liquidity and hedge themselves against interest rates by selling higher quality and liquid bonds (Fung & Hsieh, 2004). As leverage can be added to those positions, liquidity also influences the financing costs and is thus taken into account in this factor. The credit risk factor, developed by Fung & Hsieh (2004), is calculated as the monthly change of the difference between Moody's Investors Service Baa bonds yield [2] and

[1] Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] Retrieved from https://fred.stlouisfed.org/series/DBAA

the 10-year constant maturity T-bond's yield [3]. As fixed income products are known to be less liquid, fund managers should thus earn a liquidity premium for this type of assets which is measured by Pastor & Stambaugh (2001)'s non-traded liquidity factor [4]. As stated by Sadka (2010), the liquidity factor of Pastor & Stambaugh (2001) is computed with NYSE-listed assets but evidence shows that there is a correlation between the bond and stock market which means this factor can reflect the liquidity of multiple markets. The model is thus as follows:

$$Rp_t - Rf_t = \alpha p_t + \beta 1 p_t\,(Rm_t - Rf_t) + \beta 2 p_t\, SMB_t + \beta 3 p_t\, HML_t$$
$$+ \beta 4 p_t\, CREDITSPREAD_t + + \beta 5 p_t\, LIQPREMIUM_t + \epsilon_{pt}$$

Where

- $\boldsymbol{Rp_t}$ is the return of the fund p at month t, in %
- $\boldsymbol{Rf_t}$ is the risk-free rate at month t, in %
- $\boldsymbol{\alpha p_t}$ is the intercept of the regression at month t and measures the fund's p manager's skills
- $\boldsymbol{Rm_t - Rf_t}$ is the risk premium at month t, in %
- $\boldsymbol{SMB_t}$ is the small minus big factor at month t which is a size premium
- $\boldsymbol{HML_t}$ is the high minus low factor at month t which is a value premium
- $\boldsymbol{CREDITSPREAD_t}$ is the credit risk factor at month t
- $\boldsymbol{LIQPREMIUM_t}$ is the liquidity premium factor at month t
- $\boldsymbol{\beta 1, 2, 3, 4, 5\ p_t}$ are the coefficient of the factors at month t
- $\boldsymbol{\epsilon_{pt}}$ is the residual of the regression for fund p at time t

The risk-free rate, the risk premium and the two factors are retrieved from the Fama- French factors 'website as in the previous section. The credit risk and liquidity risk factors are computed and retrieved as stated above. The fund's alpha for each month will be estimated using a rolling window of 36 months on Matlab. The Matlab code can be consulted in **appendix B** and the results of the regression will be discussed in the following chapter. As the methodology to compute the flows and the performance is determined, the panel regression model will now be explained.

[3] Retrieved from https://fred.stlouisfed.org/series/DGS10
[4] Retrieved from http://finance.wharton.upenn.edu/~stambaug/liq_data_1962_2019.txt

3.5. Panel Regression

Panel data models are used when the data has two dimensions: a cross-sectional dimension which can be seen as different individuals and a time-series dimension (Hsiao, 2007). This type of analysis allows for better estimation of the parameters but also better captures the complex interactions between individuals over time. Furthermore, it allows to deduct a common behaviour by analysing different individuals over time which is not possible with other methods. Furthermore, according to Gujarati (2011), there is also less collinearity between the variables and panel data regressions are more efficient and have higher degrees of freedom. Since the goal of this research is to examine the relationship between the flows and the performance of all funds over the sample period to detect a global trend, the panel regression seems like the appropriate methodology. The panel data is qualified as unbalanced as the number of observations (flow and performance measures) over the sample period is different for each individual (each fund). The hedge fund panel is classified as long since the number of hedge funds (80) is lower than the time periods (120) while the liquid hedge fund panel is short since we have more funds (215) than time periods (120) (Gujarati,2011).

As panel data pools together different individuals, heterogeneity arises which means that each individual is different (Gujarati, 2011). However, these differences might not be observable and panel regression models can account for this heterogeneity with variables that are specific to each individual. The data can have time invariant variables which are constant for the individual over time such as the strategy and time variant variables which evolve with time for each individual such as the age or the performance for instance (Hsiao, 2007). The one way fixed effects model assumes that each individual has a different intercept to account for the heterogeneity whereas the random effects model assumes that the individuals are drawn from a larger population and thus have the same intercept. Nonetheless, the heterogeneity is still included in the error term for this model as well. With the fixed effects model, the intercepts vary for each individual but not with time and are thus time-invariant (Gujarati, 2011). The within fixed effects model allows to estimate the coefficients by looking at how much they differ from their mean value however, the time-invariant variables will not be included in the analysis as their coefficients will automatically be zero (Gujarati, 2011).

The difference between the two models lies in the correlation of the error term and the repressors where the correlation is assumed for the fixed effects model and this can be verified with a statistical test. The Hausman test can verify which model is more appropriated according to the data and the model and has as null hypothesis that the two models are not substantially different (Gujarati, 2011). Panel regressions can be performed with the Software SAS, provided by the University, and when using the panel procedure for the random effects model, the Hausman test is automatically computed. The model is explained in the following paragraphs in details, meanwhile, the Hausman test was performed on the first data set used to analyse hedge fund flows with the alphas computed with the CAPM and the output can be observed in **Figure 11.** The test shows that the number of degrees of freedom is equal to the number of repressors. The null hypothesis in SAS is that the random effects model is a good fit for the data. The null hypothesis and thus the random effects model is rejected in this case as the p-value is very low and thus a fixed effects model needs to be estimated.[5] This test was executed for the three other models and the same conclusion applies for each (**appendix C**). In addition, previous research over the relationship between fund flows and performance use the fixed effect regression demonstrating that this model type is adapted to the goal of this research (e.g., Gupta & Jithendranathan, (2012), Marzuki & Worthington, (2015), Cao et al., (2017), Agarwal et al., (2018). Finally, as stated by Gujarati (2011), even if the fixed effects model is not the appropriate model, the coefficients are always consistent which further motivates this choice.

Figure 11: Hausman Test for the Hedge Fund & CAPM model

Hausman Test for Random Effects			
Coefficients	DF	m Value	Pr > m
16	16	69.14	<.0001

The model is as follows:

$$\begin{aligned} Flow_{p,t} = \alpha + \beta_1\alpha_{p,t-1} + \beta_2\alpha_{f,t-1} + \beta_3 Flow_{p,t-1} + \beta_4 STRAT_{p,t} + \beta_5 SIZE_{p,t} \\ + \beta_6 YEAR11_{p,t} + \beta_7 YEAR12_{p,t} + \beta_8 YEAR13_{p,t} + \beta_9 YEAR14_{p,t} \\ + \beta_{10} YEAR15_{p,t} + \beta_{11} YEAR16_{p,t} + \beta_{12} YEAR17_{p,t} + \beta_{13} YEAR18_{p,t} \\ + \beta_{14} YEAR19_{p,t} + \beta_{15} STDEV_{p,t} + \beta_{16} LOGAGE_{p,t} \\ + \beta_{17}\, \alpha_{f,t-1} x\ STRAT_{f,t} + \beta_{18}\, \alpha_{p,t-1}\, x\ STRAT_{p,t} + \varepsilon_{p,t} \end{aligned}$$

[5] Information retrieved from SAS'website https://documentation.sas.com/?docsetId=casecon&docsetTarget=casecon_cpanel_details48.htm&docsetVersion=8.4&locale=en

Where:

- $\boldsymbol{Flow_{p,t}}$ is the dollar flow of fund p at month t
- $\boldsymbol{\alpha}$ is the intercept of the regression
- $\boldsymbol{\alpha_{p,t-1}}$ is the lagged alpha of fund p (at month t-1)
- $\boldsymbol{\alpha_{f,t-1}}$ is the lagged alpha of fund f (at month t-1)
- $\boldsymbol{Flow_{p,t-1}}$ is the lagged fund flow of fund p (at month t-1)
- $\boldsymbol{STRAT_{p,t}}$ is a dummy variable taking the value of 1 if the fund strategy is liquid (long short) or 0 if it is not liquid (fixed income) for fund p at month t
- $\boldsymbol{SIZE_{p,t}}$ is a dummy variable taking the value of 1 if the fund is in the small category or 0 if it is not (mid & large sized category) for fund p at month t
- $\boldsymbol{YEAR\ 11_{p,t}, YEAR\ 12_{p,t}, \ldots}$ **are** dummy variables each taking the value of 1 if the observation corresponds to the year 2011, 2012,… for fund p at month t
- $\boldsymbol{STDEV_{p,t}}$ is the fund's standard deviation over the last 12 months at month t
- $\boldsymbol{LOGAGE_{p,t}}$ is the logarithm of the fund's age at time t
- $\boldsymbol{\alpha_{f,t-1}\ x\ STRAT_{f,t}}$ is the lagged alpha of fund f at month t-1 times the dummy strategy
- $\boldsymbol{\alpha_{p,t-1}\ x\ STRAT_{p,t}}$ is the lagged alpha of fund p at month t-1 times the dummy strategy
- $\boldsymbol{\beta_1, \beta_2, \beta_3, \ldots}$ are the coefficient of the independent variables
- $\boldsymbol{\varepsilon_{p,t}}$ is the residual of the regression for fund p at month t

The model will be performed four times as we will first analyse the relationship between hedge funds 'flows, their past performance (lagged alpha) and liquid hedge funds' past performance (lagged alphas of fund f). As alphas with two different asset pricing models were calculated, two regressions will be analysed for each type of fund: one with the alphas obtained with the CAPM and one with the alphas obtained with the multifactor model as they cannot directly be compared in the same regression providing us with four panel regressions in total. The model will be performed using SAS and the code can be consulted in **appendix D**.

As this research aims at determining whether the flows are linked to the fund's past performance, the alphas need to be lagged as investors do not immediately acknowledge the performance of the fund. In addition, this is also proven by previous literature, as stated in the introduction and is thus common practice. To capture qualitative factors which can also influence the flows, such as the strategy or the fund size, dummy variables are used. Dummy variables are equal to one if the attribute is present and to zero if the attribute is missing

(Gujarati, 2011). In this model, the dummy strategy takes the value of one if the fund has a liquid strategy (long short) and the value of zero if the strategy is less liquid (fixed income). As for the size dummy, if the fund is categorised as small, the dummy is equal to one and if the fund is not categorised as small, the dummy takes the value of zero. As stated before, hedge funds can have strategies that are capacity constrained and thus the size can affect the flows.

Dummy variables are also introduced to capture the time effect with YEAR 11, YEAR12 and so on, respectively taking the value of one if the observation is in 2011, 2012 and so forth. Indeed, the flow determinants of 2010 are not the same in 2019 which is why such dummies need to be taken into account. Instead of year dummies, monthly dummies could be used if a cyclical trend is to be observed in the data, meaning certain months would get more flows than others no matter the year. However, after checking the data, such trend could not be observed but markets have evolved over the years and so have investors. For these reasons, the year effects were presumed to be a better fit for this model. When multiple dummy variables are used to capture a common effect, if every dummy is included in the model, their sum is equal to one leading to perfect collinearity (Gujarati, 2011). For this reason, a benchmark needs to be defined and will be removed from the model. In this model, YEAR10 is removed as it is the first observation period. Dummy variables can also interact with quantitative variables when one suspects that the interaction can have a significant effect on the dependent variable. In this research, it is to be determined whether the good or bad performance of liquid hedge funds and hedge funds drives their respective flows. However, one might switch from a long short hedge fund to a long short liquid hedge fund more easily than for the fixed income strategy as it might not be as easy to find and as it is less liquid. To account for this style effect, the lagged alphas and the strategy dummy are included in the model but an additional interactive variable where these two variables are multiplied, is also added.

Another control variable is the lagged fund flows which is also common in similar literature (e.g., Agarwal et al., 2018, Cao et al., 2017, Berk & Tonks, 2007). This is justified by the fact that the flows of a fund experience autocorrelation meaning previous fund flows explain current fund flows. Indeed, studies such as Del Guercio & Tkac (2002), finds autocorrelation in mutual fund flows. In addition, Getmansky (2012) also discovers a positive relation between past and current hedge fund flows.

According to Berk & Tonks (2007), the fund age influences the fund flows and this variable was extensively used by other papers such as Agarwal et al. (2018), Cao et al. (2017) and Berggrun & Lizarzaburu (2015). In addition, another widely used measure, is the fund's standard deviation over the last year since the risk measure is important to investors.

Panel regressions thus determine the trend for the population over time as there are many individuals over a sample period. The individuals have many characteristics that can vary over time or not and which are thus used as independent variables in the panel regression. As this research not only aims at determining whether the flows of a particular fund category depend on its characteristics but also on the characteristics of another fund category, a matching approach has to be used. For instance, the hedge fund flows are not only influenced by the hedge fund alphas but also by the liquid hedge fund alphas which are not considered as a hedge fund characteristic. To allow for better comparability, hedge funds and liquid hedge funds were divided by category (long short equity vs fixed income) and were categorised according to their sizes. Indeed, according to Getmansky (2012), literature has shown that the performance and the fund size are positively linked (e.g., Agarwal et al., 2009 & Goetzmann et al., 2003). In addition, Goetzmann & Brown (2003) discovered that the strategy of a hedge fund accounts for 20% of the variability in returns when compared to other hedge funds. Furthermore, the choice of strategy for liquid hedge funds affects the performance of the fund since some hedge fund-like strategies might be difficult or impossible to replicate because of the restrictions set up by the UCITS directives or the Investment Company Act. As these two criteria are important factors that influence the performance, funds will be matched according to which strategy they chose and which size category they belong to. Nevertheless, as stated in the literature review chapter, liquidity restrictions such as redemption periods and lock up systems can also determine the fund's performance and will thus be used as criteria. Evidently, funds also need to report over the same period otherwise, the relationship cannot be unfolded. As younger funds usually need to prove themselves to attract investors, the age of a fund is an important determinant and thus the inception dates will also be matched. Funds will thus be exactly matched based on their strategy, size category and whether they have a lock up system. As for the inception date, the reporting period and the notice period for redemptions, funds with the most similar characteristics will be matched.

In this chapter, the data collecting process was described and the different steps of the methodology were detailed. The flow and performance measures were presented and were then used in the panel regression which will determine the conclusion of this thesis and thus answer the research question. The following chapter will provide summary statistics and various insights about the sample in general and will then study the performance and flow measures. Finally, the results of the panel regressions will be discussed in the last section.

4. Results

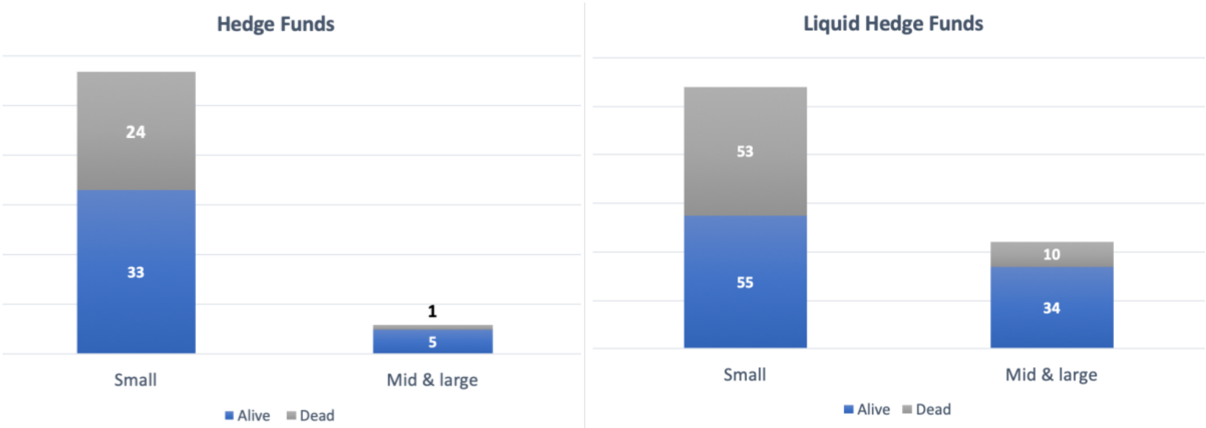
4.1. Summary Statistics

This first section of the results chapter will look into the different characteristics of the funds in the sample by separating them by strategies and size. Summary statistics will allow to provide a global picture of what differentiates hedge funds and liquid hedge funds.

4.1.1. Summary Statistics for the Long Short Equity Strategy

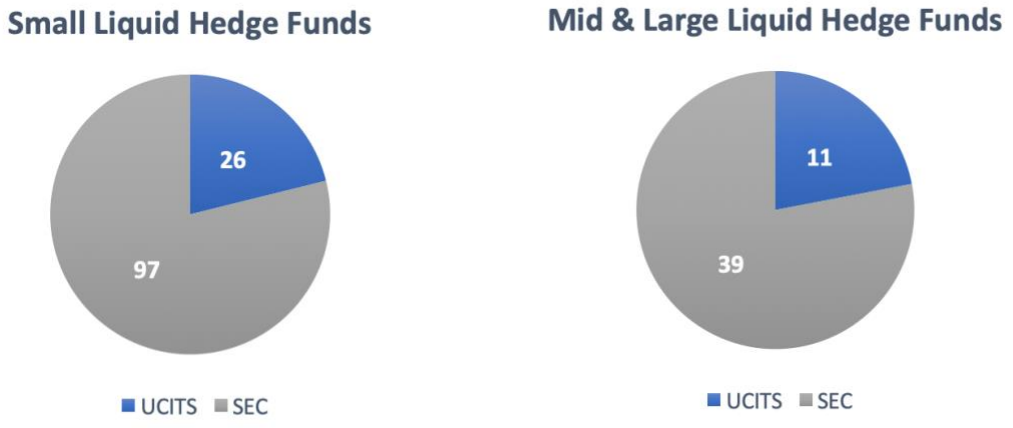
As stated in the previous section, two strategies with a different degree of liquidity are examined. By filtering the original data as stated in the previous section, 63 hedge funds and 152 liquid hedge funds with a long short equity strategy are obtained. The liquid hedge fund sample shows a greater proportion of dead funds (41,44%) than the hedge fund sample (39,7%). For both size categories, small funds have a higher proportion of dead funds which is consistent with Eurekahedge's conclusion that small funds have a harder time surviving the competition. The majority of both samples is located in the small sized fund category which is relevant as the industry is known to be highly fragmented (**Figure 12**).

Figure 12: Repartition of Dead and Alive Funds



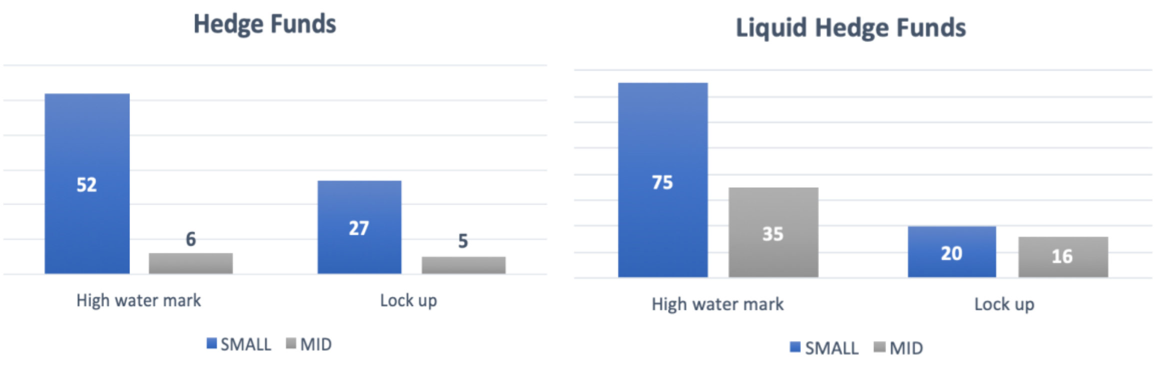
As the liquid hedge fund sample comprises both UCITS compliant and SEC registered funds, the repartition of funds between these two categories was also studied as shown on **Figure 13**. Both the small and mid & large size liquid hedge funds categories are dominated with mutual hedged funds which is not surprising as selection criteria included the North American mandate and USD as a reporting currency.

Figure 13: Repartition of UCITS Compliant and SEC Registered Funds



Looking closer at typical characteristics of hedge funds, we can observe on **Figure 14** that the majority of funds has a high-water mark system. The high-water mark feature is more popular in the hedge fund sample (92% of funds having the feature) than in the liquid hedge fund sample (72% of funds having the feature). Lock up periods however, are less popular for small funds (28% of funds having the feature) when compared to mid and large sized funds (42% of funds having the feature).

Figure 14: Number of Funds Having a High-water Mark and Lock Up System



Additionally, various risk and performance measures are examined because one cannot only compare returns between funds as they do not have the same strategy, nor the same benchmark which leads to different levels of risks (Hubner & François, 2019). Annualised returns in percentages can be observed in **Figure 15** with liquid hedge funds underperforming on average when compared to hedge funds. The distribution of the annualized returns for hedge funds seems to be asymmetric as the median slightly differs from the mean which is not the case for liquid hedge funds.

Funds might have a higher absolute return than others by taking way more risk. The Sharpe's ratio allows us to better compare funds on an equal basis as it is a measure of excess return with regard to the risk-free rate (constant over the period) per unit of risk (Hubner & François, 2019). As the Sharpe ratio is a scalar number, it is difficult to interpret its value and it should thus be compared between funds. There is not an ideal result, however, a Sharpe ratio close to 0, which is the case for small liquid funds on average, means that the funds deliver the risk-free rate and are thus poorly performing. On the other hand, a Sharpe ratio close to 1, as for the hedge fund sample and the mid & large sized liquid funds, shows that the funds are able to deliver excess returns for the risks taken which is positive for investors. Means and medians for all samples are close which means the distribution is symmetric. Small funds seem to be taking more risks as the annualised standard deviation is higher on average than for the other size category. Liquid hedge funds yield lower annualized returns than hedge funds, even though they have a similar level of risk which is consistent with the Sharpe's ratio results.

Since hedge funds do not exhibit much volatility but more extreme risk, the downside deviation is more appropriate in this context, which measures the standard deviation of returns below a certain level called "tail risk" (Busack, Drobetz & Tille, 2014). This is justified by the non-normality of the hedge funds' returns which leads to a non-symmetrical distribution (Kouwenberg & Ziemba, 2004). Surprisingly, this measure is slightly below the traditional standard deviation which leads to comparable Sharpe and Sortino ratios as the Sortino ratio replaces the volatility by its left-hand side and also takes into account the minimum return that the fund has to make. Hedge funds have a larger downside deviation and Sortino ratio than liquid hedge funds on average suggesting that they outperform liquid hedge funds on a risk-adjusted basis. Another widely used risk measure for hedge funds is the maximum drawdown which represents the highest decline in cumulative returns. Small sized funds in both samples exhibit the highest drawdown with hedge funds having larger values than liquid hedge funds on average. However, the value at risk is higher for hedge funds which shows that it is slightly more likely that they generate negative returns during a period of time at the 99% confidence level. The fact that liquid hedge funds exhibit a lower value at risk can also be due to VaR restrictions imposed upon alternative UCITS which can lower the average for the liquid sample.

Both mid and large sized samples exhibit more and less the same size while small hedge funds are smaller than small liquid hedge funds. The corresponding size categories have a similar age on average with about 6 years for small funds and 5 years for mid & large sized funds. Dead funds not reporting their death date are thus not included in this measure. Small liquid hedge funds require a higher minimum investment size (above 1million USD) than mid and large sized liquid funds which seems unusual as the opposite conclusion can be observed for the hedge fund sample. Indeed, small hedge funds require a lower minimum investment than the mid & large size hedge funds. The average of the minimum investment for small liquid funds and mid & large sized hedge fund is way above the median which means the distribution is extremely asymmetric and skewed to the right.

Management fees for both samples are in line with industry standards (between 1-2%) with hedge funds charging slightly higher fees on average. As for the performance fees, hedge funds charge close to 20% while liquid hedge funds charge closer to 15%. On average, larger funds tend to charge larger fees as it can be seen in this case as well. As for the notice period for redemptions, hedge funds' periods are doubled when compared to liquid hedge fund which is logical as liquid hedge funds are supposed to be more liquid.

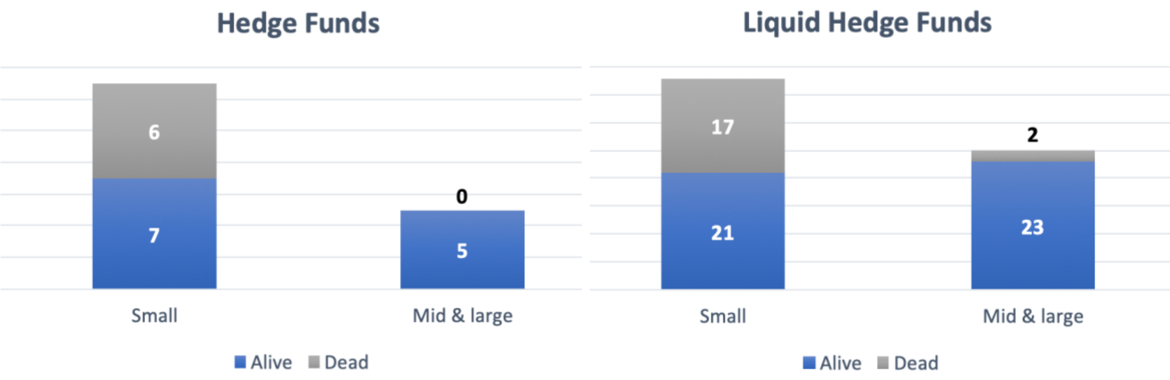
Figure 15: Summary Statistics for the Long Short Equity Samples

	Hedge Funds						Liquid Hedge Funds					
	Small sized			Mid & Large sized			Small sized			Mid & Large sized		
	N	MEAN	MEDIAN	N	MEAN	MEDIAN	N	MEAN	MEDIAN	N	MEAN	MEDIAN
Annualised return (%)	57	10,32	7,78	6	18,51	12,74	108	4,29	4,10	44	6,58	6,63
Sharpe Ratio	57	0,73	0,75	6	1,88	1,50	108	0,47	0,44	44	0,84	0,93
Annualised stdev (%)	57	16,96	12,15	6	11,74	8,86	108	9,74	8,48	44	9,22	7,49
Downside dev (%)	57	9,79	6,97	6	6,07	5,18	108	6,47	5,62	44	5,67	4,77
Sortino	57	2,58	1,20	6	9,52	2,93	108	0,89	0,67	44	1,60	1,49
Max Drawdown	57	-21,90	-16,38	6	-14,54	-11,95	108	-16,56	-15,32	44	-14,27	-10,11
VaR (99%)	57	-10,38	-7,31	6	-6,43	-5,37	108	-6,16	-5,49	44	-5,62	-4,27
Fund size ($m)	57	16	10	6	336	319	108	34	31	44	500	322
Age (months)	44	74	74	5	62	47	101	66	62	42	73	76
Minimum investment size	55	503.636	500.000	6	1.308.333	750.000	100	1.302.020	500.000	40	816.925	500.000
Management fee (%)	57	1,43	1,50	6	1,58	1,50	108	1,40	1,50	44	1,43	1,50
Performance fee (%)	57	19,25	20,00	6	19,17	20,00	108	13,93	20,00	44	16,65	20,00
Notice period (days)	0	41	30	0	49	53	103	20	10	40	32	30

4.1.2. Summary Statistics for the Fixed Income Strategy

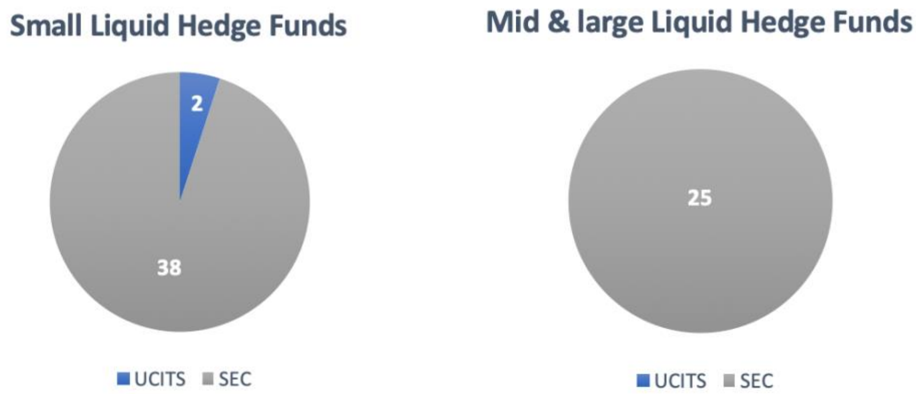
As the long short samples were analysed in the previous section, this section will thus be dedicated to the analysis of the fixed income samples. By filtering the original data, 18 hedge funds and 63 liquid hedge funds who report at least 24 monthly returns over the sample period are obtained. The proportion of dead funds for hedge funds (33,33%) and liquid hedge funds (30%) is similar and both categories have more small than mid & large sized funds like the long short strategy samples as **Figure 16** shows. Small funds have the largest proportion of dead funds similarly to the long short sample stating that small funds have a harder time surviving the competition.

Figure 16: Repartition of Dead and Alive Funds



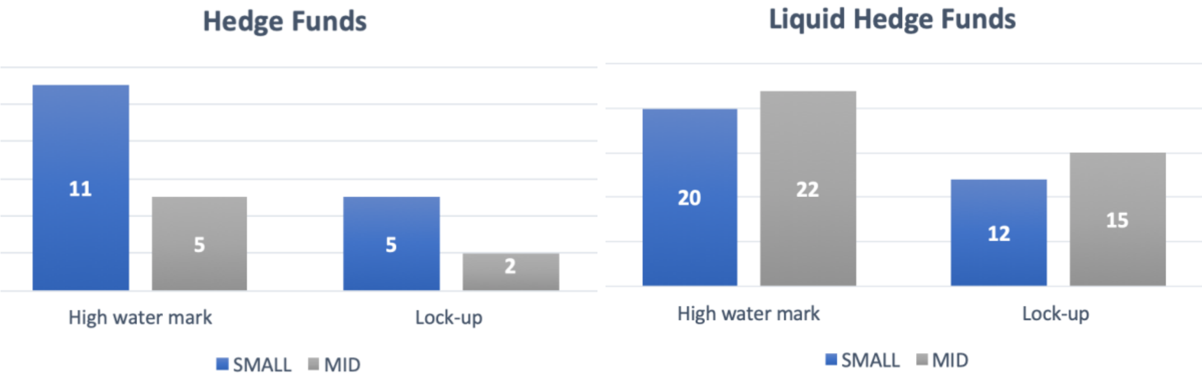
Regarding the repartition of liquid hedge funds between UCITS hedge funds and mutual hedged funds, the sample is dominated by the later as only 2 alternative UCITS are included (**Figure 17**). As the long short strategy is more popular for newcits funds, it is thus normal to have a lower proportion of these funds for the fixed income strategy with a North American mandate.

Figure 17: Repartition of UCITS Compliant and SEC Registered Funds



As for the characteristics, as shown on **Figure 18**, a majority of funds have a high-water mark system. The high-water mark feature is more popular in the hedge fund sample (88% of funds having the feature) than in the liquid hedge fund sample (66% of funds having the feature) similarly to the long short sample. Lock up periods however, are less popular for small funds (33% of funds having the feature) when compared to mid and large sized funds (56% of funds having the feature).

Figure 18: Number of Funds Having a High-water Mark and Lock Up System



Annualised returns (**Figure 19**) show that small hedge funds outperform small liquid funds on average and the opposite can be observed in the mid & large sized category. The small hedge fund sample has a median way below the mean which means the distribution is skewed to the right. As the samples are smaller, we have to consider that numbers might not be representative. Furthermore, each sample has a Sharpe ratio way above 1 which means they can deliver excess returns for the risks taken which is positive for investors. Sharpe's ratios are higher than for the long short sample suggesting this strategy yields better risk-adjusted returns on average. Additionally, hedge funds have a higher Sharpe's ratio than their corresponding liquid hedge fund size categories. Looking at the annualized standard deviation, liquid hedge funds appear to be taking more risks on average than hedge funds for both size categories which is surprising as they have more risk restrictions. For both samples, the small size category is also taking more risks with regards to the other size categories. These results are consistent with hedge funds' Sharpe ratio above one. The fixed income samples take lower risks than the long short samples for a similar level of annualized returns which explains the higher Sharpe ratios.

The downside deviation is lower than the annualized standard deviation for all categories. Liquid hedge funds also exhibit larger downside deviation than hedge funds however, hedge funds' Sortino ratios are higher showing that they outperform liquid hedge funds on a risk-adjusted basis. Another risk measure is the maximum drawdown which is also higher for liquid hedge funds. In general, small funds seem to have a larger maximum drawdown than mid & large sized funds for both samples. The value at risk is higher for hedge funds which shows that it is slightly more likely that they generate negative returns during a period of time at the 99% confidence level. This is consistent with the value at risk restrictions for the UCITS hedge funds which should lower the liquid hedge funds' average.

Hedge funds seem to be smaller in size when compared to the same size category of liquid hedge funds. In addition, liquid hedge funds are larger in size on average than their comparable size category. Small hedge funds and mid & large sized liquid funds' size distribution is skewed to the right with medians way below averages. Small sized funds have on average the same age with a lifespan of about 5 and a half years. However, mid & large liquid hedge funds seem to outlive small hedge funds (4 and a half years) on average with a lifespan of 6 and a half years. It is to be noted that a few dead funds do not report their death date and thus their age cannot be computed and is left as blank.

Surprisingly, small liquid hedge funds have a higher minimum investment (about 1,7 million USD) than small hedge funds with a minimum investment of about 773 thousand USD. Performance fees of hedge funds (between 17-20%) are higher on average than those for the liquid hedge funds (around 15%) which could explain why small liquid hedge funds charge higher management fees than the small hedge funds as they need to compensate. The results of the notice period before redemption are surprising as liquid hedge funds require a larger notice period for redemptions or they are supposed to be more liquid than their counterparty. The opposite can be observed for the long short sample which makes sense as the long short strategy is more liquid. However, it is unsure why liquid hedge funds require a longer notice period.

Figure 19: Summary Statistics for the Fixed Income Samples

	Hedge Funds						Liquid Hedge Funds					
	Small sized			Mid & large sized			Small sized			Mid & large sized		
	N	MEAN	MEDIAN	N	MEAN	MEDIAN	N	MEAN	MEDIAN	N	MEAN	MEDIAN
Annualised return (%)	13	9,09	6,24	5	7,45	7,75	38	4,58	4,41	25	7,91	7,98
Sharpe Ratio	13	5,81	2,17	5	3,72	3,53	38	2,51	1,02	25	3,05	2,77
Annualised stdev (%)	13	4,42	3,39	5	2,17	1,51	38	5,49	4,93	25	3,76	3,48
Downside dev (%)	11	3,25	2,29	5	0,67	0,40	33	3,88	2,95	22	1,95	1,56
Sortino	10	5,31	2,38	5	13,93	15,54	33	3,87	1,22	22	7,88	7,14
Max Drawdown	13	-7,80	-5,87	5	-1,26	-0,61	38	-10,21	-6,23	25	-4,97	-2,48
VaR (99%)	13	-2,24	-1,63	5	-0,85	-0,58	38	-1,69	-1,36	25	-0,75	-0,51
Fund size ($m)	13	29	9	5	266	260	38	41	38	25	1.070	683
Age (months)	9	67	72	5	55	50	31	66	65	25	80	89
Minimum investment size	13	773.077	500.000	5	2.620.000	1.000.000	36	1.755.806	1.000.000	25	1.794.300	1.000.000
Management fee (%)	13	1,35	1,00	5	0,80	1,00	38	1,30	1,25	25	1,35	1,50
Performance fee (%)	13	17,00	20,00	5	21,00	20,00	38	14,55	16,50	25	14,10	20,00
Notice period (days)	12	43	30	5	51	60	38	52	60	25	71	65

4.2. Fund Flows

The flow average and median for each strategy and its corresponding size categories were computed using a code in Matlab in order to regroup all the flows in a matrix and to take the average and median over the sample period. The code can be consulted in **appendix E**.

As demonstrated in **Figure 20**, funds in each categories experience, on average, monthly negative flows over the reporting period. This result thus suggest that funds have more capital outflows than inflows. Medians for each category are well below averages suggesting a positively skewed flow distribution. This implies that most of the flows are located on the left side of the mean and thus are mostly negative. Liquid hedge funds have higher negative flows when compared to hedge funds on average regardless of the size category. Mid & large sized funds experience larger negative flows than small funds on average. The result is consistent as hedge funds having smaller capital outflows is due to their liquidity restrictions such as lock up periods, redemption and notice periods as stated by Baquero et al. (2005).

Figure 20: Flow Statistics for the Long Short Equity Strategy (in million USD)

	Hedge funds		Liquid hedge funds	
	Small sized	Mid & large sized	Small sized	Mid & large sized
Flow average	-6,11	-17,54	-12,34	-124,54
Flow median	-3,15	-3,58	-4	-47,08

As for the fixed income sample, mid & large sized funds experience the largest capital outflows as shown in **Figure 20**. Small hedge funds have larger capital outflows than small liquid funds while the opposite can be observed for the mid & large sized category. This result is surprising as hedge funds should have more liquidity constraints and have thus lower capital outflows. The flow distribution is also skewed to the right suggesting most of the population is negative. We can also observe that the fixed income samples have larger capital outflows on average than the long short sample which could be explained by the lower degree of liquidity of the fixed income strategy but needs to be confirmed with a more detailed analysis. When taking a closer look into relative flows, fixed income hedge funds experience on average larger negative flows than long short funds taking into account their average fund size. For both strategies, small funds always have higher relative flows than mid & large sized funds even though their absolute flow are lower.

Figure 21: Flow Statistics for the Fixed Income Strategy (in million USD)

	Hedge Funds		Liquid Hedge Funds	
	Small sized	Mid & large sized	Small sized	Mid & large sized
Flow average	-127,57	-136,26	-12,26	-235,90
Flow median	-16,39	-22,08	-8,88	-72,55

4.3. Measuring the Fund's Performance

The methodology chapter shed a light on how the fund manager's skills can be estimated which thus measures the fund's performance. Two different models are used to compute the alphas: The Capital Asset Pricing model and a multi-factor model to capture different risk factors and the investors preferences. This section is dedicated to the analysis of these results.

As it can be observed on **Figure 22 and 23**, the R_2 of the fixed income CAPM alphas are, on average, higher than those of the long short CAPM alphas. The R_2 measures the goodness of fit of the regression and thus the long short CAPM alphas seems to have a better model than the fixed income CAPM alphas even though their R_2 measure is still quite low on average. These conclusions are also confirmed by the adjusted R_2 of the long short samples being higher than those of the fixed income. The fact that the adjusted R_2 is always lower than the ordinary R_2 is normal as it is measured based on R_2 taking into account the number of independent variable and the sample size. It is important to compute the adjusted R_2 when comparing different models with different numbers of factors as R_2 always increases when adding factors whereas adjusted R_2 will not increase if the added factor is not relevant as it will be analysed afterwards.

As there are more funds in in the long short sample, more alphas are obtained than for the fixed income sample. Fixed income alphas are, on average, higher than the long short alphas which means the fixed income managers have more skills on average. However, due to the low R_2, the model is not a good fit and thus one cannot rely on these alphas. In the long short sample, hedge funds tend to have a higher alpha on average than liquid hedge funds which would mean that hedge funds managers have more skills than liquid hedge fund managers. Small liquid hedge fund managers also underperform on average which is concluded based on the negative alpha. As Gujarati (2011) states, p-values of a coefficient reflect their statistical significance and thus whether the coefficient has a statistically significant influence on the excess returns. On average, none of the alphas for the long short sample are statistically significant as they are between 27% and 40% and are thus above the level of significance of 1%, 5% and 10%. This result shows that the manager's skills for the long short strategy does not statistically impact the excess returns of funds on average.

For the fixed income sample, small hedge fund managers have more skills than small liquid hedge fund managers on average while the opposite can be observed for the mid & large sized funds. In addition, for both strategies, standard deviations of alphas are very high suggesting that alphas are very volatile in the samples. As for the statistical significance of the alphas, small funds' alphas are not significant at any of the significance levels while the mid & large sized hedge funds' alphas are significant at the 5 and 10% level on average. In addition, mid & large sized liquid hedge funds' alphas are significant only at the 10% level. The median of the p-values shows that all alphas are statistically significant at the 5% and 10% level which suggests that the distribution is positively skewed and that most of the alphas in the samples are significant.

Figure 22: CAPM Alphas for the Long Short Sample (in %)

Long short	N	Mean	Median	Stdev
Small HF Alpha	4459	0,265	0,315	3,511
p-values		0,375	0,320	0,308
R2		0,294	0,194	0,284
Adjusted R2		0,231	0,130	0,288
Mid sized HF Alpha	369	1,074	1,155	1,247
p-values		0,279	0,148	0,302
R2		0,217	0,197	0,198
Adjusted R2		0,130	0,144	0,197
Small Liquid HF Alpha	8068	-0,122	-0,027	7,625
p-values		0,387	0,334	0,307
R2		0,364	0,314	0,288
Adjusted R2		0,308	0,266	0,301
Mid sized Liquid HF Alpha	3466	0,194	0,110	1,646
p-values		0,391	0,349	0,301
R2		0,420	0,407	0,302
Adjusted R2		0,372	0,377	0,321

Figure 23: CAPM Alphas for the Fixed Income Sample (in %)

Fixed Income	N	Mean	Median	Stdev
Small HF Alpha	919	0,681	0,731	0,884
p-values		0,196	0,023	0,285
R2		0,161	0,066	0,229
Adjusted R2		0,079	0,015	0,203
Mid sized HF Alpha	275	0,495	0,413	0,432
p-values		0,043	0,005	0,089
R2		0,132	0,048	0,222
Adjusted R2		0,061	-0,003	0,179
Small Liquid HF Alpha	2761	0,306	0,411	1,074
p-values		0,215	0,065	0,283
R2		0,188	0,104	0,221
Adjusted R2		0,110	0,046	0,221
Mid sized Liquid HF Alpha	2141	0,598	0,567	0,657
p-values		0,098	0,002	0,197
R2		0,114	0,056	0,169
Adjusted R2		0,045	0,013	0,163

As for the results shown in **Figure 24 and 25**, the fixed income sample has, on average, a higher alpha than the long short sample as for the CAPM model. The goodness of fit of the model is higher for the long short sample but remains below 50% which means the model is not reliable. For the fixed income sample, it is to be seen that small hedge fund managers tend to outperform, on average, small liquid hedge funds and the opposite can be seen with mid & large sized funds. Alphas for small funds are not significant at any of the significance level while the alphas of mid & large sized funds are significant at the 10% level on average. However, similarly to the CAPM alphas, the median p-values are significant at the 5% and/or 10% level suggesting that the distribution is positively skewed and that most of the alphas are thus significant at the 5% level at least.

For the long short sample, small liquid hedge fund managers tend to underperform small hedge funds and the opposite can be seen for the mid & large sized funds. None of the alphas are negative on average which shows that managers tend to outperform. Alphas are not significant on average, for any level of significance. However, the mid & large sized hedge funds' alphas have a median p-value which is significant at the 10% level suggesting that most of their alphas are significant.

Figure 24: Multifactor Alphas for the Long Short Sample (in %)

Long short	N	Mean	Median	Stdev
Small HF Alpha	4346	0,314	0,274	6,219
p-value		0,384	0,348	0,309
R2		0,491	0,450	0,289
Adjusted R2		0,263	0,213	0,351
Mid sized HF Alpha	358	1,413	1,256	3,062
p-value		0,234	0,071	0,288
R2		0,448	0,387	0,287
Adjusted R2		0,171	0,137	0,252
Small Liquid HF Alpha	7864	0,008	0,035	5,729
p-value		0,382	0,334	0,307
R2		0,557	0,561	0,275
Adjusted R2		0,363	0,366	0,334
Mid sized Liquid HF Alpha	3392	0,206	0,122	1,378
p-value		0,396	0,362	0,308
R2		0,591	0,602	0,264
Adjusted R2		0,426	0,474	0,349

Figure 25: Multifactor Alphas for the Fixed Income Sample (in %)

Fixed Income	N	Mean	Median	Stdev
Small HF Alpha	883	0,644	0,708	1,816
p-value		0,211	0,043	0,300
R2		0,415	0,340	0,292
Adjusted R2		0,138	0,069	0,264
Mid sized HF Alpha	268	0,552	0,357	1,186
p-value		0,083	0,015	0,157
R2		0,349	0,236	0,273
Adjusted R2		0,022	0,049	0,338
Small Liquid HF Alpha	2693	0,322	0,429	2,250
p-value		0,239	0,085	0,294
R2		0,406	0,329	0,283
Adjusted R2		0,138	0,106	0,309
Mid sized Liquid HF Alpha	2095	0,638	0,554	1,723
p-value		0,094	0,004	0,185
R2		0,313	0,242	0,243
Adjusted R2		0,049	0,037	0,258

When comparing the two asset pricing models, the R_2 of the multi-factor model is, on average, higher than the R_2 of the CAPM for both strategies. This conclusion is normal as more factors are added into a model, the R_2 increases which is why the adjusted R_2 needs to be computed. The multifactor factor model provides higher alphas on average for the long short sample with higher adjusted R_2. This result is not surprising as a value and size premium were added into the models which can better explain the returns of stock portfolios. Long short liquid hedge funds have a higher adjusted R_2 on average than long short hedge funds suggesting than hedge fund’s returns might be better explained by models with even more exotic and complex factors. Evidently, liquid hedge funds are still constrained with regards to the type of assets they can purchase and diversification restrictions while hedge funds are not which could explain why their returns are not only captured by these factors but by others.

For the fixed income funds, alphas obtained with the multifactor model are higher on average with higher adjusted R_2 except for mid & large sized hedge funds. As fixed income strategies’ returns are not influenced by an equity risk premium such as in the CAPM, the multifactor model should be a better model as it takes into account the credit and liquidity risk that fixed income strategies face. This model provides higher adjusted R_2 to liquid hedge funds when compared to pure hedge funds which can also be observed for the long short strategy.

Each fund had thus, over the sample period, alphas computed with the CAPM and the multifactor model. As alphas for both model are computed using the fund’s returns, theory states that the same number of alphas obtained with both model should be equal. Unfortunately, due to Matlab precision issues, as some computed factors approached zero, some alphas were not computed. Let us now analyse the results of the panel regressions in order to deduct whether fund flows are due to their respective past performance.

4.4. Panel Regression

This section will thus analyse the results of the four panel regression models as described in the data and methodology chapter. As the relationship between the flows of both the hedge funds and liquid hedge funds and the alphas computed with the CAPM and a multifactor model are studied, four subsections with one for each model will now be discussed.

4.4.1. Hedge Fund Flows and the CAPM Alphas

The results of the fixed effects panel regression analysing the relationship between the hedge fund flows and the performance measured by the CAPM alphas can be observed in **figure 26.** As stated before, 80 hedge funds (cross-sectional units) are observed over 120 months. However, as month 1, 2 and 3 did not have more than two characteristics available for each cross-sectional unit, SAS studied the model over the 116-remaining time period. The measure of goodness of fit is quite low suggesting that the independent variables have a low explanatory power (8%) over the independent variable (the monthly hedge fund flows). However, this result is not surprising as similar studies obtain R_2 in the same range (e.g., Agarwal et al., 2009, Cao et al.,2017, Berggrun & Lizarzaburu, 2015). As for the statistical significance of the repressors, only the lagged hedge fund flow variable is significant at the 1%, 5% and 10% level whereas all the other coefficients have a p-value ranging from 20% to 96%.

The coefficient for the lagged hedge fund flows is positive suggesting a positive relationship between past and current flows which is consistent with prior literature results as stated in the previous chapter. As the flows are measured in million dollars and not in percentages, a one million dollar increase in the previous monthly flow will increase the current monthly flow of the hedge fund by 0,16 million dollars. The positive coefficient (3,92) of the lagged hedge fund alphas, demonstrates that investors invest according to the fund's past performance as Berggrun & Lizarzaburu (2015) also discovered in their study. A 1% increase in the previous monthly alpha of the hedge fund will thus result in a 3,92 million dollar increase in the fund flow. The interaction variable between the hedge fund lagged alphas and the strategy dummy allows to determine whether the fund's strategy affects the performance and flow relationship. The interaction variable is thus equal to zero when the fund's strategy is not liquid (fixed income) and equal to one when the strategy is liquid (long short equity). This means that for fixed income funds, the lagged performance has a positive impact on the fund flows that is bigger than for long short equity funds as the coefficient of the interaction variable is equal to -3,78 leading to a total lagged alpha coefficient of 0,14 (3,92 – 3,78) for the long short strategy as Gujarati (2011) explains. The past alpha has thus more impact on the flows of fixed income funds than on those of the long short equity funds. This result is surprising as it should be easier to find another long short equity hedge fund than fixed income hedge fund as the first strategy is one of the most popular leading thus to a larger choice for the investor, leading to a higher sensitivity between the flows and the performance.

With the matching method described in the panel regression section of the methodology chapter, liquid hedge funds were assigned to pure hedge funds based on similar characteristics in order to study the impact of the liquid hedge funds' performance on the hedge fund flows. The coefficient of the lagged alphas for liquid hedge funds, is positive (5,41) showing that positive performance for liquid hedge funds should increase the hedge fund flows. This result is striking as investors should be rational and switch to a fund with better performance which would be depicted by a negative coefficient for this regressor. The interaction variable between the lagged alphas of liquid hedge funds and their corresponding strategy has a positive coefficient (0,55) suggesting that long short equity liquid hedge funds' performance has a slightly bigger impact (5,96) on the hedge fund flows when compared to fixed income liquid hedge funds (5,41).

With the fixed effects model, coefficients are computed based on the difference from the mean value of the characteristic. This thus implies that if a variable or characteristic does not vary over time, its coefficient will be equal to 0 which is the case for the size and the strategy dummy. The strategy is still taken into account with the interaction variable as mentioned above. The effect of the fund size cannot be estimated as Eurekahedge provides the size of the fund as of December 2019 and not as a monthly and evolving measure which is why a dummy variable was used to estimate the effect.

Furthermore, the past risk of the fund positively affects the monthly flow as the coefficient is positive (0,43). A possible explanation is that funds taking more risk could slightly attract more capital inflows since hedge funds are well known by investors for taking more risks and yielding thus higher returns. In addition, the fund age has a positive coefficient (40), suggesting that older funds receive more flows on a monthly basis. One could justify this result with the assumption that older funds are well established and have a track record which could possibly attract new investors into the fund. This result, however, is not consistent with previous studies discovering that the fund age and the flows but also the fund's past risk and the flows are both negatively related (e.g., Berggrun & Lizarzaburu, 2015, Getmansky, 2012).

The year fixed effects are represented by the dummy variables YEAR11, YEAR12 and so on and must be interpreted with reference to the year 2010 which was removed from the model in order not to fall into the dummy trap. These dummies show how the hedge fund flows in 2011, 2012, and so on differ from the hedge fund flows in 2010 on average, as explained by Gujarati

(2011). We can deduct for instance that the average monthly hedge fund flow is higher in 2011 than in 2010 by 3,75 million dollars. However, for each other year, the coefficient of the dummy is negative suggesting that the corresponding average monthly fund flow is lower than the average monthly fund flow of 2010. Indeed, the average monthly flow of 2019 is lower than the average monthly fund flow of 2010 by 71 million dollars. As time goes by, the coefficients become more negative suggesting that the monthly fund flows are lower than for previous years with 2011 as a peak. This finding could be justified by the fact that the number of hedge funds has been growing since 2010 and that the industry has become more fragmented which leads to lower average monthly flows for each fund as investors' wealth could spread across many funds.

Figure 26: Fixed Effects Panel Regression for Hedge Fund Flows and the CAPM Alphas

Model Description	
Estimation Method	FixOne
Number of Cross Sections	80
Time Series Length	116

Fit Statistics			
SSE	500176955.6	DFE	4049
MSE	123530.9843	Root MSE	351.4697
R-Square	0.0804		

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-71.5806	90.5513	-0.79	0.4293	Intercept
FLOWHFLAGGED	1	0.160585	0.0155	10.37	<.0001	
ALPHAHFLAGGED1	1	3.92902	3.0477	1.29	0.1974	
ALPHAHFSTRAT	1	-3.78246	3.4875	-1.08	0.2782	ALPHAHFSTRAT
ALPHALIQLAGGED	1	5.415622	22.7918	0.24	0.8122	ALPHALIQLAGGED
ALPHALIQSTRAT	1	0.552388	23.4781	0.02	0.9812	ALPHALIQSTRAT
STRAT	0	0	.	.	.	STRAT
SIZE	0	0	.	.	.	SIZE
STDEV	1	0.433545	2.8583	0.15	0.8794	STDEV
LOGAGE	1	40.17986	48.6881	0.83	0.4093	LOGAGE
YEAR11	1	3.759848	73.9412	0.05	0.9594	YEAR11
YEAR12	1	-13.8425	76.4762	-0.18	0.8564	YEAR12
YEAR13	1	-33.6422	79.5204	-0.42	0.6723	YEAR13
YEAR14	1	-36.7971	82.7701	-0.44	0.6567	YEAR14
YEAR15	1	-29.5024	87.3758	-0.34	0.7356	YEAR15
YEAR16	1	-16.8863	91.1960	-0.19	0.8531	YEAR16
YEAR17	1	-33.7701	94.6829	-0.36	0.7214	YEAR17
YEAR18	1	-33.3937	98.1782	-0.34	0.7338	YEAR18
YEAR19	1	-71.1267	103.1	-0.69	0.4901	YEAR19

4.4.2. Hedge Fund Flows and the Multifactor Alphas

The results of the fixed effects panel regression analysing the relationship between the hedge fund flows and the performance measured by the Multifactor alphas can be observed in **figure 27.** 80 funds are analysed over 114 months as each fund had more than two missing variables for the first 6 months. The relationship between hedge fund flows and the performance estimated with multifactor alphas seems to have a slightly lower explanatory power (7,92%) than the previous model where the performance was estimated with CAPM alphas. In addition, none of the coefficients, but the lagged hedge fund flows, are significant at any of the significance level.

As in the previous model, lagged hedge fund flows have a positive relationship with current hedge fund flows as the coefficient is equal to 0,16. However, unlike in the CAPM model, a negative relationship (-0,18) between the lagged hedge fund alphas and the fund flows can be observed. Good performance obtained by the managers should attract capital inflows instead of leading to capital outflows and thus the negative coefficient is not consistent with this hypothesis. This could mean that the CAPM alpha better predicts and explains hedge fund flows as previous studies suggest (e.g., Agarwal et al., 2018 & Cao et al., 2017). When taking into account the effect of the strategy by looking at the interaction variable, it is to be concluded that long short hedge funds' performance has an overall positive impact on the flows with a coefficient of 0,58 while the performance of the fixed income funds has a negative impact on the flows (-0,18). Even though, the relationship is positive for long short hedge funds, it is lower than the effect obtained with the CAPM model suggesting the CAPM alphas better predict the hedge fund flows than the multifactor model alphas for both strategies as the flows are more sensitive to those alphas.

The coefficient for the lagged liquid hedge funds' alphas is positive (3,47) but lower than in the previous model. When interacting with the strategy dummy, the effect is lowered and becomes negative (-0,05) for the long short liquid hedge funds which is consistent with the conclusion that investors should withdraw their capital from hedge funds if the liquid hedge funds perform well. With the CAPM model, long short and fixed income liquid hedge funds' performance had a higher positive impact on hedge fund flows when compared with the multifactor model which even obtains a negative effect for the long short strategy. This could reflect the indifference of hedge fund investors with regards to the performance of liquid hedge funds which seems not to affect the capital flows of hedge funds. As hedge funds tend to provide higher risk-adjusted returns despite lower liquidity and transparency, investors might not be inclined to trade this performance for tighter regulations.

The effects of the fund's past risk and the fund's age are similar to the previous model with a positive coefficient for the past year's standard deviation (0,34) and for the log of the fund's age (70). The age seems to have a bigger impact on the fund flows in this model as the coefficient almost doubled. The year effects have similar coefficients when compared to the model with the CAM alphas as the average monthly flow is higher in 2011 than in 2010 and slowly becoming lower than 2010 over the years. In 2019, the average monthly flow is lower than the one in 2010 by 103 million dollars which suggests that the year effects have more impact on the fund flows with the multifactor model.

Figure 27: Fixed Effects Panel Regression for Hedge Fund Flows and the Multifactor Alphas

Model Description	
Estimation Method	FixOne
Number of Cross Sections	80
Time Series Length	114

Fit Statistics			
SSE	497387817.4	DFE	3940
MSE	126240.5628	Root MSE	355.3035
R-Square	0.0792		

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-81.7291	123.1	-0.66	0.5069	Intercept
FLOWHFLAGGED	1	0.162088	0.0157	10.30	<.0001	
ALPHAHFLAGGED1	1	-0.18694	4.5923	-0.04	0.9675	
ALPHAHFXSTRAT	1	0.769994	4.9884	0.15	0.8773	
ALPHALIQLAGGED	1	3.472273	17.3700	0.20	0.8416	ALPHALIQLAGGED
ALPHALIQSTRAT	1	-3.52283	17.3760	-0.20	0.8393	ALPHALIQSTRAT
STRAT	0	0	.	.	.	STRAT
SIZE	0	0	.	.	.	SIZE
STDEV	1	0.34586	2.9788	0.12	0.9076	STDEV
LOGAGE	1	70.74745	56.3275	1.26	0.2092	LOGAGE
YEAR11	1	2.226302	110.6	0.02	0.9839	YEAR11
YEAR12	1	-24.024	111.9	-0.21	0.8300	YEAR12
YEAR13	1	-50.0235	114.3	-0.44	0.6617	YEAR13
YEAR14	1	-56.9953	116.6	-0.49	0.6250	YEAR14
YEAR15	1	-51.7668	120.3	-0.43	0.6671	YEAR15
YEAR16	1	-43.1924	123.7	-0.35	0.7271	YEAR16
YEAR17	1	-62.0922	126.5	-0.49	0.6236	YEAR17
YEAR18	1	-63.8339	129.5	-0.49	0.6221	YEAR18
YEAR19	1	-103.992	133.8	-0.78	0.4370	YEAR19

To conclude the analysis of these two models studying hedge fund flows, the CAPM seems better suited to evaluate the performance-flow relationship as there is a positive and stronger impact of the past performance of the current flows. With these two models, it is to be concluded that hedge fund investors appear to react positively to riskier funds and to older funds which could be due to their increased experience. Surprisingly, liquid hedge funds' performance has a positive impact on the hedge fund flows which could imply that hedge funds investors do not seek to invest in liquid hedge funds and disregard their performance, with both asset pricing models. Finally, as for the year effects with both models, average monthly flows were larger in 2010 and decreasing ever since which is consistent with the recent increased in competition leading to a more fragmented industry.

4.4.3. Liquid Hedge Fund Flows and the CAPM Alphas

The results of the fixed effects panel regression analysing the relationship between the liquid hedge fund flows and the performance measured by the CAPM alphas can be observed in **figure 28.** The goal of this model and the following one is thus now to determine whether the performance of liquid hedge funds and hedge funds, measured both by the CAPM and the multifactor model, has any impact on the flows of the liquid hedge funds. 215 liquid hedge funds are studied over 113 months as there were more than 2 variables missing for the first seven months of the sample period. The first model where the managers 'skills are measured with the CAPM alphas, has a low R_2 (5,6%) which is lower than the previous hedge fund flow models. However, the intercept, the lagged liquid hedge fund flows and the lagged liquid hedge fund alphas have significant coefficients. Indeed, the intercept is significant at the 1% and 5% level while the lagged flows are significant at all levels and the lagged alphas are significant only at the 10% level.

Even though the previous monthly flow is a significant regressor, a surprising result arises since the coefficient is negative (-0,11) implying that previous monthly flows are negatively correlated with current monthly flows. As stated in the hedge fund models, fund flows are known to be positively auto correlated and especially for mutual funds. The fact that capital outflows would motivate investors to invest in a fund is an intriguing concept which is in contradiction with the hypothesis of this research. As for the effect of the performance of liquid hedge funds on their fund flows, the effect is important (66,16) and more pronounced than for the previous models studying the hedge fund flows where the impact was of about 3 million dollars. The liquidity of alternative UCITS and hedged mutual funds could be an explanation of this result since investors could more easily withdraw their capital from underperforming funds. In addition, as there are regulations on the reporting which is not the case for hedge funds, investors could be aware of the performance of the fund more quickly and could then decide whether to stay on board. However, when taking into account the effect of the strategy with the interaction dummy, the effect of performance on the flows drops to 0,67 dollars for the long short strategy. This result is indeed surprising as there are more long short liquid hedge funds than fixed income liquid hedge funds. One could interpret it as fixed income investors being more concerned about the performance of the fund since the choice of fund is limited while the long short investors are certain that they could find an alternative if necessary. The hedge fund flow model with the performance measured with the CAPM also had a negative coefficient for the interaction dummy leading to a lower effect for the long short strategy but not for the fixed income funds.

In line with the expectations of this research, the lagged alphas of hedge funds are negatively linked with the liquid hedge fund flows since the coefficient is of -30,83. This means that if hedge funds perform well, it will negatively affect the liquid hedge funds' flow as investor will supposedly withdraw their capital from liquid hedge funds to invest in hedge funds. Even when taking into account the interaction dummy for the strategy effect, the effect of the performance remains negative with a coefficient of -12 meaning that whether the liquid hedge fund has the fixed income or the long short strategy, the effect of hedge funds' performance remains similar. Hedge fund flows were positively affected by the performance of liquid hedge funds which was a surprising result as the opposite was expected. After studying the flows of liquid hedge funds, the opposite can be observed for this model which could mean that investors are attracted by the performance of hedge funds and perhaps are inclined not to benefit from the liquidity and transparency that liquid hedge funds offer.

The coefficients of the past standard deviations and of the fund's age are consistent with standard literature stating that investors do not like when the funds take more risks. This effect was positive for hedge funds which could depict the preference of sophisticated investors for more risk. In the context of regulated mutual funds, investors might be less inclined for the fund to take additional risk. The age of the fund also has a negative impact on the liquid hedge fund flows which is a result previously discovered by standard literature as well. Results of the year effects are mixed when compared to those of the hedge funds models. The average monthly flow in 2018 is 177 million dollars higher than the average monthly flow in 2010. However, in 2019, the average monthly flow is -137 million dollars lower, providing mixed results. On average, liquid hedge funds receive higher flows than 2010 however, certain years have a negative coefficient such as 2013, 2017 and 2019.

Figure 28: Fixed Effects Panel Regression for Liquid Hedge Fund Flows and the CAPM Alphas

Model Description	
Estimation Method	FixOne
Number of Cross Sections	215
Time Series Length	113

Fit Statistics			
SSE	10522261492	DFE	11189
MSE	940411.2514	Root MSE	969.7480
R-Square	0.0560		

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-420.263	202.7	-2.07	0.0382	Intercept
FLOWLIQLAGGED	1	-0.11934	0.00938	-12.72	<.0001	
ALPHAHFLAGGED	1	-30.8383	39.3424	-0.78	0.4331	ALPHAHFLAGGED
ALPHAHFSTRAT	1	17.95631	40.9435	0.44	0.6610	ALPHAHFSTRAT
ALPHALIQLAGGED	1	66.16802	39.9303	1.66	0.0975	ALPHALIQLAGGED
ALPHALIQSTRAT	1	-65.4912	39.9788	-1.64	0.1014	ALPHALIQSTRAT
STRAT	0	0	.	.	.	STRAT
SIZE	0	0	.	.	.	SIZE
STDEV	1	-12.6363	9.8916	-1.28	0.2015	STDEV
LOGAGE	1	-27.9458	81.7691	-0.34	0.7325	LOGAGE
YEAR11	1	93.18716	169.0	0.55	0.5814	YEAR11
YEAR12	1	36.83702	169.9	0.22	0.8283	YEAR12
YEAR13	1	-27.8259	173.7	-0.16	0.8727	YEAR13
YEAR14	1	20.01421	177.5	0.11	0.9102	YEAR14
YEAR15	1	131.5293	182.2	0.72	0.4704	YEAR15
YEAR16	1	66.8612	188.0	0.36	0.7221	YEAR16
YEAR17	1	-56.5121	193.9	-0.29	0.7707	YEAR17
YEAR18	1	177.3111	199.2	0.89	0.3734	YEAR18
YEAR19	1	-137.057	204.0	-0.67	0.5017	YEAR19

4.4.4. Liquid Hedge Fund Flows and the Multifactor Alphas

The results of the fixed effects panel regression analysing the relationship between the liquid hedge fund flows and the performance measured by the Multifactor alphas can be observed in **figure 29.** As more than two variables were missing for the first nine months, the 215 liquid hedge funds are studied over the remaining 111 months. The independent variables have a slightly higher explanatory power than the previous model as the R_2 is of 6%. However, for this model, only the intercept and the lagged liquid hedge fund flows are statistically significant at the 5% and 10% level.

As for the previous model, the lagged liquid hedge fund flows have a negative impact (-0,12) on the current liquid hedge fund flows. The effect of the liquid hedge funds' previous performance is lower (9,58) than for the previous model but still positive on the liquid hedge funds' flows. Literature discovered that investors rely more on the CAPM than multifactor model to evaluate the performance of funds as it is simpler, as stated in the methodology chapter. This thus could be one of the reasons why the effect of the lagged alpha is lower with the multifactor model when compared to the CAPM. A higher sensitivity for a specific model shows that investor use the model and thus that it is more representative. When taking into account the effect of the strategy with the interaction dummy, the performance even has a negative impact (-0,56) on the fund flows for the long short strategy whereas the effect is positive for fixed income funds (9,58). The fact that long short liquid hedge funds would perform badly and attract capital inflows is not realistic, especially when there are many alternatives since the long short strategy is very popular. This counterintuitive finding may be related to the CAPM being better suited to represent investors' beliefs than the multifactor model. This could be also reflected in the lagged hedge funds' performance which has a positive coefficient (4,06) and thus a positive impact on the liquid hedge fund flows as opposed to a negative effect with the previous model. In fact, the positive effect is increased (6,38) when the strategy is taken into account leading to long short hedge funds' performance having a higher and positive impact on the liquid hedge fund flows.

Similar conclusions as for the previous model can be applied for the effect of the past risk of the fund and its age as the coefficients remain negative and in similar ranges. Year effects are once again, provide mixed results with the average monthly liquid hedge fund flow in 2018 being 498 units above the average in 2010. We observe only positive coefficients for all the year dummies leading to 2010 being the year with the lowest monthly flows on average. These results could confirm the interest of investors for these new types of fund after the financial crisis, however, as the previous model provides more realistic conclusions, year effects appear to be somewhat unclear.

Figure 29: Fixed Effects Panel Regression for Liquid Hedge Fund Flows and the Multifactor Alphas

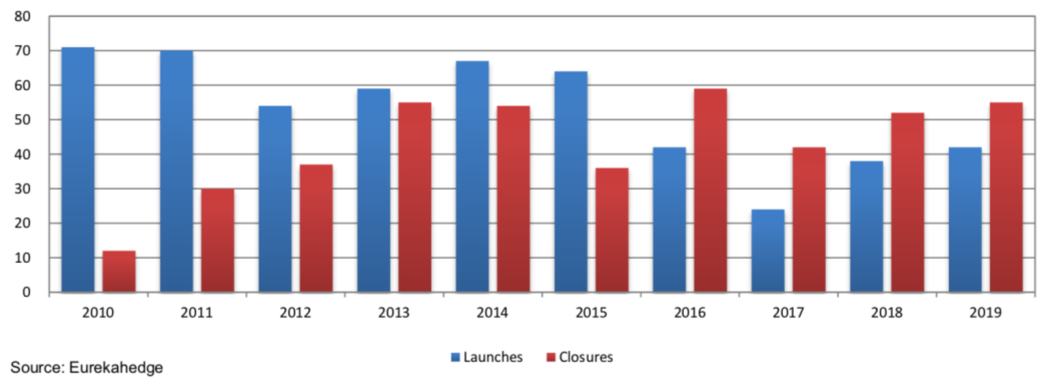
Model Description	
Estimation Method	FixOne
Number of Cross Sections	215
Time Series Length	111

Fit Statistics			
SSE	10315208019	DFE	10885
MSE	947653.4699	Root MSE	973.4749
R-Square	0.0600		

Parameter Estimates						
Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Label
Intercept	1	-778.869	368.7	-2.11	0.0347	Intercept
FLOWLIQLAGGED	1	-0.12321	0.00949	-12.98	<.0001	
ALPHAHFLAGGED1	1	4.064106	8.1374	0.50	0.6175	
ALPHAHFXSTRAT	1	2.329572	8.7851	0.27	0.7909	
ALPHALIQLAGGED1	1	9.581126	9.8410	0.97	0.3303	
ALPHALIQXSTRAT	1	-10.1414	10.0246	-1.01	0.3117	
STRAT	0	0	.	.	.	STRAT
SIZE	0	0	.	.	.	SIZE
STDEV	1	-11.2937	10.1941	-1.11	0.2679	STDEV
LOGAGE	1	-15.0539	93.7906	-0.16	0.8725	LOGAGE
YEAR11	1	420.5578	350.3	1.20	0.2300	YEAR11
YEAR12	1	357.4525	350.9	1.02	0.3083	YEAR12
YEAR13	1	296.7963	353.2	0.84	0.4008	YEAR13
YEAR14	1	338.1736	355.0	0.95	0.3409	YEAR14
YEAR15	1	440.9257	357.4	1.23	0.2173	YEAR15
YEAR16	1	358.1517	361.1	0.99	0.3213	YEAR16
YEAR17	1	261.4728	365.1	0.72	0.4739	YEAR17
YEAR18	1	498.9442	368.0	1.36	0.1752	YEAR18
YEAR19	1	181.0981	371.4	0.49	0.6258	YEAR19

The last two models can provide an answer to whether the hedge fund's performance has any impact on the liquid hedge fund flows. As for the hedge fund models, liquid hedge fund investors seem to react positively to good performance and a higher effect can be observed with the CAPM. This could suggest that the increased liquidity and mandatory reporting of these liquid funds allows investors to react more quickly to the performance. However, a negative effect between hedge funds' performance and liquid hedge fund flows is obtained suggesting liquid hedge fund investors pay more attention to their counterparty's performance than hedge fund investors do. This pressure could be the reason why the alternative hedge funds have decreased in popularity over the recent years. Consistent with standard literature, a negative effect is found for the fund's age and the risk as retail investors do not seem to seek for riskier funds. An increase in the fund flows is to be observed after 2010 and the financial crisis with the year effects. However, as time goes by, the results are mixed and cannot provide any insights. Looking at **Figure 30**, from Eurekahedge's report of April 2020, a decline in the number of launches and an increase in the number of closures of UCITS hedge funds is to be observed and confirms the decline in popularity of such funds. As reported by Agarwal et al. (2009) and Joenväärä & Kosowski (2014), both hedged mutual funds and alternative UCITS underperform pure hedge funds. The latter conclusion was also reached by Hartley (2016) and Newton (2009) who found that liquid hedge funds underperform hedge funds as well. This underperformance is due to the numerous restrictions from which the liquid hedge funds suffer and might lead investors to change their minds and invest back into the hedge fund industry. Agarwal et al. (2009) also discovers that this outperformance of hedge funds can be attributed to the higher fee structure which leads to better incentives for hedge fund managers. A comparative study between the performance of hedge funds and Alternative UCITS was also performed by ESMA (2013) and showed that they tend to have a lower performance due to the regulations. However, liquid hedge funds still provide flexibility with regards to the liquidity and are more transparent which can seem more attractive to some investors when compared to higher risk-adjusted returns. For this reason, liquid hedge funds have decreased in popularity but are still established and continue to exist to satisfy the needs of other types of investors.

Figure 30: Launched and Closures of Alternative UCITS funds



5. Conclusion

Many innovations have been arising on the financial markets over the years, trying to satisfy constantly evolving investors' needs. From traditional mutual funds to alternative funds, more complex investment vehicles were developed to satisfy those who were looking for higher risk-adjusted returns. However, with higher returns comes with disadvantages such as liquidity restrictions, lack of transparency and reporting or even excessive performance fees. The financial crisis of 2008, where financial institutions sold sketchy products to clients without being fully transparent about the toxic components, triggered new investors' needs who were demanding more transparency, liquidity and protection. Hedge fund managers, who were not going to go down without a fight, saw in the UCITS directives and in the Investment Company Act of 1940 an opportunity to replicate their strategies within a more restricted vehicle, thus addressing investors' concerns. Liquid hedge funds thus try to implement hedge fund like strategies but have liquidity, reporting, diversification, and asset restrictions to ensure the investors' protection. As these liquid hedge funds became more popular after the crisis and hedge funds' assets grew more slowly, this research studied whether the capital outflows and inflows of these funds were linked to their respective past performance. Previous literature has shown that fund flows are indeed driven by the fund's performance but the relationship between two different types of funds and the flows had not been yet studied. This thesis thus aimed at better understanding what influences investors' decisions and how directives and tighter regulations can affect the performance and thus flows.

In order to do so, the sample was retrieved from Eurekahedge and made of pure hedge funds and liquid hedge funds with a North American mandate reporting in USD who were created from 2010 onwards. Two strategies with a different degree of liquidity divided the sample in two to study the relationship between the performance and the flows and whether the strategy had any impact on it. In addition, the sample was split in two size categories to allow for better comparison. Summary statistics were computed to provide a global picture and to compare characteristics of both industries. Regarding the methodology, performance measures were obtained by using the capital asset pricing model (CAPM) and a multifactor model to capture what drives the returns but also the investors' preferences. The intercepts (alphas) of these regressions reflect the abnormal performance of the fund which can be interpreted as the managers' skills. A rolling window of 36 months was used to perform the regression on Matlab and in order to obtain a minimum of alphas, funds reporting less than 24 monthly returns were removed from the sample. As for the dollar flows of funds, they were calculated on excel using a formula retrieved from standard literature. Finally, a panel regression was computed using the software SAS to analyse the relationship between the flows and the alphas of both hedge funds and liquid hedge funds. As the Hausman test revealed that the random effects model was not appropriate for the sample, a one way fixed effects panel regression was performed. Control variables were added into the model as current fund flows do not only depend on the past performance but also on factors such as the strategy, the fund size, the fund age and its risk. The determinants of flows in 2010 were also different from the ones in 2019 and thus a time fixed effect was added as control variable as well. In order to study the effect of the fund's characteristics on its flows but also the effect of characteristics of another type of fund, a matching method had to be used. Liquid hedge funds and hedge funds were matched based on their strategy, size, inception date, reporting period, redemption notice period and whether they imposed a lock up period. Of course, as a perfect match is unrealistic for this sample size, exact match based on the strategy, size and lock ups were performed while making sure that the reporting and notice periods were as similar as possible.

Summary statistics provided a global picture of the sample and revealed that hedge funds tend to deliver higher risk-adjusted performance, on average, than liquid hedge funds, which was measured by the Sortino and Sharpe ratio. As fixed income funds appear to be taking less risk than long short equity funds, they are thus able to deliver higher risk-adjusted performance on average. As alternative UCITS have restrictions on their value at risk for instance, this measure was higher for hedge funds across strategies as expected. In line with industry standards, hedge funds also charge higher fees than liquid hedge funds for both strategies. The liquid hedge fund sample has more mutual hedged funds than newcits funds which can be justified by the choice of the North American mandate for this research. Furthermore, a smaller proportion of dead funds is obtained when compared to active funds but a 50% inactivity ratio amongst small funds confirms the hypothesis that small funds have a harder time surviving the accrued competition. As for the flow statistics, both strategies experience on average, negative monthly flows with liquid hedge funds experiencing higher capital outflows than hedge funds which is consistent with the lower liquidity provided by hedge funds. Larger outflows for mid & large size samples for both strategies are observed. Finally, fixed income funds experience larger capital outflows. However, without a more detailed analysis of the flows, it remains unclear what drives this result. The performance analysis revealed that fixed income funds have higher alphas on average than long short equity funds regardless of the chosen model. As for the difference between pure hedge funds and their liquid counterparties, fixed income funds provide mixed results with both models while long short hedge funds tend to outperform long short liquid hedge funds with the CAPM. The multifactor model seems to be a better fit for the long short equity funds as more complex equity factors are added which appear to better capture the returns. However, this model remains better suited for liquid hedge funds than pure hedge funds which could mean that hedge funds' returns come from additional complex risk factors. As for the fixed income strategy, the multifactor model is a better fit, based on the R^2, than the CAPM as it accounts for liquidity and credit factors. The multifactor model also provides higher adjusted R^2 for the long short liquid hedge funds suggesting that additional factors are to be added for long short hedge funds.

The fixed effects panel regression provided insights about the relationship between the performance and the flows. First, the model was studied on the hedge fund flows and the performance was measured by the CAPM and a multifactor model. As discovered by previous studies, investors seem to prefer the CAPM to evaluate the performance of hedge funds as the model delivered higher sensitivities and consistent results. Indeed, there is a positive relationship between the previous hedge funds' performance and its capital flows suggesting that investors rely on past performance to decide whether to invest. For both models, a negative relationship between the hedge funds' past risks and its flows is to be observed but also between the fund's age and the flows which could imply that investors seek riskier and older hedge funds since they are probably well established. Surprisingly, a positive relationship between the alphas of the liquid hedge funds and the hedge fund flows is obtained for both asset pricing models. This could imply that hedge fund investors are indifferent whether liquid hedge funds exhibit good performance and thus have a preference for pure hedge funds despite the liquidity restrictions and lack of transparency. For both models, the year effects also reveal that average monthly flows were higher in 2010 confirming the industry has become more fragmented over the years with an increased number of small funds. The liquid hedge fund flow models provide a counterintuitive result as the past fund flows are not positively correlated with the current fund flows which was the case for hedge funds and a conclusion also obtained by standard literature. However, the past performance of liquid hedge funds has a bigger impact on the liquid hedge funds' flows when compared to the hedge fund models. Indeed, this could be due to the higher liquidity and facility to withdraw capital which is provided by those funds and the mandatory reporting which would lead to an increased effect of the performance on the capital flows. As for the hedge fund models, the CAPM seems better suited than the multifactor one as the effect is more pronounced for the CAPM. In addition, a lower and even negative effect is observed for the long short equity funds when compared to fixed income funds with the multifactor model, supporting the hypothesis of the better fit of the CAPM. Indeed, good performance leading to capital outflows is not a realistic conclusion as investors should not want to lose their capital. Looking at the impact of the performance of hedge funds on the flows of liquid hedge funds, a negative relationship is obtained which could mean that liquid hedge fund investors pay more attention to hedge funds' performance than hedge funds investors do about the liquid hedge funds' performance. This effect is obtained with the CAPM model and seems to be consistent with the recent decrease in popularity of alternative hedge funds. Furthermore, the strategy does not seem to have an impact on the effects as they remain positive. Consistent with literature, a negative effect for the fund's past risk and age on the flows is obtained as retail investors usually do not wish that the funds take more risk. On average, monthly fund flows are higher for each year when compared to 2010 with mixed results for a couple of years. Still, it is to be observed that there was an increased interest for these funds after the financial crisis thanks to these year effects.

Further research could study whether this relationship holds for funds with a global mandate and for other strategies. As seen in the data and methodology chapter, hedge fund databases are known to be biased and one could perform this research by combining multiple databases to verify the consistency of the information and to collect more data to see if the relationships hold. With this methodology, one could also decrease the survivorship bias as different databases might report different funds. More complicated and sophisticated matching methods such as propensity scores could be used to better match funds. This would also be facilitated by merging database leading to an increased number of funds in the sample allowing for better matches. In addition, as the alphas were not significant and that the models yielded low R_2, it would be interesting to estimate the performance with other sophisticated models to discover whether they are more adapted. The research could also be studied by applying other models such as a vector auto regressive model allowing to incorporate more lags for certain variables such as the fund flows and the fund's performance to determine how investors perceive the persistence. Finally, as the goodness of fit of the models are not high, it would be interesting to reflect on which additional characteristics to include in order to obtain better models which could shed light on what actually drives investors to allocate to particular categories of funds.