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Mutual fund characteristics and their ability to generate alpha under stress: Evidence from mutual fund performance and flows during COVID-19 (in Europe)

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Abstract

In this master thesis, I present a comprehensive study of the performance and flows of European equity mutual funds during the COVID-19 crisis of 2020. This helps to understand what drives mutual fund performance and how do people allocate money into funds in times of distress during the large economic shock caused by the COVID-19 pandemic. Throughout this thesis, I examine 1209 European equity mutual funds and their different characteristics such as the fund's investment strategy, the heterogeneity of its investors and its level of sustainability in relationship to the fund performance and flows. The results suggest that actively managed fund underperformed and received less inflows during the COVID-19 crisis. This contradicts prior literature that suggests that actively managed funds are able to successfully reduce volatility and consequently outperform passive funds during recessions which also leads to higher inflows due to investors seeking more certain outcomes in volatile times. Furthermore, in my sample majority-held institutional funds did not outperform mutual funds mainly-held by retail investors and received less net fund flows during the COVID-19 crisis. Controversially, this suggest that institutional investors might not be sophisticated enough to continue their outperformance and that retail investors are less responsive to the experienced negative returns during the major crash in the market. Lastly, similar to earlier literature, I find a strong positive relationship between high ESG-rated funds and the performance and flows of these mutual funds. The large inflows to high-ESG rated funds imply that investors preferences for sustainability remained strong even during the COVID-19 crisis.

Keywords: equity mutual funds, fund performance, fund flows, fund characteristics, COVID-19

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1. Introduction

Mutual funds are currently the most popular investment vehicles used by individual investors to invest in the stock market. The benefits of investing in mutual funds are diversification, low cost due to economies of scale and advanced portfolio management. Mutual funds generally hold 50 to 200 different securities, depending on the focus of the fund. Furthermore, the size of the US mutual fund industry was worth $22.5 trillion in assets in 2019 (O'Connor, 2021). Meanwhile, in Europe the mutual fund industry had €12.3 trillion assets under management of which €5.1 trillion held in equity mutual funds in 2019[1]. The amount of people that owns mutual funds in Europe is significantly lower than in the US. In the US, 45%[2] of the households owns mutual funds compared to 10-25% in most European countries (Guiso et al. 2003). Although, the percentage of people investing in Europe is lower. Recently, it has been growing more rapidly. For example, in the Netherlands a total of 1.75 million people are investing, which is 17% more than last year (NOS, 2020). In other European countries a rise between 15% and 25% of new retail investors was observed. In total, the European fund industry experienced net inflows of €574.3 billion in 2020 of which €212.4 billion was allocated into equity mutual funds. (REFINITIV, 2020). In fact, mutual funds have been and continue to represent a growing part of people's wealth. Therefore, it is important to understand what drives mutual fund performance and how do people allocate their money into funds. Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a positive relationship between the fund's past returns, the fund size and its fund flows. This flow-performance relationship is striking, because the Efficient Market Hypothesis presented by Fama (1970) suggest that information from the past should not be relevant for predicting future returns. However, in general, mutual fund investors will naïvely chase returns, allocating their wealth to funds with high past performance.

Currently, a pronounced shift is happing from active to passive investment strategies. A reason for this could be the relative lower expenses for investing in passive funds (Financial Times, 2021). According to PWC (2021), which forecast that the percentage of passive investing will grow from 39% in 2019 to 55% in 2025. This expected change can be explained by the well-documented evidence that active equity managed funds tend to underperform their passive benchmarks (Jensen, 1968; Elton, Gruber, Das, and Hlavka, 1993). However, a explanation for

[1] Refinitiv Lipper - EUROPEAN FUND MARKET REVIEW: 2020
[2] Statista - Share of households owning mutual funds in the United States from 1980 to 2020

the bigger size of actively managed mutual fund industry is that actively managed funds outperform their peers during a period when investors value returns the most. Huang and Wang (2013) find that the returns of actively managed mutual funds during the 2007-2009 crisis are higher than passive index funds. Could this mean that we would also see a similar reversal in the performance and flows during the COVID-19 crisis?

Furthermore, both institutional investors and retail investors invest in equity mutual funds. Currently, approximately 25% of the funds assets under management are owned by retail investors (EFAMA, 2020). In general, institutional investors are seen to be more sophisticated and better at picking “winners” and monitoring their investments (Evans and Falhenbrach, 2012). They tend to outperform funds that are majority-held by retail investors and also react differently to shifts in sentiment and preferences (see Frazzini and Lamont, 2008, Ben-Rephael et al., 2012; Wang and Young, 2020). Subsequently, this has an impact on the flow-performance sensitivity. Institutional investors feel less the desire to naïvely chase past returns. Therefore, the observed convex flow-performance relationship tends to be less pronounced for institutional majority-held mutual funds (Mazur et al. 2017). According to Salganik-Shoshan (2017), business cycles have an impact on the investment flows of retail and institutional mutual funds. During recessions, institutional mutual funds demonstrate weaker return-chasing behaviour, while playing higher attention to Jensen’s alpha than during expansions. Could this imply, that we would see a similar less sensitive flow-performance relationship for institutional investors during the COVID-19 pandemic at the beginning of 2020?

Moreover, socially responsible investing is on the rise in the mutual fund industry. These funds take in consideration environmental, social and governance (ESG) criteria in their investment strategy. This way, the funds is not only profit-driven but also value-driven. In 2020, 50.5% of the inflows in the European fund industry were invested in ESG-related fund and in total approximately 22% of the equity mutual funds have some link with ESG (REFINITIV, 2020). The recent large inflows could be due to a shift in preferences to invest more consciously or it could be attributed to the positive relation between ESG-investing and performance. On the contrary, in line with the traditional neoclassical economics theory is that sustainability issues, such as environmental quality are “luxury goods”. These issues are only a concern to those whose more basic needs for food, housing and a certain quality of living is met (Martins, 2013).

Could this mean that ESG related investments are heavily affected by the COVID-19 crisis which caused a major income-shock for a lot of people?

In this thesis, I will study the impact of COVID-19 on equity mutual funds. The COVID-19 pandemic presents a unique opportunity to research the effect of different mutual fund characteristics on the performance and flows of equity mutual funds.

The crisis is particularly suitable to examine this for four reasons. First, the COVID-19 crisis brought a major shock to the global economy. This resulted in an unprecedented output contraction and the fastest increase in unemployment on record. In the face of such turmoil, every investors wants to hedge against this increased volatility. Second, it presents active managers an opportunity to perform well during this crisis because the crisis has created unusually large price dislocations in the financial markets. The STOXX Europe 600[1] experienced its steepest downturn, losing 32% of its value in the five-week period between February 19 and March 23, 2020. Thereafter, bouncing back by 28% till June 5, 2020. The actively managed funds should be able to profit from this event and prove why they are worth the higher expenses for their investors. Third, institutional investors are generally characterized as more sophisticated than retail investors. It is interesting to observe whether this translates into better performance and less outflows of funds which are majority-held by institutions.
Fourth, the COVID-19 pandemic triggered the first major economic shock of its magnitude since the substantial growth and increasing popularity of sustainable investing in recent years. It is interesting to see whether the impact on the economy has any affect towards the performance and flows of social responsible investing and whether sustainable investing is actually a luxury good.

This leads me to the following research question:

RQ: Do differences in investment strategy, the heterogeneity of investors and the level of sustainability matter for the performance and flows of Mutual Funds in Europe during COVID-19?

[1] Represents the 600 largest companies within Europe

This master thesis contributes to the exiting literature on the performance and flows of mutual funds in several ways. This is the first study to concentrate on the European equity mutual fund industry in terms of the performance and fund flows during the COVID-19 crisis. Moreover, this thesis uses the very recent COVID-19 crisis as a shock to measure the performance and flows of mutual funds under stress and increased volatile markets. Furthermore, this thesis uses the updated 2019 Morningstar[2] ESG rating, which is enhanced with an ESG risk factor. This master thesis highlights six hypotheses to try to answer three practical and relevant questions. First, whether the ongoing trend form active to passive investing should continue or does active investing have any benefits during a crisis period with increased volatility. Second, this thesis provides an answer on whether institutional investors are able to outperform retail investors in volatile markets or do retail investors have become more or as sophisticated as institutional investors. Third, this thesis provides an answer on the intriguing question whether sustainable investing is a luxury good and experienced large outflows or is likely here to stay.

This thesis consists of five chapters. Following the introduction the earlier literature will be discussed in Chapter 2. Thereafter, in Chapter 3 the the methods will be presented and how the data is obtained to analyse the performance and flows of the mutual funds. Subsequently, the results will be discussed in Chapter 4. Finally, in Chapter 5 the conclusion will be given with some additional limitations of the performed research and possible add-ons for future research will be discussed.

[2] Morningstar Sustainability Rating Methodology

2. Literature review

This section gives an overview of the already existing literature related to the performance and flows of mutual funds. Furthermore, based on earlier research and findings the stated hypotheses are introduced and explained.

2.1. Investors naïvely chase returns and seek managerial skill

Investors use mutual funds as one of the primary vehicles to invest in the stock market. A large part of the literature on fund flows investigates whether investors are able to identify managerial skill. Investors would prefer to direct their flows to mutual funds managed by highly skilled managers that are able to generate excess-returns. The "smart money" hypothesis of Gruber (1996) and Zheng (1999) implicates that some mutual fund managers do have skill and some individual investors are able to detect that skill. Consequently, investors are able to allocate their capital to skilled managers. Gruber (1996) and Zheng (1999) show that funds that receive inflows subsequently perform significantly better than those that experience outflows. This suggest that mutual fund investors have a selection ability. However, Franzzini and Lamont (2008) find contradicting evidence and argue that the smart money effect is short-lived. Their evidence implies that on average retail investors direct their money to funds which invest in stocks that have low future returns. These contradicting results imply that it is very difficult for investors to allocate their money to funds with skilled managers and investors don't have knowledge about future returns. As a consequence, as suggested by Sirri and Tufano (1998), investors only have information on past returns, risks and fees and base their decision on this when allocating money into funds. Nonetheless, according to the efficient market hypothesis presented by Fama (1970) past information should not be relevant for predicting future returns.

2.2. Flow-performance relationship

The existence of the controversial relationship between fund flows and past returns is established by Ippolito (1992), Chevalier and Ellison (1997) and Sirri and Tufano (1998). Mutual fund investors will naïvely chase returns, allocating their wealth to funds with high past performance. Likewise, more recent in studies of Barber, Huang and Odean (2016) and Kim (2019) they find that flows are positively related to the performance of mutual funds. This discovered relationship between past performance and the received flows is called the flow-performance relationship. Furthermore, as shown by Ferreira et al. (2012) this flow-performance relationship exist around the world. The only difference is that mutual fund investors from developed countries sell loser more. This is because investors in more developed countries are more sophisticated. Consequently, the flow-performance relationship is less sensitive.

The relationship between past performance and flows tends to be convex. Mutual funds with superior recent performance enjoy disproportionately large new money inflows, while funds with poor performance suffer smaller outflows (Chevalier and Ellison 1997; Huang et al. 2007). As described by Sirri and Tufano (1998), mutual funds investors chase returns and increase their flows to funds with the highest past returns, even though they fail to flee from poor performers. This convex relationship creates incentives for fund managers to alter the riskiness of their funds to secure a favourable year-end performance and achieve additional flows (Chavalier & Ellison, 1997). Especially, since the fund manager's compensation is affected by capital flows to the fund because the management fee is directly based on the amount of assets under management. Chavelier and Ellision (1997) suppose that these incentives might be created, because of the limited information availability or some other reason, many mutual fund investors react to the year-end performance. This implies that given a fund's characteristics and year-to-date performance at the end of September, the fund investment company knows that its future inflows of investments will depend on its fourth-quarter performance. Subsequently, a fund can increase its expected growth by increasing the variance of its fourth-quarter return. This striking convex relationship between performance and flows is even stronger for younger funds. As described by Chevalier and Ellison (1997), younger funds that are performing worse than the market tend to try and take a late year "gamble" to catch the market. On the other hand, funds that are ahead of the market have an incentive to play it save and act more like an index fund. These funds ultimately, want to make the year-end list of "top performers". In general, in September mutual funds have an incentive to change and take risk calculated from the flow-performance relationship.

This theory is supported by Huang et al. (2007), who suggest that investors face participation costs, which includes the costs of getting informed about the fund. Investors can freely observe past performance of all funds. It is a huge benefit for a mutual fund to be high on the list with best performing funds. This way, it will be easily noticed by investors and this would reduce the cost of gathering information for the investor. Furthermore, Huang et al. (2007) find that the sensitivity of the flow-performance relationship is also dependent on a fund's characteristics such as age, size, volatility of past performance and marketing expenditures. Another method funds can influence their flow-performance relationship is by selecting their own self-designated benchmark. Sensoy (2009) find that almost one-third of the actively managed, diversified U.S. equity mutual funds specify a size and value/growth benchmark index in the fund prospectus that does not match the fund's actual style. As a consequence, it becomes easier to beat their benchmark. Consequently, these "mismatched" benchmarks matter to investors and can lead to improved flows.

Recently, evidence of Kim (2019) implies that besides the cross-sectional variation of funds dependent on performance, age, size, past volatility, market expenditures and chosen benchmark. Alternatively, there is time variation in the flow-performance relationship. Fund flows became less sensitive to high performance after 2000, thereby decreasing convexity of the flow-performance relationship (Kim, 2019). Note, that in this thesis I try to combine both elements and ask a more general question: How do a fund's characteristics such as the fund's investment strategy, the heterogeneity of its investors and its level of sustainability matter for the performance and flows of equity mutual funds in Europe during COVID-19?

The performance of mutual funds differs over time as does it effect on the fund flows. As described by Cederburg (2008), mutual fund investor behaviour changes across business cycles. In expansions mutual fund investors chase returns, heavily allocating new capital to recent winners. This results in funds with more inflows to outperform funds with less inflows which allows investors to generate alpha by pursuing this strategy. This behaviour can be partially explained by the momentum effect. However, during recessions investors do not chase past returns and exhibit a weaker tendency to seek alpha. Instead, investors base their investment decision during recession on their exposure to aggregate risk factors and decrease their exposure to the market and book-to-market factors. This results in a reversal in flows and returns. For example, funds that used to experience outflows or less inflows now earns better returns and alphas than funds that used to receive very large inflows (Cederburg, 2008). Another paper by Wang, Watson and Wickramanayake (2018) finds that investors react negatively to fund volatility during the global financial crisis. They suggest that during a recession investors seek to reduce risk and direct their wealth to funds with lower volatility. They find evidence that funds with low volatility experience a higher flow-performance relationship compared to high volatility funds. For this reason, low volatility funds generated greater net flows in relation to past performance during the global financial crisis.

To summarize, the inflows to high performing funds tends to decrease when the average performance is high and when performance dispersion is low (Kim, 2019). Thus, a fund with high past performance and flows will receive less inflows and might even experience outflows during a recession. This is caused by the large aggregate shock to asset payoffs which creates more co-movement between assets which will lead to more co-movement of mutual funds and imply less dispersion of fund flows (Kacperczyk, van Nieuwerburgh, & Veldkamp, 2016). Subsequently, during a recession, investors will seek to find low volatile funds that generate more stable and less negative returns.

These papers all suggest that there is a substantial change in investor behaviour which responds to past performance and results in changes in fund flows. Note, that it would be interesting to see whether I observe similar reversal in performance and flows of the mutual funds based on the fund's characteristics during the recent COVID-19 crisis examined in this thesis.

2.3. Performance and flows of actively managed mutual funds

Most actively managed equity mutual funds are underperforming passive benchmark, net of fees. This underperformance was first established by Jensen (1968) and confirmed by many others[1]. Despite this overwhelming evidence, the actively managed industry has grown fast and remains large. The existence of such a large and growing industry which generates inferior returns to that of index funds seems puzzling (Gruber, 1996). Especially, since passive funds are easily available to investors (Elton; Gruber & Blake, 1996). This well-document underperformance raises the question why investors allocate their wealth to actively managed funds?

A hypothesis that can explain this puzzle according to Moskowitz (2000) might be that actively managed mutual funds add value when investors care about performance the most. He finds that active mutual funds appear to generate on average higher returns from 1975 to 1995 by 6% per year during recessions. This evidence seem to suggest that active managers deliver

[1] See Jensen (1968), Elton, Gruber, Das, and Hlavka (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), Pastor and Stambaugh (2002), and Fama and French (2010), and others.

returns when investors need them the most and provide a hedge against recessions. According to Glode (2011) this can explain why it is rational for investors to accept negative average alphas if funds outperform in bad states of the economy when marginal utility is high. He builds a model in which a fund manager can generate state-specific returns that depend on the economy. In equilibrium, the managers will optimally increase his effort towards realizing good performance when an investor's marginal utility of consumption is high during recession, On the other hand, the investor is willing to pay for this insurance when the investor's marginal utility of consumption is lower. Moreover, Glode (2011) finds that funds with poor unconditional poor performance tend to charge high fees and generate risk-adjusted returns that are highly countercyclical from 1980-2005.

Another study done by Kosowksi (2011), finds that active mutual funds generate risk-adjusted returns (or alpha) that are 3% to 5% higher per year in recessions compared to those in expansions from 1962 to 2005. Furthermore, recently in a study performed by Kacperczyk, van Nieuwerburgh, and Veldkamp (2016), they documented that fund risk-adjusted returns are around 1.6% to 4.6% per year higher in recessions over the 1980-2005 period. Note, that in this thesis I will examine the COVID-19 crisis which is a recession substantially stronger than examined in the studies mentioned above. According to the discussed literature, I interpreted my first hypothesis as the following:

H1: Actively managed equity mutual funds performed better than passive equity mutual funds during the COVID-19 crisis.

The positive relation between performance and mutual flows indicates that the expected higher performance of actively managed mutual funds as stated in hypotheses 1 will also contribute to higher flows compared to passive funds. There are other arguments that support this relationship. First, the COVID-19 crisis has had a major impact on the financial markets and this provides the active managers with an opportunity to perform well and profit of the unusually large price dislocations of stocks. This gives them an edge compared to passive mutual funds that cannot actively change their portfolio of holdings in the fund. Second, the financial markets are more volatile during recessions and the actively managed funds can anticipate on this by reducing the volatility of the fund. As shown, in prior studies the risk-adjusted returns are higher during recession. Kacperczyk, van Nieuwerburgh, and Veldkamp

(2016) attribute this to fund manager's ability to profit from the higher aggregate volatility in the market. Funds that reduce systematic risk when conditional market volatility is high can earn higher risk-adjusted returns (Busse, 1999). An active mutual fund will make changes to reduce the volatility of the fund during a recession which is not possible for a passive fund . As a consequence active managers will reduce volatility of the fund's investments. They will be eager to do this because as suggested by Wang, Watson and Wickramanayake (2018), investors seek more certain outcomes in volatile times, hence funds with a lower volatility. Ultimately, this will lead to higher flows to actively managed mutual funds compared to passive funds. Thirdly, as suggested by Gruber (1996) and Zheng (1999) the impact of changes in the flow-performance relationship should be visible on short notice and the effect should be observed short-lived. To summarize, according to the discussed literature, I interpreted my second hypothesis as the following:

H2: Actively managed equity mutual funds experienced less outflows during the COVID-19 crisis compared to passive equity mutual funds.

2.4. The heterogeneity of investors and the performance and flows of mutual funds

The heterogeneity of investors has an impact on the flow-performance sensitivity. In general, institutional investors are more sophisticated and are better at picking quality investments compared to retail investors. They tend to have more resources and time to analyse industries and companies and pick "winners" and monitor their investments better. As described by Evans and Fahlenbrach (2012), institutional investors are better at reducing agency problem from greater monitoring. Subsequently, this leads to institutional funds to outperform retail funds by 1.5% per year. This implies that mutual funds that are majority-held by investors are more likely to outperform mutual funds mainly-held by retail investors. Pastor and Vorsatz (2020) find that U.S. institutional funds perform better than retail funds during the COVID-19 crisis based on benchmark-adjusted performance, but the opposite is true based on alphas. They find that during a crisis "institutional" funds with with 2/3 of institutional investors outperforms their prospectus benchmark with 0.25% per year and "non-institutional" funds underperforms its prospectus benchmark by -13.67% per year. However, in their Carhart 4-factor model the institutional funds alphas are -11.96% per year compared to -5.54% per year for retail funds. Note, that this interesting contradicting is intriguing and allows me to search for a more definitive answer on whether funds with a majority-held by institutional investors outperform retail funds during the COVID-19 crisis. To conclude, according to most literature institutional investors seem outperform retail investors. This is why I interpreted my third hypothesis as the following:

H3: Mutual funds that are majority-held by institutional investors are likely to outperform mutual funds mainly-held by retail investors during the COVID-19 crisis.

Besides, institutional investors and retail investors experiencing different returns. Also, the sensitivity of the flow-performance relationship differs. Retail investors tend to reallocate capital across different funds more often and are more reactive to shifts in sentiment and preference (Frazzini and Lamont, 2008; Ben-Rephael et al., 2012; Wang and Young, 2020). This results in a more convex flow-performance relationship for retail investors compared to institutional investors (Evans and Fahlenbrach, 2012). They find that institutional investors are more sensitive to high fees and to poor risk-adjusted performance compared to retail investors and even suggest that the flow-performance relation for institution investors is concave. In addition, Evans and Fahlenbrach (2012) and Del Guercio et al. (2014) both find that investor sophistication has an impact on the flow-performance convexity. This is why according to literature, I interpreted my fourth hypothesis as the following:

H4: Mutual funds that are majority-held by institutional investors experienced less severe outflows than mutual funds mainly-held by retail investors during the COVID-19 crisis.

2.5. The impact of sustainability on the performance and flows of mutual funds

The market size of sustainable has been growing rapidly this last decade (Ibikunle and Steffen, 2015). Sustainable responsible investing has become more popular across institutional and retail investors. This trend accelerated when Environmental, Social and Governance (ESG) factors were introduced. These factors which combined result in an ESG-rating made it possible to compare funds and stocks based on their individual ESG-score.

The majority of the existing literature finds a positive relationship between the ESG criteria and corporate financial performance which can be traced back to the beginning of the 1970s (Friede, Busch & Bassen, 2015). However, there seems to be less of a consensus between the relationship of ESG investing and the mutual fund performance. In a recent study done by

Dolvin et al. (2019) they find that funds with high sustainability scores have about the same risk-adjusted returns as other funds. However, in the research from Abate et al. (2021) they do find evidence of a positive relationship in their sample of 634 European mutual funds. Funds with a high Morningstar Sustainability rating achieved higher returns than lower rated funds. In addition, Steen et al. (2019) searched for evidence if this relationship was also existint in Norway. But, they found that no evidence of the level of ESG ratings on the abnormal risk-adjusted returns for 146 funds domiciled in Norway. This discrepancy in results is quite intriguing and a possible explanation suggested Ibukunle and Steffen (2015) could be a documented shift around 2012. They find that high sustainable funds tend to underperform during the 1991-2012 period. But, significantly outperform their low sustainable peers over the 2012-2014 period. Moreover, recent studies performed by Maiti (2019) and Kumar et al. (2016) also find a more pronounced positive relationship. In the research from Kumar et al. (2016) they find that fund with a higher ESG rating have lower volatility in their performance and generate higher returns. Although, these papers suggest that the relationship between sustainability and fund performance appeared after the financial crisis in 2008. Nofsinger and Varma (2014) find that socially responsible mutual funds tend to outperform during a market crash. Their sample consist of 240 U.S. domestic equity mutual funds and covers the period of 2000 through 2011. The paper focuses on much shorter time-span based on the market crashes which includes two recessions (2001 and 2007–2009). The sustainable funds tend to outperform by 1.61% to 1.70% during a crisis. To summarize, according to the discussed literature, I interpreted my fifth hypothesis as the following:

H5: Mutual funds with a high (Morningstar) ESG-rating should outperform low (Morningstar) ESG-rated mutual funds during the COVID-19 crisis.

In general, ESG funds have seen major inflows these last couple of years. Recently, in studies from Hartzmark and Sussman (2019) and Ceccarelli et al. (2020), a causal evidence is found that investors market-wide value sustainability. A fund being categorized as a low sustainable fund resulted in net outflows and categorized as a high sustainable fund let to net inflows. In addition, Öttling and Kim (2020) find that funds with a high Morningstar sustainability ratings receive higher average weekly flows prior to the COVID-19 crisis. Furthermore, these relatively large high flows disappear after the onset of the COVID-19 pandemic lead to a market crash. Subsequently, Pastor and Vorsatz (2020) find that low sustainable funds suffer outflows of 2.6% of assets under management, while high sustainable funds' net flows are roughly zero during the COVID-19 period between February 20 and April, 2020.

An import and interesting feature discovered by Ferriani and Natoli (2021) is that the ESG factors do not all contribute similarly to the fund flows. They find that overall that high ESG risk positively affected the inflows during the COVID-19 crisis. But that only, the Environmental factor remained strong and relevant during the crisis. They suggest that the ESG factor are of different importantance. Note, that this is a interesting additional feature to research in this thesis. To conclude, as described Pastor and Vorsatz (2020), I interpreted my six hypothesis as the following:

H6: Mutual funds with a high (Morningstar) ESG-rating did experience less outflows than lower (Morningstar) ESG-rated mutual funds during the COVID-19 crisis.

2.6. Overview of hypotheses

H1: Actively managed equity mutual funds performed better than passive equity mutual funds during the COVID-19 crisis.

H2: Actively managed equity mutual funds experienced less outflows during the COVID-19 crisis compared to passive equity mutual funds.

H3: Mutual funds that are majority-held by institutional investors are likely to outperform mutual funds mainly-held by retail investors during the COVID-19 crisis.

H4: Mutual funds that are majority-held by institutional investors experienced less severe outflows than mutual funds mainly-held by retail investors during the COVID-19 crisis.

H5: Mutual funds with a high (Morningstar) ESG-rating should outperform low (Morningstar) ESG-rated mutual funds during the COVID-19 crisis.

H6: Mutual funds with a high (Morningstar) ESG-rating did experience less outflows than lower (Morningstar) ESG-rated mutual funds during the COVID-19 crisis.

3. Methods

In this section the data that will be used for research will be discussed. First a description of the databases that are used to extract the data will be given. Thereafter, the data itself will be presented and the decisions to filter the data and obtain the final dataset will be discussed. After that, the methods that are used to perform our regressions and interpreted our results will be discussed in two separate parts. With part one being the performance and part two being the fund flows of mutual funds. Finally, the sample descriptive statistics will be presented and briefly described.

3.1. Data

The database that is used to gather data on the mutual funds is Morningstar. This is a database that provides data on most mutual funds around the world. In total, it covers more than 300,000 mutual funds in its survivorship-bias-free database and it helps investment professional managers change or create new investment portfolios. From the Morningstar database, I obtain the funds in my sample by filtering on mutual funds that are only open-end funds, domiciled in Europe and the fund invest more than 80% of their portfolio in equities. Moreover, Morningstar should have assigned a sustainable rating to the fund and the investment area of the fund should be global. After which, outliers are excluded from the dataset. Outliers are funds that have seen an increase in value greater than 10 times their initial size and a decrease 5 times their initial size. This results in 2205 funds still in my first dataset. However, to obtain my final dataset I make some additional exclusions. First, I exclude funds that have no daily return data between February 20 and April 30 (2020), which are needed to research the effect of COVID-19. This results in 348 funds being excluded from the sample. Second, I exclude funds without a missing Total Net Asset Value (TNA) on January 31 (2020), which I use to determine the size of the fund before the COVID-19 crisis. This results in another 116 funds being excluded from the sample. Furthermore, to properly study the flow-performance relationship it is necessary to address another filter in my data. This is because two necessary components of the flow-performance relationship are the fund's returns and size which are needed to measure the fund's capital in and out flows (Barbet et al, 2016). This data is used to calculate the actual flow in euros and relative flow percentage while accounting for the returns made during a particular period in comparison to the change of the Total Net asset Value in euros of a fund. Thus, the fund's size is essential and I will restrict my sample to funds without missing weekly TNA data. However, I consider this will lead to a survivorship bias in my sample which I account for by still including funds in my sample with missing TNA data at the end of their life.

In total, my final dataset contains 1400 funds. To arrive at my main sample which I will use to test my hypotheses, I will filter down the funds in my dataset on size ang age, including only funds with more than €10m TNA and funds that exist longer than 24 months. According to Elton, Gruber and Blake (2001) small and generally younger funds report their returns and fund flows inconsistently. Moreover, excluding smaller and younger funds is particularly relevant for changes in a fund's TNA, because limited changes can result into extreme percentage flows for these funds. This results in my main sample containing 1209 funds which combined have TNA of €696 billion on January 31, 2020.

Criteria	**Restriction**
Fund type	Open-end
Domicile	Europe
Global Category Group	Equity
Asset allocation	>80% Equity
Morningstar sustainability rating	Not = NA
Investment Area	Global
Outliers	Increase > 1000% or decrease to < 20%
Inception date	=< 19/02/2018
Fund size	> €10m AUM

Thereafter, I separate this main sample in different sub-samples or categories to test my hypotheses. First, I separate the main sample between actively managed mutual funds and passive mutual funds. To obtain the actively managed mutual funds subsample I exclude passive funds that are identified by Morningstar as passive or as a index fund. This way I obtain two sub-samples. This results in 1125 actively managed funds and 84 passive funds.

Secondly, to test the third and fourth hypothesis I construct the main sample in 3 groups. "Institutional", "retail" and "neither" by using the Morningstar share class-level institutional indicator. To identify which fund belongs to which group, I use the methodology described by Pastor and Vorsatz (2020). For each fund, I sum the January 31, 2020 TNA across all of the fund's institutional share classes, and I do the same for retail share classes. I label a fund "institutional" if the institutional fraction of its TNA exceeds two-thirds. A fund is "retail" if the retail fraction of its TNA exceeds two-thirds. The rest of the funds are labelled as "neither". Consequently, I have 1095 "retail" funds, 69 institutional funds and 45 funds that are characterised as "neither" in my main-sample.

Thirdly, I divide the main sample based on sustainability. I obtain the ESG-score of every mutual fund I use the Morningstar sustainability rating[1]. The Morningstar Sustainability Rating is a measure of financially material Environmental, Social, and Governance, or ESG, risks in a portfolio relative to the portfolio's peer group. This rating is a monthly reported moving average of the trailing 12 months months' portfolio level sustainability score, computed as the weighted average of firm level ESG Risk Ratings provided by Sustainalytics. Morningstar assigns funds a discrete "globe rating", which ranges from one globe (lowest sustainability) up to five globes (highest sustainability). I create 3 groups within my sample, indicating the level of sustainability which are the groups "high" (4-5 globes), "conventional" (3 globes) and "low" (1-2) globes). This results in 435 high sustainable funds, 480 conventional and 294 low sustainable funds. Furthermore, to test the ESG factors and their importance individually. I separate the sample along each component of the Environmental, Social and Governance score. The top 30% in their class are labelled as "greener" and bottom 30% of the funds are labelled as "browner".

[1] Morningstar Sustainability Rating Methodology

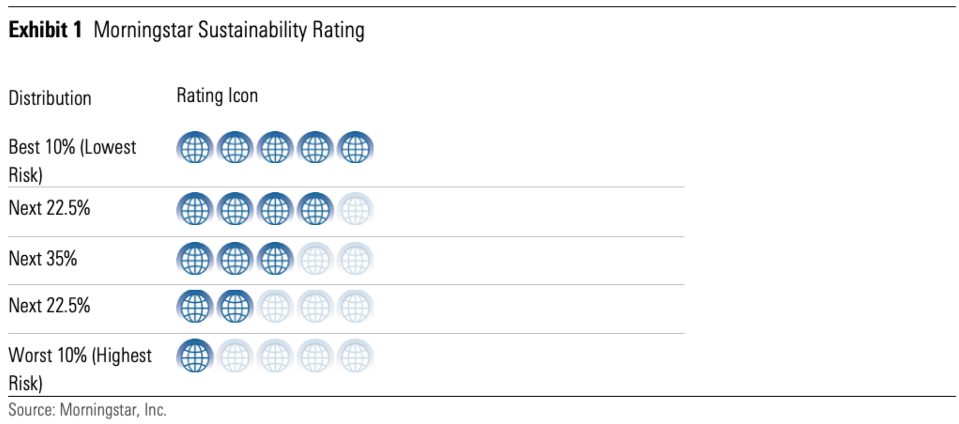

Figure 1. Morningstar Sustainability Globes

This figure shows what amount of globes are assigned to a fund based on the distribution of the Morningstar Sustainability rating.

After I create the sub-samples, I collect the funds' daily returns, total net asset value and corresponding ISIN codes. I use these ISIN codes to collect data on the mutual funds' benchmarks in DataStream and measure the adjusted performance. Moreover, to analyse returns according to the factor models presented in earlier research, I obtain daily factor returns from Ken-French's data library[1].

Finally, I collect additional variables that are used as control variables in the performance analysis and the regressions for the fund flows. These are variables for the fund's industry distribution and characteristics. Similar to Pastor and Vorsatz (2020), I control for industry as the fund's TNA as a percentage allocated in each industry. Morningstar separates the industries in: basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Furthermore, I included several fund-level controls. First, I use the fund annual fee expenses as control variable, as Barber et al. (2005) showed that these fees explain fund flows. For this control variable, I use the net expense ratio as of January 2020 which I set to missing if the value is equal to zero. Second, like Ferreira et al. (2012) I include an age control variable as younger funds generate generally higher inflows than older funds. I use the log of the fund age in days. Third, I control for the size of the fund as the log of the funds' TNA at 31 January 2020, as Barber et al. (2016). Fourth, I control for the funds' style similar to Kim (2009), I use the

[1] Ken-French's data library

Morningstar Category variable[3]. This variable is built on the 3-by-3 equity style box of size tilts (large-cap versus small-cap) and growth versus value style tilts.

3.2. Methodology

To measure the performance and fund flows of the mutual funds in my final sample. I begin with aggregating share classes of a fund with the same Morningstar FundID variable (Ferreira et al, 2012). A fund can have different share classes with different fee structures catering to different investors (Handy et al, 2020). I calculate the size of the fund by summing the TNA across the fund's share classes and I set the earliest inception date of one of the share classes as the fund's age starting point. Moreover, a fund's return and net expense ratio is calculated as the weighted average of the individual share classes of their combined TNA (Pastor and Vorsatz, 2020). After obtaining the fund's daily return and TNA, I make an important distinction between researching the performance and the fund flows. I will analyse the fund's return on a daily basis and the fund's flows on a weekly basis. This contrast is first of all pragmatically reasonable due to the lack of data with most mutual funds only reporting their TNA once or twice a week. Second, this is theoretically valid because according Edelen & Warner (2001) and Sias & Starks (1997), there exists a lag between investors responding to the recent past returns and the observed flows. To address these issues, I have chosen to use weekly returns and flows to reduce noise in the daily series for researching the mutual fund flows. Similar to Döttling & Kim (2020), I aggregate daily data on the fund's returns, total net assets, and net flows in euros and aggregate them to weekly values to reduce noise in the daily series. To achieve this, I only obtain the latest total net assets value of the week and sum the returns and flows during the week.

Furthermore, to measure the performance and the fund flows during the beginning of the COVID-19 pandemic, I divide the years 2019 and 2020 into 5 periods based on the performance of the MSCI World Index which can be seen as a generic benchmark. The periods are:

- Pre-crisis (January 1, 2019 to January 31, 2020 / Week 1 2019 – Week 5 2020)
- Crisis (February 20 to April 30, 2020 / Week 8 2020 – Week 18 2020)
- Crash (February 20 to March 23, 2020 / Week 8 2020 – Week 12 2020)
- Recovery (March 24 to April 30, 2020 / Week 13 2020 – Week 18 2020)
- After-crisis (May 1 to December 31, 2020 / Week 19 – Week 53)

[3] Morningstar Category variable

Figure 2, provides a preliminary indication of how the MSCI World Index and the fund average performance was during the COVID-19 crisis. The crisis period is when the market experiences the biggest impact of COVID-19 crisis. This is between February 20 and April 30, 2020. It starts on February 20 because the market reached its peak on the 19th before the market tumbled. The end of the crisis is on the 30th of April because the market bounced back from its lowest point on 23 March, 2020. In total, the market experienced a loss of 34% (23 March) before climbing back up 28% (30 April). I have chosen this as the end date of the crisis period because most countries announced reopening plans at the beginning of May. For example, in the Netherlands, relaxations of strict measures were announced on 6th of May (*COVID19 in The Netherlands: a timeline,* 2020). Moreover, a majority of the states in the USA adopted policies loosening lockdowns and restrictions around May[4]. This contributed to the recovery of the stock market and resulted in a positive sentiment among investors.

3.2.1. Mutual fund performance

The returns I collect from Morningstar are reported as a net returns. This corresponds with my goal of analysing the returns after fees that are actually delivered to mutual fund investors. The returns reported in Morningstar are simple returns, computed as the following:

$$R_{i,t} = \frac{R_{i,t-} R_{i,t-1}}{R_{i,t-1}} \tag{1}$$

Where $R_{i,t}$ is the value of the net return in on day t for a fund i. Subsequently, I analyse the performance of the mutual funds with benchmark-adjusted returns (deltas) and factor-adjusted returns (alphas). First, for the delta returns I measure the performance of a fund against their primary prospectus benchmark and the MSCI World Index. Second, I estimate the alpha returns which are calculated with multifactor models. For both, the delta and alpha returns, I report annualised returns and use equal-weighted and value-weighted averages.

The delta or benchmark-adjusted returns are obtained by taking the fund's daily returns and subtract the daily returns of the benchmark which are the fund's prospectus benchmark and the

4 CNN - This is where all 50 states stand on reopening. (2020, 26 April)

MSCI World Index. The average benchmark-adjusted equal-weighted returns of the funds are computed with the following formula:

$$\Delta R_t = \frac{1}{\mathrm{N}} \sum_{t=1}^{N} (R_{i,t} - R_{b,t}) \tag{2}$$

Where ΔR denotes the expected average delta return of the mutual funds on day t, N is the amount of funds in the sample, R_i is the return mutual fund i and R_b is the return of the fund's particular benchmark b.

Additionally, the value-weighted averages of the estimated deltas, are weighted by each fund's TNA in a certain category which could be active, passive, institutional, retail, neither, high sustainability, conventional and low sustainability. These returns are computed as the weighted average, weighted by the previous week's percentage TNA of the fund compared to the total TNA of all other funds in the same category (Kim, 2020). The value-weighted returns are estimated as the following:

$$\Delta R_t = \frac{TNA_{i,t-1}}{Total\ TNA_{i,t-1}} \sum_{t=1}^{N} (R_{i,t} - R_{b,t}) \tag{3}$$

To clarify, for example to establish the weight from an institutional fund i, its TNA will be divided by the sum of all the institutional funds' TNA.

After using benchmark-adjusted returns, I also analyse the funds' performance estimating the average fund abnormal returns or factor-adjusted returns or also simply called alpha returns using multifactor models. These include the Capital Asset Pricing Model (CAMP), the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997) and the five-factor model of Fama and French (2015).

First, Jensen's alpha (1998) is used a measure, it is a performance measure that calculates the excess returns of a portfolio or individual investment. To obtain Jensen's alpha I will perform a simple regression analysis based on the Capital Asset Price Model (CAPM). This method will estimate the relationship between variables. If the output results in a significant and positive alpha, the fund has abnormal returns over a given period. The opposite is true for a negative alpha, *ceteris paribus*.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + \varepsilon_{i,t} \tag{4}$$

$$\alpha_i = (R_{i,t} - R_{f,t}) - \beta_i\left(R_{M,t} - R_{f,t}\right) - \varepsilon_{i,t} \tag{5}$$

Where $R_{i,t}$ denotes the expected return on mutual funds portfolio i on a day *t*, $R_{f,t}$ is the risk free rate which corresponds with the current month's T-bill rate and β_i measures the mutual fund's exposure to the market premium. Moreover,$R_{M,t}$ represents the return on market index, Jensen's alpha α_i measures the unexpected or abnormal returns net of the expected returns as calculated by the CAPM and finally $\varepsilon_{i,t}$ captures the error term, the idiosyncratic risk of the fund.

The second model I use is Fama and French three-factor model (1993). As the name of the model suggest, three factors will be used by adding the factors SMB_t ("Small Minus Big") and HML_t ("High Minus Low") to the single-factor CAPM. The SMB_t factor refers to the difference between the returns of small-cap and big-cap stock portfolios. This factor accounts for the difference in returns of smaller market capitalization stocks and bigger stocks, in our case for the difference in exposure to size of the mutual funds. The other factor, HML_t refers to the difference in returns between high and low book-to-market valued stocks. Consequently, this accounts for the difference between mutual funds having a more exposure to value stocks with corresponding high book-to-market ratios and growth stocks known to have low book-to-market ratios (Fama and French, 1993).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t} \tag{6}$$

$$\alpha_i = (R_{i,t} - R_{f,t}) - \beta_i\left(R_{M,t} - R_{i,t}\right) - \beta_2 SMB_t + \beta_3 HML_t - \varepsilon_{i,t} \tag{7}$$

Moreover, the third model I will use to estimate alpha and perform a comprehensive analysis is the Carhart four-factor model (1997). This model adds another factor to the Fama and French three-factor model (1993). The momentum factor MOM_t captures the difference in returns between winners and losers in the past. Carhart (1997) demonstrated that common factors in stock returns and investment expenses pretty much explain the persistence in equity mutual funds mean and risk-adjusted returns. This implies that returns from the past have impact on the expected returns in the future. To account for this, I add the MOM_t factor and balance out the effect of the past well or bad performing mutual funds on their future returns.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{i,t} \tag{8}$$

$$\alpha_i = (R_{i,t} - R_{f,t}) - \beta_i\left(R_{M,t} - R_{f,t}\right) - \beta_2 SMB_t + \beta_3 HML_t - \beta_4 MOM_t - \varepsilon_{i,t} \tag{9}$$

Finally, the last model I will use to calculate abnormal returns is Fama and French five-factor model (2015). It extends the earlier three-factor model with the RMW_t and CMA_t, also known as quality factors. In this equitation RMW_t is the difference between returns on diversified portfolios of stocks with robust and weak profitability capturing the idea that stocks from profitable companies perform better than unprofitable companies. Furthermore, CMA_t is the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which can be seen conservative and aggressive and explains the thought of companies that are able to invest more also perform better (Fama & French, 2015). Overall, as described by Fama and French (2015), this model performs better than the three-factor model when predicting average stock returns. Consequently, I use this five-factor model to account for investment style of the mutual fund which can be more towards growth or value stocks.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_{i,t} \tag{10}$$

$$\alpha_i = (R_{i,t} - R_{F,t}) - \beta_i\left(R_{M,t} - R_{f,t}\right) - \beta_2 SMB_t + \beta_3 HML_t - \beta_4 RMW_t - \beta_5 CMA_t - \varepsilon_{i,t} \tag{11}$$

For all of these models, I use the same principle for calculating the equal-weighted and value-weighted average returns. The equal weighted average alpha returns are estimated as the following:

$$\alpha_t = \frac{1}{N}\sum_{i=1}^{N}(\alpha_{i,t}) \tag{12}$$

The value weighted average alpha returns are estimated as the following:

$$\alpha_t = \frac{TNA_{i,t-1}}{Total\ TNA_{i,t-1}} \sum_{i=1}^{N} (\alpha_{i,t}) \tag{13}$$

Furthermore, to determine which characteristics have an impact on the fund benchmark-adjusted performance and factor-adjusted performance I analyse this using the following regressions:

$$\Delta R_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t} \tag{14}$$

$$\alpha^{Car4}{}_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t} \tag{15}$$

In the first regression the delta return is the dependent variable where the prospectus benchmark returns are subtracted of the fund returns. In the second regression the Carhart four-factor model alpha is the dependent variable. In both regressions the C denotes the constant and the $\beta_1 Active$, $\beta_2 Institutional$, $\beta_3 High_{sustainability}$ and $\beta_4 Low_{sustainability}$ are all dummy variables accounting for the fund's characteristics. Finally $X_{i,t}$ represents the control variables which are fund-level and industry controls.

In addition to the performance regressions, I try to give a more clear view of the clear view of the performance of the mutual funds. I visualise the performance of the mutual funds relative to its prospectus benchmark. To accomplish this, I normalize the levels of each fund's net value and the prospectus benchmark to 100 as of February 19, 2020. For each day *t after* February 19, I compute price indices for each fund and the benchmarks by compounding the corresponding weekly returns:

$$\begin{aligned} F_t &= 100(1 + r_1^F)(1 + r_2^F) \dots (1 + r_3^F) \\ B_t &= 100(1 + r_1^B)(1 + r_2^B) \dots (1 + r_3^B) \end{aligned} \tag{16}$$

Where F_t is the fund price index, B_t is the price index for the corresponding benchmark, r_t^F is the fund's net return on day t *and* r_t^B is the benchmark's return. In the figures, I plot both the average value of F_t and B_t and measure the relative performance by log(F_t) - log(B_t).

3.2.2. Mutual fund flows

Following the majority of the prior literature on fund flows, I calculate the fund's net cash flow as done by Sirri and Tufano (1998), Chevalier and Ellison (1997), Barber et al (2016) and many others. The fund's net cash flow is defined as the following:

$$F_{i,t} = TNA_{i,t} - \left(1 + R_{i,t}\right)TNA_{i,t-1} \tag{17}$$

Where a positive net cash flow indicates the fund received more money than was withdrawn and a negative flow figure indicates more money was withdrawn (outflow) from the fund than invested (inflow). This formula calculates the net cash flow because it accounts for returns that have an impact on the fund's TNA. $TNA_{i,t}$ is fund i's total net asset value at the end of the week t. Thereafter, I multiply the fund's $TNA_{i,t-1}$ of the previous week by the current week's return $(1 + R_{i,t})$ and subtract it from the current week's total net asset value. In this way, I capture the absolute difference between the actual value of a fund's TNA and a fund's TNA if it had not attracted any new in and outflow but instead only grown at the rate of return during that week. Consequently, I only estimate the newly invested or withdrawn money into the fund an assume that all the flows occur at the end of the week. Furthermore, to convert the net flows into a relative flow (percentage) I sum up the net cash flows $F_{i,t}$ over a particular period and divide this by the fund's TNA at the beginning of the period ($TNA_{i,t-1}$). This is computed with the following formula:

$$FLOW_{i,t} = \frac{F_{i,t}}{TNA_{i,t-1}} \tag{18}$$

To clarify, for example to calculate relative flow ($FLOW_{i,t}$) for fund i during the the crisis period. I will sum up the net flows $F_{i,t}$ between week 8 and week 18 in 2020 and divide this by the fund's TNA in week 7. In addition, similar to Barber et al (2005), the $FLOW_{i,t}$ variable is winsorized at the 1% and 99% to correct for extreme values. This limits the impact of outliers on my results and is necessary because new new mutual funds can experience large inflows at the beginning of their establishment.

To analyse the fund flows during the COVID-19 period, I first compare the average net funds flows across the different sub-samples over the five periods. These average net funds flows are simply averaged across funds in its own sub-sample according the following formula:

$$FLOW_{i,t} = \frac{1}{N}\sum_{i=1}^{N}(FLOW_{i,t}) \tag{19}$$

After this comparison, I try to answer my hypotheses about the fund flows using cross-sectional regressions. I regress the dummy variables which represent the fund's characteristic on the fund's net flows. The most comprehensive regression is the following:

$$FLOW_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t} \tag{20}$$

Where $(FLOW_{i,t})$ are the fund's net flows, C denotes the constant and the $\beta_1 Active$, $\beta_2 Institutional$, $\beta_3 High_{sustainability}$ and $\beta_4 Low_{sustainability}$ are all dummy variables accounting for the fund's characteristics. Finally $X_{i,t}$ represents the control variables which are fund-level and industry controls.

3.3. Robustness checks

In addition, I will perform a few robustness checks to verify whether my findings are valid and consistent. First, I will use logarithmic (LOG) returns instead of simple returns when analysing the performance and fund flows of the funds. These LOG returns are assumed to be normally distributed and capture the compounding effect of returns. Secondly, I will test my hypotheses without excluding funds based on size (TNA above €10m) and age (older than 24 months).

3.4. Sample descriptive statistics

Table 1 presents the descriptive statistics of my main sample which consist of 1209 mutual funds and contains data from 1 January, 2019 to 31 December, 2020. Panel A shows that the average daily fund return is modestly positive with 0.07%, but has a large standard deviation of 1.33% which implies there is a considerable large cross-sectional variation. Moreover, both benchmarks have a slightly higher average return which results in negative delta returns. This would mean that the funds on average underperform both benchmarks across the sample. The alphas are close to zero and only the CAPM and Fama-French 3-factor alphas are positive. The others are slightly negative. Moreover, the fund's mean total net asset value is €523m, but again the standard deviations is quite large with the largest fund having 17.1 billion euros. The LOG TNA is simply the logarithm of the fund's TNA which also applies for LOG Age being the logarithm of the fund's age. The fund's average age is 3.586 days which is circa 14 years. The mean net expense ratio is 1.05% with the median even lower at 0.70%. After this, the sustainability score is presented which is on average 24.32 and is a combination between the ESG factors. Furthermore, the dummy variables: Active, Institutional, High- and Low Sustaintainability indicate the fund's characteristics. In total my sample consists for 93.10% out of active funds, 5.70%out of institutional funds and 36.00% and 24.30% are high and low sustainable funds. Finally, the weekly descriptive statistics are the Capital flows and FLOW variables. The Capital flows are on a weekly basis on average 504.000 euros, but the standard deviation is very large and this results in a large cross-sectional variation. This is also the case for the relative flow percentage (FLOW) of the funds in my sample. The mean of the relative flow 9.10% also differs a lot from its median -0.79% which is even negative.

Panel B presents the allocation of the fund's assets under management in the different industries. The top-3 industries with the largest allocation and the highest means and medians are Technology, Healthcare and Financials. While the three industries with the lowest percentage of allocation are Real Estate, Utilities and Energy. In panel C, the obtained Fama-French and Carhart factors are presented which are obtained from the Ken-French data library. The Market Risk premium on average 0.08% % which is similar to the benchmark returns in Panel A. The other factor with the largest impact on the funds is the High Minus Low factor which is on average -0.08%.

Table 2 shows the correlation matrix of the fund returns and fund flow components. In Panel A, I interpreted whether there is a high degree of correlation among the different measures of returns as a high correlation between my delta and alpha returns would potentially limit my ability to analyse the fund's returns using two different methods. The pairwise correlations between the delta and alpha returns are between 1.60% and 3.10% which allows me to argue that the measuring the fund's performance can be done with both. Moreover, the LOG TNA is positively correlated with the delta and alpha returns, but this correlation is very modest. LOG Age and the Net Expense Ratio are only positively correlated with the alpha returns and the correlations are quite low and thus are suited as control variables. Furthermore, the Sustainability score and Environmental risk score seem to be negatively correlated with fund returns. Overall, all the sustainable factors except the Environmental risk score are negatively correlated with the different delta and alpha returns. Finally, the fund's characteristics active, institutional and low sustainability have a negative correlation with the fund return which is significant, while high sustainable funds are positively correlated. The characteristics are not correlated with the delta returns, but are with the alpha returns. Both active and low sustainable funds show a clear positive correlation with the different alpha returns throughout the sample. However, this correlation is very modest and is not larger than 2.80%.

Panel B presents the correlation between the fund flow components. The fund's TNA is negatively correlated with -0.60% to the fund flows which implies that smaller funds have relatively larger flows than larger funds. The fund's return has a 1.70% positive relation with the fund's flows. This would confirm earlier theory that suggest there is a positive relationship between returns and flows. The other component that is positively correlated (12.20%) with the fund fund flows are the capital flows which is reasonable since a larger capital inflow will result in a larger relative flow percentage. Furthermore, the control variables LOG TNA, LOG Age and Net expense ratio are correlated with the relative flow percentage. The large negative correlation of -17.70% between LOG Age and the FLOW variable seems reasonable because older funds tend to be larger and similar inflows for old and young funds will have a smaller effect on the relative flow percentage of older funds. Also, all the sustainability variables seem to have a negative correlation on the relative fund flows with the Environmental risk score having the least negative correlation. Finally, the dummy variables active, institutional and low sustainability are negatively correlated with the independent variable, while high sustainability is positively correlated and will result in a 14.00% higher relative flow. This implies that I throughout the sample I expect only high sustainable funds to experience inflows while for the other fund characteristics I expect outflows.

Table 1. Descriptive statistics main sample

Panel A. Fund characteristics						
Daily	#Obs	Mean	SD	Median	Min	Max
Fund return (%)	632307	0.067	1.330	0.091	-32.915	21.880
Primary prospectus benchmark return (%)	631098	0.079	1.370	0.114	-19.858	16.971
MSCI World Index return (%)	631098	0.082	1.286	0.113	-9.502	8.403
Delta primary prospectus benchmark return (%)	631098	-0.012	1.035	-0.005	-19.944	23.956
Delta MSCI World return (%)	631098	-0.016	1.051	-0.007	-25.855	19.031
CAPM alpha return (%)	632307	0.001	0.058	-0.005	-3.549	1.421
Fama-French 3-factor alpha return (%)	632307	0.001	0.048	-0.003	-2.380	2.161
Carhart 4-factor alpha return (%)	632307	-0.002	0.050	-0.007	-2.247	2.019
Fama-French 5-factor alpha return (%)	632307	-0.002	0.046	-0.005	-2.212	2.140
Fund's TNA (€ millions)	632307	523.000	1142.000	158.800	0.000	17080.000
LOG TNA	632307	8.256	0.651	8.236	6.999	10.175
Fund's Age (days)	632307	3854.784	2.168	4466.836	717.794	30338.912
LOG Age	632307	3.586	0.336	3.650	2.856	4.482
Net expense ratio (%)	632307	1.053	1.127	0.700	-0.890	7.420
Sustainability score	632307	24.321	3.275	23.890	0.000	46.790
Environmental risk score	632307	4.161	2.324	3.830	0.030	16.930
Social risk score	632307	9.019	1.468	9.170	2.500	15.100
Governance risk score	632307	6.999	1.087	7.200	1.800	11.280
Active	632307	0.931	0.254	1.000	0.000	1.000
Institutional	632307	0.057	0.232	0.000	0.000	1.000
High sustainability	632307	0.360	0.480	0.000	0.000	1.000
Low sustainability	632307	0.243	0.429	0.000	0.000	1.000
Weekly						
Capital flows (Fi,t) (€ thousands)	126945	504.144	22235.636	3.306	-3572000.000	3378000.000
FLOW (%)	126945	9.104	45.551	-0.787	-88.917	319.333

(Continued)

Table 1. Continued

Panel B. Industry allocation (%)						
	#Obs	Mean	SD	Median	Min	Max
Basic Materials	632307	5.173	12.151	3.288	-3.274	99.752
Communication Services	632,307	7.102	7.205	7.084	-0.005	90.859
Consumer Cyclical	632307	8.159	7.603	8.509	-1.439	77.730
Consumer Defensive	632307	6.844	7.804	6.531	-0.001	98.247
Energy	632307	3.903	9.896	1.807	-2.542	99.259
Financial Services	632,307	12.186	10.918	13.936	-0.099	99.469
Healthcare	632307	13.588	18.680	11.620	-0.003	98.058
Industrials	632307	9.794	8.726	9.933	0.000	63.976
Real Estate	632307	1.910	2.783	1.020	-0.024	36.006
Technology	632307	13.600	12.758	13.861	-2.721	88.212
Utilities	632307	3.125	7.714	1.014	-0.569	89.483

Panel C. Fama-French/Carhart Factors (%)						
	#Obs	Mean	SD	Median	Min	Max
Risk-free rate	632307	0.006	0.005	0.010	0.000	0.010
Market premium (Mkt-Rf)	632307	0.079	1.290	0.120	-9.620	8.320
FF3 SMB	632307	-0.002	0.523	0.010	-5.370	2.050
FF3 HML	632307	-0.077	0.714	-0.100	-3.110	4.150
MOM	632307	0.019	1.043	0.060	-9.380	3.560
FF5 SMB	632307	-0.011	0.530	0.000	-5.260	1.990
FF5 HML	632307	-0.077	0.714	-0.100	-3.110	4.150
FF5 RMW	632307	0.022	0.249	0.020	-1.510	0.960
FF5 CMA	632307	-0.035	0.332	-0.040	-1.910	1.890

This table present the summary statistics of the key variables over the period 1 January 2019 to 31 December 2020 of my main sample consisting out of 1209 mutual funds. The sample includes 632,307 daily observations and 126945 weekly observations. The delta returns are the fund returns adjusted for the benchmark returns. LOG TNA is the logarithm of the Total Net Assets. LOG Age is the logarithm of the fund's age in days since inception. Net expense ratio is the annual expenses for 2020. The FLOW variable is winsorized at 1% and 99% level. The variables are defined in more detail in the methodology section. Panel A reports the fund’s characteristics in my sample. Panel B presents statistics on the industry allocation of the mutual funds on 31 Jan, 2020. Panel C presents the daily Fama-French and the Carhart Factors obtained from the Ken-French data library.

Table 2. Pearson's correlation mix

Panel A. Correlation between fund return measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Fund return	1									
(2) Return primary benchmark	0.707***	1								
(3) MSCI World Index return	0.678***	0.926***	1							
(4) Delta primary b	0.350***	-0.415***	-0.355***	1						
(5) Delta MSCI World Index b	0.437***	-0.239***	-0.365***	0.878***	1					
(6) CAPM alpha return	0.026***	0.011***	0.000	0.019***	0.031***	1				
(7) FF3 alpha return	0.022***	0.009***	0.000	0.016***	0.026***	0.788***	1			
(8) Carhart 4-factor alpha return	0.021***	0.008***	0.000	0.016***	0.025**	0.768***	0.983***	1		
(9) FF5 alpha return	0.023***	0.010***	0.000	0.017***	0.028**	0.757***	0.975***	0.968***	1	
(10) LOG TNA	0.002	0.000	0.003*	0.005***	0.005***	0.053***	0.008***	0.003***	0.001***	1
(11) LOG Age	0.002	0.000	-0.002	0.000	0.000	0.073***	0.051***	0.054***	0.044***	0.117***
(12) Net expense ratio	0.002	0.000	0.000	0.002	0.002	0.043***	0.005***	0.011***	0.014***	0.017***
(13) Sustainability Score	-0.004***	-0.002	0.000	-0.003*	-0.006***	-0.091***	-0.066***	-0.049***	-0.022***	-0.124***
(14) Environmental risk score	-0.006***	-0.004**	0.000	-0.003*	-0.008***	-0.067***	0.018***	0.031***	0.015***	-0.140***
(15) Social risk score	-0.001	0.000	0.000	-0.002	-0.002	-0.037***	-0.118***	-0.112***	-0.087***	0.0513***
(16) Governance risk score	-0.002	-0.001	0.000	-0.002	-0.003*	-0.090***	-0.047***	-0.056***	-0.063***	0.077***
(17) Active	-0.161***	-0.121***	0.000	-0.001	-0.002	0.012***	0.014***	0.011***	0.007***	-0.214***
(18) Institutional	-0.032***	-0.027***	0.000	0.000	0.000	-0.001***	0.010***	0.011***	-0.003***	-0.036***
(19) High sustainability	0.041***	0.021***	0.001	0.003	0.003	0.001***	-0.003***	-0.002***	-0.004***	0.047***
(20) Low sustainability	-0.085***	-0.054***	-0.001	-0.003	-0.003	0.017***	0.027***	0.028***	0.019***	-0.114***

(continued)

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(11) LOG Age	1									
(12) Net expense ratio	0.126***	1								
(13) Sustainability Score	0.022***	0.118***	1							
(14) Environmental risk scoı	0.008***	0.065***	0.573***	1						
(15) Social risk score	0.0400***	0.011***	0.098***	-0.012***	1					
(16) Governance risk score	0.043***	-0.067***	-0.231***	-0.128***	0.712***	1				
(17) Active	0.146***	0.199***	0.016***	0.025***	-0.048***	-0.064***	1			
(18) Institutional	-0.031***	-0.025***	-0.003***	0.019***	0.033***	0.024***	0.011***	1		
(19) High sustainability	-0.014***	-0.003***	-0.491***	-0.219***	-0.088***	-0.033***	0.090***	-0.028***	1	
(20) Low sustainability	-0.071***	0.019***	0.456***	0.183***	-0.046***	-0.110***	0.041***	0.027***	-0.425***	1

(continued)

Table 2. Continued

Panel B. Correlation between fund flow components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) FLOW	1														
(2) Fund TNA	-0.006***	1													
(3) Fund Return	0.017***	0.071***	1												
(4) Capital flows (Fi,t)	0.122***	0.060***	0.142***	1											
(5) LOG TNA	0.034***	0.661***	0.002	0.031***	1										
(6) LOG Age	-0.177**	0.099***	0.002	-0.009**	0.117***	1									
(7) Net expense ratio	0.010***	0.028***	0.002	0.024***	0.017***	0.126***	1								
(8) Sustainability Score	-0.102***	-0.084***	-0.004***	-0.012***	-0.124***	0.022***	0.118***	1							
(9) Environmental risk score	-0.025**	-0.070***	-0.006***	-0.007**	-0.140***	0.008**	0.065***	0.573***	1						
(10) Social risk score	-0.045***	0.032***	-0.001	-0.011***	0.051***	0.040***	0.011***	0.098***	-0.012***	1					
(11) Governance risk score	-0.045***	0.060***	-0.002	-0.015***	0.077***	0.043***	-0.070***	-0.231***	-0.128***	0.712***	1				
(12) Active	-0.032***	-0.161***	-0.001	0.015***	-0.214***	0.146***	0.199***	0.016***	0.025***	-0.048***	-0.064***	1			
(13) Institutional	-0.040***	-0.032***	-0.001	-0.002***	-0.036***	-0.031***	-0.025***	-0.003***	0.019***	0.033***	0.024***	0.011***	1		
(14) High sustainability	0.140***	0.041***	0.006	0.027***	0.047***	-0.014***	-0.003***	-0.491***	-0.219***	-0.088***	-0.033***	0.090***	-0.028***	1	
(15) Low sustainability	-0.107***	-0.085***	-0.006	-0.015***	-0.114***	-0.071***	0.019***	0.456***	0.183***	-0.046***	-0.110***	0.041***	0.027***	-0.425***	1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table present the correlation matrix for the key variables. Panel A shows the correlation between the fund return components based on fund-daily observations. Panel B shows the correlation between the fund flow components based on weekly observations. The fund return is the return of the past week t-1. The FLOW variable is winsorized at 1% and 99% level.

4. Results

In this section the results of my research will be presented and discussed. First, I will show the results of the tests performed to observe the presence of multicollinearity and heteroskedasticity. After this, I will present the empirical results of the performance and fund flows of the equity mutual funds in my sample which provide answers to my hypotheses.

4.1. Multicollinearity and heteroskedasticity

To test for multicollinearity between the variables used in my regressions, I performed two Ordinary Least Squared (OLS) regressions including fund-level and industry level controls for both the performance[5] and the fund flows[6]. In Table 3, in the appendix the VIF and 1/VIF values are displayed for the performance regression. None, of the variables have high VIF values that could indicate problems with multicollinearity. To verify this result, I also performed an OLS regression with the $FLOW_{i,t}$ variable as dependent variable and obtained similar results. This confirms that the variables used in the regressions to analyse the fund's performance and fund flows contain no sign of severe multicollinearity.

Subsequently, I test for heteroskedasticity for both cross-sectional regressions using the Braun-Pagan test. The test determines the residuals are disturbed with constant variance or not. The null hypothesis assumes homoscedasticity and must be rejected for heteroskedasticity to be present in the residuals. I reject the null hypothesis (p=0.000) and use the command Robust in Stata to control for the variance of the residuals. The Robust command computes a robust variance estimator and tend to provide more accurate standard errors (Statology, 2020).

[5] $\alpha^{Car4}{}_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t}$

[6] $FLOW_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t}$

4.2. Empirical results

As shown in Pearson's correlation matrix the fund's characteristics have different effects on the fund performance and fund flows in my sample. This relationship might change when other variables are introduced in the cross-sectional regressions. The following section will present the results and discuss the implications on the earlier stated hypotheses.

4.2.1. Mutual Fund Performance

Based on the Pearson's correlation matrix in Panel A of Table 2, I would expect that the fund's characteristics are only correlated with the alphas. Both active and low sustainable funds showed a positive correlation, while the other two characteristics reported a negative correlation for the period between January 1, 2019 to December 31, 2020. To test whether active funds also outperformed passive funds during the COVID-19 crisis. I compare the average delta and alpha returns and perform several cross-sectional regressions. Tables 4-9 report average annualized benchmark-adjusted performance (deltas) and factor-adjusted performance (alphas) for each characteristic during the five different periods.

In the first two columns of Panel A of Table 4 it is shown that the average delta return based on the fund's prospectus benchmark is significantly negative with -5.56% per year for active funds during the crisis. This estimated average delta return has t-statistic of -2.09 and is significant on a 5% level. Although, this underperformance is not the case for the MSCI World Index benchmark. The average active fund tends to outperform both benchmarks with 10.05% to 14.98% per year during the crash sub-period, but underperform during the recovery with -18.38% to -19.32% per year. This is interesting and could imply that active managers were successfully able to reduce volatility which resulted in higher deltas during the crash sub-period. However, they were not able to profit as much of the rebound in the market during the recovery. Ultimately, this could have led to the average active fund underperforming its prospectus benchmark during the whole crisis period. Subsequently, when comparing this to Panel A in Table 5, the average delta returns for the passive funds do not significantly differentiate from zero for both benchmarks. This indifference could be due to the passive fund's strategy which is limited to replicating its benchmark and explains why they obtain similar returns (Matallin & Nieto, 2002). Moreover, in Panel B of Table 4 and 5, the estimated average value weighted delta returns which are weighted by the fund's TNA are for both groups of funds not significantly different from zero.

The remaining columns in Panels A and B of Table 4 and 5 report the average alpha returns from four multifactor models. The Capital Assets Pricing Model (CAPM), the Fama-French three-factor model (FF3), the Carhart four-factor model (Car4) and the Fama-French five-factor model (FF5). Both active and passive funds have equal and value weighted average alphas which are significant during the five periods on a 1% significance level. Panel A shows that the average alphas are more negative for active funds during the crisis period. The average estimated annual alphas from the active funds compared to the passive funds for the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French five-factor model are -25.54%, -11.69%, -10.33% and -11.26% versus -17.91%, -10.81%, -8.63% and -10.95% per year. This implies that active funds underperform passive funds during the recent Covid-19 crisis which goes against the theory that active funds are able successfully react to the downturn in the market and generate higher alphas (Hung and Wang, 2013 & Kosowksi, 2011). However, this could still be true when looking at the crash and recovery sub-periods. During the recovery the average active fund tends to outperform generating higher alphas. This could imply that they were potentially better able to re-position their investments during the crash. But, this could also be due to the rebound in the general market and large negative average alphas during the crash. The average active fund had more severe negative alphas between -5.18% (FF5) to -66.01% (CAPM) per year compared to the average passive fund during the crash sub-period.

In Panel B of Table 4 and 5, the estimated value weighted average alpha return give a unclear image on the difference in performance of both groups during the crisis. The active funds performs less worse based on Fama-French three-factor and five-factor models with average alphas of -7.81% and -9.89% per year versus -8.34% and -11.67% per year for the average passive fund. On the other hand, the passive funds generate less negative alphas with the CAPM and the Carhart four-factor model and the difference here is larger. The value-weighted average alphas during the crash and recovery obtain similar results to the equal-weighted performance. The estimated average alphas are severely more negative during the crash, but larger during the recovery period for all the multifactor models. This outperformance continues when looking at the after-crisis period were active funds on average generated less negative alphas for both weighted methods.

Table 10-14 reports the determinants of fund performance in cross-sectional regressions with fund-level and industry controls during the crisis, crash recovery, pre-crisis after-crisis periods.

Panel A considers benchmark-adjusted performance using the prospectus benchmark. Panel B focuses on the factor-adjusted performance using the Carhart four-factor model. Table 10 shows that during the period before the crisis active firms underperformed their respective benchmark between -2.07% to -3.28% per year which is significant on a 1% significance level. This corresponds with earlier literature that found that actively managed funds are underperforming passive benchmark (Jensen , 1968). Furthermore, Table 11 shows that the performance of active funds did not significantly differentiate based on benchmark-adjusted and factor-adjusted returns during the whole crisis period lasting from February 20 to April 30, 2020. This contradicts the findings of Huang and Wang (2013) that found that the performance of actively managed funds experiencing higher returns during the 2007-2009 crisis and underperforming before the crisis period. This implies that no such similar shift is observed during the COVID-19 crisis.

In Panel A of Table 12 suggest that active funds generated higher delta of 18.69% (t = -3.13) per year during the crash sub-period. However, notice that the adjusted R-squared of this cross-sectional is 0.00 which improves to 0.07 when the variables institutional, high and low sustainability are added. Moreover, the significant effect reduces and even becomes unsignificant when both type of controls are used. Panel B of Table 12 confirms that active funds experienced negative alpha returns. The effect of the cross-section regression including controls is only significant on a 10% significance level is -23.07% per year. Table 13 presents similar results to Table 4 and 5 during the recovery with the dummy variable active having a negative effect on the delta returns and positive effect on the alpha returns. The delta returns are more negative between -7.95% to -16.02% per year, although the R-squared are quite low for these cross-section regressions. Furthermore, the annual alpha return is 19.37% per year higher for the 8^{th} cross-sectional regression with an R-squared of 0.35. Table 14 shows that the active dummy had a positive effect on the benchmark-adjusted returns between 3.08% to 3.22% per year after the crisis. However, again notice that the R-squared for both regressions are very low. Furthermore, there is no significant effect on the factor-adjusted returns which disputes the observed outperformance after the crisis in Table 4 and 5.

To summarize, the results indicate that active funds do not show any significant sign of outperformance during the crisis. They are even more likely to underperform based on the equal weighted average delta return using the prospectus benchmark and alphas from every multifactor model. Overall, I reject my first hypotheses and conclude there is no significant sign of actively managed mutual funds performing better than passive funds during the COVID-19 crisis.

To test whether funds that are majority-held by institutional investors are outperforming funds that are mainly-held by retail investors during the COVID-19 crisis. The Tables 6 and 7 report the average delta and alpha returns for both groups. In panel A of Table 6, the average estimated delta returns for institutional funds show a negative sign for both benchmarks during the crisis, but they are not significant. Moreover, institutional funds performed similar to their respective benchmarks during the crash and recovery sub-periods. Meanwhile, Panel A of Table 7 shows that retail funds underperformed their prospectus benchmark with -5.70% per year during the crisis, which is significant on an 5% level. This suggest that institutional investors indeed might be more sophisticated and are better at picking quality investments compared to retail investors and explain why funds mainly-held by retail investors underperformed (Fahlenbrach, 2012). However, this underperformance is not the case for the MSCI World Index as benchmark. Although, retail funds experienced for this benchmark 14.41% per year higher average annual delta returns during the crash and -18.81% per year lower average delta returns during the recovery this does not result in a significant different average delta return during the overall crisis. Furthermore, Panel B of Table 6 and 7 indicate that for both groups the value-weighted delta returns are not significant in any period.

When looking at the multifactor models, institutional and retail funds both experienced negative alphas during the crisis which are significant on a 1% level. Institutional funds generated on average higher negative alpha returns in three out of four models. Only, the -9.59% alpha return per year from the Carhart four-factor model is slightly less negative than the average alpha return for retail funds which is -10.28% per year. The result is more mixed for the value-weighted alphas. Here, the average institutional funds only underperforms for the CAPM and Fama-French three-factor model, but outperforms for the other two multifactor models. Furthermore, institutional funds generated more negative equal-weighted average alphas during the crash and the difference becomes even bigger in Panel B of Table 6 and 7 for the value-weighted average alphas. The average institutional fund underperforms the average retail fund between -2.40% (CAPM) per year and -44.34% (Car4) per year for the value weighted averages during the crash period. On the other hand, institutional funds have higher estimated average equal weighted alphas except for the CAPM model during the recovery and the value-weighted alphas are all in favour of institutional funds, but this does not not lead to institutional funds outperforming during the overall crisis.

Table 10 shows that there is significant positive effect between the dummy variable institutional and the benchmark-adjusted performance of 1.40% to 2.00% per year. This is similar to the average delta returns in Panel A of Table 6 during the pre-crisis period. This outperformance implies that institutional investors indeed might be more sophisticated and better at picking quality investments. However, Table 11 reports that there is no significant effect of the dummy variable institutional on the benchmark-adjusted and factor-adjusted performance cross-sectional regressions during the crisis. This includes the regressions with both controls added and although it shows a positive coefficient of 2.19% per year for both performance measures it is still not significant. I obtain similar results for the crisis and recovery sub-periods in Table 12 and 13. Overall, before the COVID-19 pandemic started institutional funds outperformed its passive peers based on the deltas and alphas. The prospectus benchmark was outperformed by 1.79% per year (t = 1.67) and the MSCI World Index by 2.20% (t = 1.96) per year. Moreover, the average alpha returns are higher for the institutional funds for both weighted methods. Table 10 shows that the institutional dummy variable had a positive significant effect between 1.40% to 2.00% per year on the deltas before the crisis started. However, this outperformance does not continue during the crisis period. Although, the retail funds underperform based on the estimated average delta returns for the prospectus benchmark I do not observe a significant negative effect in Table 11 for the institutional dummy variable.

The results are similar to the results obtained by Pastor and Vorsatz (2020). They also find that institutional funds outperform with the Carhart four-factor model but underperform with the other multifactor models. This contradiction is not confirmed with the performed cross-sectional regressions, where I find no significant effect for institutional funds on performance. Consequently, I reject my third hypotheses and do not find a strong evidence of fund that are majority-held by intuitional investors outperforming funds mainly-held by retail investors during the COVID-19 crisis.

Figure 2 shows the cumulative return densities across sustainability categories during the crisis. Panel A of Figure 3 reports that the total return of high sustainable funds with 4 or 5 Morningstar sustainability globes are more concentrated and that low sustainable fund experience more dispersion. However, Panel B of Figure 3 shows very similar results for the benchmark-adjusted returns which does not hint towards any outperformance of a single group. To further analyse whether high ESG-rated funds outperform low ESG-rated mutual funds, I set side by side the performance of both groups and perform cross-sectional regressions to try to find a significant effect of sustainability on performance.

Panel A of Table 8 shows that high sustainable funds significantly outperformed both benchmarks with 1.62% and 3.50% per year during the pre-crisis period, while Panel A of Table 9 shows that low sustainable funds underperformed their respective benchmark with -1.69% per year . This outperformance of high sustainable funds continues with 31.39% and 37.56% per year during the crash. Meanwhile, Panel A of Table 9 reports that low ESG-rated funds underperformed their prospectus benchmark with -19.94% per year during the crash which is significant on a 5% significance level. Moreover, the estimated average benchmark-adjusted returns for the high sustainable funds are severely worse than the delta returns from its low sustainable peers. The average low sustainable funds again only underperformed its prospectus benchmark, this time with -12.12% per year. Overall, during the crisis high sustainable funds performed on average similar to both benchmarks, while low ESG-rated seriously experienced lower average delta returns for both benchmarks with -15.64% (t = -2.91) and -11.86% (t = -2.12) per year. This would imply that similar to the findings from Abate et al. (2021) I find evidence of a positive relationship between a high Morningstar Sustainability rating and performance. However, a contradiction exist in the value-weighted delta returns which are not on average significantly different form zero.

For the alphas, the high ESG-rated funds only outperformed low sustainable funds with the estimated average alpha for the CAPM using equal-weights during the market crash. The results differs for the value-weighted alphas. Panel B of Table 8 and 9 report that the alphas are less negative for high sustainable funds for the CAPM and FF3 models during the crash. Furthermore, for both groups the estimated average value-weighted alphas are less negative. This implies that larger funds performed less worse than smaller funds during the crash in the market. During the recovery, low-rated sustainable funds performed better for every multifactor model with the lowest (equal-weighted) annual alpha being 75.13% per year for the CAPM and the highest alpha of high sustainable funds being 62.52% per year. Both groups have average alphas that are significant on a 1% level. Although, I obtain similar results for low ESG-rated funds outperforming based on value-weighted alphas. This does not translate into low sustainable funds outperforming during the crisis. Here, the average high ESG-rated fund generates negative alphas but these are less negative than the ones from the average low ESG-rated fund. This suggest that the positive relationship between ESG-investing and performance found by Friede, Busch and Bassen (2015) holds in the most recent COVID-19 crisis and support the evidence found by Nofsinger and Varma (2014) of sustainable funds outperforming during earlier crises.

Panel A of Table 11 confirms that a high ESG-rating has a positive effect on the benchmark-adjusted performance. The effect is between 11.68% to 4.98% per year and significant on a 1% significance level. Moreover, the effect becomes somewhat lower when additional variables and controls are added to the cross-sectional regression, but this also enhances the R-squared from 0.05 to 0.25. Panel B of Table 11 reports a very moderate positive effect of 3.34% per year which is only visible in the eighth regression and significant on a 10% significance level. This implies that although the average high sustainable fund generated higher alphas returns than the average low sustainable fund, the overall positive effect on the factor-adjusted performance might be limited. Another interesting result is that Panel A of Table 12 shows that there is a positive significant effect between high ESG-rated funds and benchmark-adjusted returns during the crash which is 16.39% (t = -3.67) for the regression with the highest R-squared of 0.24. Interestingly, this implies that the observed outperformance in Table 10 for the benchmark-adjusted returns during the pre-crisis period actually accelerated during the crash sub-period and became much larger. Furthermore, Table 13 indicates that the effect reverses and actually reduces to -4.39% per year when both controls are added and disappears completely for the factor-adjusted performance during the recovery.

To summarize, the results suggest that high sustainable funds outperform based on the estimated average delta and alpha returns. On top of that, this suggestion is supported by the strong positive effect between funds with a high ESG-rating and benchmark-adjusted performance and more moderate effect on the factor-adjusted performance during the crisis. This allows me to confirm my hypotheses which implies that mutual funds with a high

(Morningstar) ESG-rating actually outperform low ESG-rated fund during the COVID-19 crisis.

In addition, I analysed which of the ESG-factors contributed to this positive relationship between sustainability and performance. Panel A of Table 15 shows that the variable Greener Environmental has a positive effect on the benchmark-adjusted performance during the crisis for the first two regressions. However, these have a very low R-squared of only 0.02 and the effect disappears when the control variables are added. Moreover, in Panel A of Table 16 the environmental factor within ESG does have a significant effect of 10.31% on the annual delta returns in the fourth cross-sectional regression. For the factor-adjusted performance, Panel B of Table 13 and 14 shows than none of the ESG factors remain significant when adding both types of control variables. With none of the ESG factors showing a clear significant relationship throughout the cross-sectional regressions for both the deltas and alphas, I find it hard to draw a clear conclusion on which ESG factor actually predicts performance.

4.2.2. Mutual Fund Flows

Figure 4 shows the total net assets in euros and the cumulative net fund flows in percentage terms into the 1209 funds of my main sample. Panel A indicates that the combined fund's experienced a large drop in total net asset value from €713bn at the start of the COVID-19 pandemic to €506bn on March 23, 2020. During this reduction of €206bn in net worth, the cumulative flows did not become negative and did not see outflows. This contradicts the idea of Wang, Watson Wickramanayake (2018),that during a recession investors seek to reduce risk and direct wealth to funds with lower volatility. Especially, since the decrease in TNA is similar to the negative return of the market during the crisis. However, a potential reason that could explain why the funds in my sample do not experience negative outflows is that their investment geography is world-wide which bears less risk a fund focused on one specific region. Moreover, after the crash the inflows continue and increase during the market recovery. Panel B shows that between January 2019 and January 2020 the cumulative flows are negative for an extensive period and only become positive in November 2019. This suggest that the flow-performance relationship was not prevalent in most of 2019 because the funds did generate positive returns which led to the increase of their TNA from €512bn to €665bn at the end of 2019. After this, the cumulative flows percentage tend to increase and potentially accelerate after market crash to circa 13.0% compared to the TNA of January 2019.

To test whether actively managed equity mutual funds did experience less outflows compared to passive equity mutual funds during the COVID-19 crisis I compare the average net fund flows of each group and perform cross-sectional regressions to analyse if there is a positive relationship between an active fund and fund flows. Table 17 adds more detail and shows the net fund flows for the different subsamples created based on the funds' characteristics. Active funds received less inflows than passive funds during the pre-crisis period. However, they received slightly higher average net fund flows of 2.10% compared to passive fund receiving 2.07% during the crisis. For which, both coefficients are significant, but only on a 10% significance level for the passive funds. Moreover, the pre-crisis inflows exceed inflows for both groups during the crisis. However, the crisis period is just 11 weeks long whereas the pre-crisis period is 58 weeks long. On a per-week basis, the weekly inflows of the active funds are larger during the crisis than the pre-crisis period (0.19% versus 0.18% per week). This is not the case for passive fund which experienced larger inflows during the pre-crisis period (0.19% versus 0.42% per week). Moreover, the average passive fund generated significant positive net flows of 0.89% during the crash on a 10% significance level. On the other hand, active funds did not generate average net flows significantly different from zero. Furthermore, active funds did on average receive larger inflows of 2.64% (t = 10.22) versus 2.25% (t =2.22) during the recovery which are 0.44% and 0.38% per week.

With active funds obtaining larger average inflows during the crisis and recovery periods, I test in Table 18-20 if there is a positive relationship between the fund characteristic active and net fund flows during the crisis, crash and recovery. Table 18 shows that none of the cross-sectional regressions indicate a significant effect during the crisis. Table 19 shows that the dummy variable active has a negative relationship which translates into significant net outflows between -0.85% and -0.81% compared to passive funds during the crash. Note, that this effect is only significant on a 10% significance level and disappears when the control variables are added and that the R-squared is 0.00. However, this confirms the earlier observation in Table 14 that passive funds did outperform active funds during the crash period. This result contradict the theory of Wang, Watson and Wickramanayake (2018) that active managers are able to reduce volatility which consequently leads to higher inflows due to investors seeking more certain outcomes in volatile times. As described by Gruber (1996) and Zheng (1999) the impact of changes in the flow-performance relationship should be visible on short notice. However, I find a negative effect during the five week crash period and in Table 20 I do not find a significant effect during the recovery sub-period.

In short, the results show that the average net fund flows were higher for active funds during the crisis and recovery periods, but lower during crash sub-period. But, these are simply averages and I do not observe a positive relationship between active funds and net fund flows in all the three periods in the cross-sectional regressions. This is why, I reject my second hypotheses and do not find a significant evidence that actively managed equity mutual funds experienced less outflows during the COVID-19 crisis compared to passive funds.

To test my fourth hypotheses on whether mutual funds that are majority-held by institutional investors experience less severe outflows than mutual funds mainly-held by retail investors during the COVID-19 crisis, I begin with comparing the average net fund flows. Table 17 shows that retail funds experienced average inflows of 11.79% (t = 6.89) during the pre-crisis period. The positive average net fund flows continued during the crisis period with retail funds obtaining larger average net fund flows of 2.29% which is significant on a 1% significance level. On the other hand, institutional funds did not receive large enough flows that are significantly different from zero during both periods. Moreover, institutional funds did experience larger average inflows of 2.22% during the recovery period which is just significant on a 10% significance level. But, even here the average retail fund outperformed its institutional peers with 0.50% having a net fund flow of 2.72% (t = 10.57). This outperformance continues during the after-crisis period. Overall, retail funds experienced larger average net fund flows than institutional funds during the pre-crisis, crisis and after-crisis periods. On a per-week basis, the weekly inflows of retail funds are larger during the crisis than the pre-crisis period (0.21% versus 0.20% per week) and the largest during the recovery period (0.22% per week). This contradicts the theory that retail investors are more reactive to shifts in sentiment which results in a more convex flow-performance relationship for retail investors compared to institutional investors (Wang and Young, 2020; Evans and Fahlenbrach, 2012). Especially, since the market saw a drawdown of -34% during the crisis period.

Table 18 indicates that there is no significant relationship between the dummy variable institutional and the net fund flows between February 20 to April 30, 2020. Furthermore, I find similar results in Table 19 and 20 for both sub-periods. This is not what I expected, I anticipated to find a negative relationship between institutional funds and net fund flows based on the larger average net fund flows of retail funds.

To summarize, both the average net fund flows and the results of the cross-sectional regressions shows no sign of institutional funds receiver larger inflows during the crisis. When looking at the average net fund flows I find evidence that retail funds are more likely to receive larger inflows during every main period. Therefore, I reject my fourth hypotheses and find that mutual funds that are majority-held by institutional investors did not experience less severe outflows than funds mainly-held by retail investors during the COVID-19 crisis.

To provide an answer to my last hypotheses on whether high ESG-rated funds experienced less outflows than lower ESG-rated mutual funds during the COVID-19 crisis, I first compare the average net fund flows and perform several cross-sectional regressions. Table 17 shows that during the pre-crisis high ESG rated funds generated 22.61% net fund flows. Meanwhile, low sustainable funds flows remained close to zero. Furthermore, the average high sustainable fund received 2.92% net fund flows during the crisis, whereas the average low sustainable fund experienced 1.00% net fund flows. This 1.92% difference is quite substantial since the crisis period is just 11 weeks long. Furthermore, I find similar results for both groups during the crash sub-period. However, high ESG-rated funds with 4 or 5 Morningstar globes outperform low ESG-rated funds with 1 or 2 globes based on the net fund flows during the recovery period. The larger average net fund flows during the crisis extend during the after-crisis period reaching 14.96% at the end of December 2020 compared to 1 May 2020. On a per-week basis, the weekly inflows of high sustainable funds are slightly lower during the crisis compared to the pre-crisis period (0.27% versus 0.39% per week). The weekly inflows are the largest during the recovery sub-period with 0.54% per week and these larger inflows continue in the after-crisis period which is 0.43% per week. This suggest that even after after the crisis sustainable investing remained very popular and even accelerated with larger weekly inflows to high ESG-rated funds during the after-crisis period. This contradicts the theory of Öttling and Kim (2020) that the relatively large high inflows disappear after the onset of the COVID-19 pandemic led to a market crash.

Table 21 shows that there exist a significant positive effect between high sustainable funds and the net fund flows from 11.01% and 17.25% before the crisis. The coefficients are significant on a 1% significant level. However, note that the R-squared of the cross-sectional regressions are quite low and between 0.03 and 0.09. Furthermore, Table 20 shows this positive significant relationship continues after the crisis and ranges between 7.76% and 12.16%. This might be slightly lower compared to the pre-crisis period. But, the after-crisis period is only 35 weeks long which implies that on a per-week basis the inflows are higher during the after-crisis period. This confirms my earlier suggestion that high ESG-rated funds experienced larger inflows during the after-crisis period and they definitely do not disappear as Öttling and Kim (2020) observed in their research. Moreover, during the crisis period, Table 18 shows that sustainability is an important determinant of net fund flows in the single variable cross-sectional regressions using high sustainability and low sustainability as independent variables. The table indicates that high ESG-rated funds show a positive significant effect of 1.28% on the net fund flows which is significant on a 5% significance level. Moreover, low sustainable funds show a negative effect of -1.45% on the net fund flows which is also significant on a 5% significance level. In addition, the low sustainable funds also show a negative effect of -1.27% when both controls are added which is significant on a 10% level. But, again the R-squared of the regressions are close to zero and do not explain much of the variance in the dependent variable. Furthermore, when I look at both crisis sub-periods I obtain similar results as in Table 17. Table 19 shows that no ESG rating can be seen as a determinant of fund flows during the crash sub-period. Table 20 indicate that high ESG-rated funds experienced 0.94% (t = -1.77) higher net fund flows and the low rated peers -1.16% (t = -2.08) during the recovery sub-period. Both coefficients are only significant in the single variable cross-sectional regressions. Overall, my observations during the COVID-19 period between February 20 and April 30 in 2020 differ from the findings of Pastor and Vorsatz (2020). First, they find that low sustainable fund suffer larger outflows of 2.60% compared to 1.27% - 1.45% in my sample. Secondly, they find that the net fund flows for high ESG-rated funds are roughly zero, while I find a significant positive coefficient of 1.28% during the crisis in the single variable cross-sectional regression. Note, that for the other cross-sectional regressions the effect seems to be not significantly different from zero and this is more in line with the research of Pastor and Vorsatz (2020).

In addition, I analysed which of the ESG-factors contributed to the positive relationship between sustainability and net fund flows. Table 23 shows that the only ESG factor that is of importance in cross-sectional regressions is the Environmental factor. I find a positive relationship between the Environmental factor in ESG and net fund flows which is only significant on a 10% significance level. These observations are similar to the findings of Ferriani & Natoli (2021) who found that the environmental preferences remained strong and resulted in higher inflows during the crisis. Note, that although I find similar results, the relationship tends to disappear when control variables are added and the R-squared is very low which makes it hard to draw a clear conclusion.

Furthermore, I observe that the relationship between sustainability and net fund flows is comparable to the relationship between the ESG factors and returns. Earlier, I suggested that there exist a positive effect between funds with a high ESG-rating and performance and that sustainable funds outperformed based on average delta and alpha returns. The same applies to the funds with a high ESG-rating and the net fund flows. High ESG-rated funds generate higher average net flows during the crisis. Furthermore, the effect of a high ESG-rating on net fund flows seems to be positive or at least close to zero, while a low ESG-rating has a negative effect on the net fund flows and will result in outflows. However, keep in mind that the cross-sectional regressions do have very low R-squared and only show a clear possible effect of the level of sustainability on the fund's net flows. To summarize, this observed possible effect combined with the large difference in average net fund flows allows me to conclude that the low ESG-rated funds did experience larger outflows than the high ESG-rated funds which even experienced net inflows during the COVID-19 crisis.

Finally, the performed robustness checks present results that do somewhat differ from the earlier discussed findings but mostly are in line with the stated observations. First, Table A1 shows that active funds on average underperform both benchmarks during the crisis when using LOG returns. Meanwhile, I find similar results in Table A2 where only the prospectus benchmark is underperformed using the full sample consisting out of the total 1400 funds. Moreover, the estimated alphas using LOG returns are lower and the value-weighted alphas present less clear of an image. Active funds now experience more negative alphas for every multifactor model compared to its passive peers. In addition, Table A13 provides evidence of a negative effect of the active dummy variable on the benchmark-adjusted performance between -3.53% per year and -4.33% per year. However, this is not the case for the full sample as shown in Table A14. Similarly, none of the additional test point towards actively managed funds outperforming passively managed funds. Furthermore, I find a minor difference for the average delta returns of retail funds using LOG returns. Table A7 shows even stronger underperformance and now present also for the MSCI World Index. However, Table A13 and Table 14 both show that there is still no significant effect for the institutional dummy variable. Moreover, regarding a fund's sustainability I obtain very similar results with Table A13 only showing that the effect of sustainability seems to be larger with larger coefficient for high ESG-rated funds and more negative coefficients for low sustainable funds. Overall, none of my conclusions change for the performance related hypotheses.

When comparing the results for the fund flows with the results from the performed robustness checks I directly observed that the estimated fund flows using LOG returns derived in almost identical results. Subsequently, I only observed slight differences when using the full sample. Table A19 reports much larger average net fund flows and controversially average positive net flows during the crash sub-period. However, Table A20-A24 do not present any different results which change the conclusion drawn earlier on any of the fund characteristics in relationship to the fund flows.

5. Conclusion and Discussion

This master thesis provides a comprehensive analysis on the performance and flows of European domiciled equity mutual funds during the recent COVID-19 crisis of 2020. Throughout this thesis, I examine different fund characteristics based on their investment strategy, the heterogeneity of its investors and the level of sustainability. Recently, the insight of how investors behave following fund performance became a increasingly relevant topic because a large number of investors joined the market in 2020. In most European countries between 15-25% more people were investing in 2020 compared to last year (REFINITIV, 2020). This means that the mutual fund industry represents a growing part of people's wealth. Therefore, this thesis helps to understand what drives mutual fund performance an how do people allocate money into funds in times of distress during the large economic shock caused by the COVID-19 pandemic.

Prior studies has established that mutual fund characteristics tend to have an effect on the performance and received fund flows. In the past, active equity managed funds have underperformed their passive benchmarks (Jensen, 1968). However, as suggested by Glode (2011) investors direct flows to actively managed funds that deliver higher returns during recessions when the investor's marginal utility is high. Furthermore, funds that are mainly-held by institutional investors tend to outperform (Evans and Fahlenbrach, 2012), and retail investors are more reactive to shifts in sentiment and reallocate capital more often (Frazzini and Lamont, 2008; Ben-Rephael et al., 2012; Wang and Young, 2020). Moreover, in recent studies from Hartzmark and Sussman (2019) and Ceccarelli et al. (2020), a causal evidence is found that investors market-wide value sustainability. In addition, Ibukunle and Steffen (2015) documented a shift in the performance of high sustainable funds around 2012 and recently research from Abate et. Al (2021) also find evidence for a positive relationship between ESG and fund performance. Subsequently, the ESG score of a mutual fund has an effect on the fund flows it receives. However, not all the ESG factors contribute similarly to the amount of fund flows (Ferriani and Natoli, 2021). Overall, earlier studies found that a fund being categorized as a low sustainable fund resulted in net outflows and categorized as a high sustainable fund led to net inflows. On the other hand, the traditional neoclassical economics theory suggest that sustainability issues, such as environmental quality are "luxury goods". These issues are only a concern to those whose more basic needs for food, housing and a certain quality of living is met (Martins, 2013). A major income-shock for a lot of people could affect the way investors value sustainability and consequently the fund flows to ESG related investments.

The findings of this study regarding the performance and fund flows of equity mutual funds largely differ from prior studies. Actively managed equity mutual funds did not perform better during the COVID-19 crisis between February 20 to April 30, 2020. This contradicts, the theory that actively managed funds outperform passive funds during recessions when investors care about returns the most. Moreover, I do not observe actively managed funds outperforming their passive peers during a recession which is observed in the earlier recessions over the 1980-2005 period by Kacperczyk et al. (2016) and during the 2007-2009 period by Huang and Wang (2013). Moreover, the actively managed funds in my sample are even more likely to underperform by 5.56% per year based on equal weighted delta returns using the prospectus benchmark and for the alphas of every multifactor model. This implies that investors that are normally willing to accept slightly lower alphas during expansions did not see the reversal in performance they might have expected during the COVID-19 crisis. In addition, actively managed equity funds did not experience less outflows during the COVID-19 crisis compared to passive funds. Although, both groups in my sample on average received net fund inflows during the crisis, I do not find evidence of a positive relationship between actively managed funds and the net fund flows. This could mean that fund managers were not successfully able to reduce volatility which consequently did not lead to higher inflows due to investors seeking more certain outcomes in volatile times.

Furthermore, although institutional funds outperformed during the pre-crisis period. The mutual funds that are majority-held by institutional investors did not outperform mutual funds mainly-held by retail investors during the COVID-19 crisis. The results show that institutional funds outperform retail funds based on the average delta returns with retail underperforming their prospective benchmark on average with -5.70% per year. The underperformance becomes larger when using LOG returns, than retail funds underperform both benchmarks with -13.49% to -11.59% per year. In addition, the results are similar to the observations obtained by Pastor and Vorsatz (2020), I find that institutional funds outperform with the Carhart four-factor model alpha but underperform with the other multifactor models. Overall, I do not find significant clear relationship between institutional funds and performance during the COVID-19 crisis. This implies that institutional investors might not be sophisticated enough to also outperform during periods of increased volatility caused by a recession. Additionally, I do not find a significant relationship between funds that are majority-held by institutional investors and the net fund flows during the COVID-19 crisis. Controversially, I find that on average retail funds are more likely to receive inflows during every main period and that on a per-week basis the flows are higher during the crisis than pre-crisis period. This implies that retail investors investors might have been less responsive to negative returns caused by the major crash in the market during the COVID-19 pandemic.

Moreover, high ESG-rated equity mutual funds did outperform low ESG-rated funds during the COVID-19 crisis. The results suggest there seems to be a strong positive relationship between a high ESG-rating and benchmark-adjusted performance and more moderate effect on the factor-adjusted performance during the crisis. A high-ESG rated fund generates higher deltas between 4.98% to 11.68%per year and higher alphas of 3.34% per year. The performance of sustainable funds during the COVID-19 crisis seems much larger than in prior studies. Nofsinger and Varma (2014) found that sustainable funds outperformed by 1.61% to 1.70% per year during the two recessions in 2001 and 2007-2009. Similarly, to the positive relationship between ESG and returns, I find a positive relationship between sustainability and net fund flows during the COVID-19 crisis. High ESG-rated funds received higher average net flows of 2.92% per year and the effect of a high ESG-rating on the net fund flows seems to be positive or at least close to zero. Meanwhile, a low ESG-rating has a negative effect on the net fund flows of -1.27% to -1.45%. The inflows to high ESG-rated funds remained large during the crisis only dropping on a per-week basis from 0.39% to 0.27% per week. This implies that that investors preferences for sustainability remained very strong and has not been heavily affect by the income-shock caused by the COVID-19 pandemic.

In addition, I find that Environmental, Social and Governance factors within ESG do not explain much of the variance in sustainable funds outperforming and receiving larger net fund flows during the COIVD-19 crisis. None, of the ESG factors show a clear significant relationship and consequently it is hard to draw a clear conclusion.

Finally, the results show that only the level of sustainability is of importance for the performance and flows of equity mutual fund in Europe during the COVID-19 crisis. This is not the case for the fund’s investment strategy and the fund’s heterogeneity of its investors.

5.1. Limitations and Future Research

The results presented and conclusions drawn in this master thesis have some exposure to several limitations and biases. The first and biggest limitation is that the sample size is relatively small and might not be representative for the mutual fund industry. In total my main sample only consists of 1,209 funds which total net asset value is €696 billion on January 31, 2020. Meanwhile, the total European equity mutual fund industry had €6.5 trillion assets under management in 2021. Additionally, other papers use more funds in their research. For example, Odean and Barber (2016) use about 4,000 equity mutual funds and Lucas and Pastor (2021) primarily focus on 3,626 funds. To obtain a larger sample size, a possible solution in future research could be to filter the equity mutual funds data in Morningstar using less restrictions for the criteria such as investment area and established domicile.

Another potential bias could be caused by the correlation between fund characteristics. In this thesis, I simply created sub-samples but there might be a sufficient correlation across the different fund characteristics that lead to biased outcomes. For example, the fund performance and flows might be affected by an active managed fund that happens to also be sustainable simultaneously. Therefore, this raises the question on how much of the observed relationship between a fund's characteristic and performance and flows can be denoted to a specific characteristic. A potential solution for this in future research could be to create the sub-samples that are more specific. For example, a sub-sample that compared actively managed high ESG-rated funds with actively managed low sustainable funds.

Furthermore, the results are subjective to the periods I have chosen to measure the performance and flows during the COVID-19 crisis. In future research the length of the periods could be changed to see if similar results are obtained. For example, it could be that a longer recovery sub-period within the crisis period leads to different results. Moreover, the delta returns based on the prospectus benchmark are very much affected by the chosen benchmark of the mutual fund. In my thesis, I do not account for the possibility that the funds have might chosen a benchmark that is easier to beat and leads to deltas that are higher.

Moreover, a strong recommendation for future research could be to include more fund-specific variables. In this thesis, I did not account for the fund's past returns and volatility which could be included to capture the effect of the fund's past on future performance and flows. The past performance of a fund can cause investors to be biased an direct their funds into these funds. Finally, the Morningstar ESG-rating assigned to a fund changes over time. However, due to data limitations I have set the ESG-rating of the fund on January 31, 2020 as constant. In future research, the changes of this ESG-rating can be taken into consideration when analyzing performance and flows in relationship to sustainability and this might result in different observations.

6. References

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Table 3. VIF values of OLS regression

	VIF	1/VIF
Sector Healthcare	4.96	0.202
Sector Technology	4.91	0.204
Sector Basic Materials	4.88	0.205
Sector Financial Services	4.32	0.231
Sector Energy	3.65	0.274
Sector Industrials	3.34	0.299
Sector Consumer Defensive	3.28	0.305
Sector Utitlities	2.85	0.351
Sector Communication Services	2.81	0.356
Sector Consumer Cyclical	2.71	0.369
Sector Real Estate	1.52	0.658
Low Sustainability	1.38	0.723
High Sustainability	1.34	0.749
Active	1.31	0.761
LOG Age	1.14	0.876
LOG TNA	1.12	0.890
Net Expense Ratio	1.11	0.899
Institutional	1.04	0.960
Mean VIF	4.76	

This is regression used to analyse the performance of the funds with the Carhart 4-factor model alpha as dependent variable. The regression includes fund-level and industry level controls. The 3-by-3 equity style boxes of size tilts (large cap versus small-cap) and growth versus value style tilts are not displayed for space-saving reasons. The OLS regression used to test for multicollinearity is the following:

$$\alpha^{Car4}{}_{i,t} = C + \beta_1 Active + \beta_2 Institutional + \beta_3 High_{sustainability} + \beta_4 Low_{sustainability} + X_{i,t} + \varepsilon_{i,t}$$

Table 4. Fund Performance of Active Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3)	(4)	(5)	(6)
			Panel A. Average Fund Performance (%)			
Pre-Crisis	0.19	1.67***	6.45***	6.43***	6.44***	5.33***
	(0.67)	(5.72)	(21.41)	(22.67)	(22.79)	(21.23)
Crisis	-5.56**	-3.85	-25.54***	-11.69***	-10.33***	-11.26***
	(-2.09)	(-1.45)	(-21.80)	(-13.26)	(-9.83)	(-11.34)
Crash	10.05**	14.98***	-141.96***	-78.71***	-68.99***	-133.31***
	(2.09)	(3.13)	(-24.57)	(-20.63)	(-17.68)	(-40.75)
Recovery	-18.38***	-19.32***	65.15***	69.18***	71.78***	71.81***
	(-6.57)	(-6.85)	(25.90)	(37.72)	(36.76)	(41.96)
After-Crisis	-9.76***	-16.74***	-1.44***	-5.63***	-8.85***	-6.46***
	(-16.96)	(-28.40)	(-2.81)	(-14.81)	(-22.53)	(-16.85)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.54	6.11	5.39***	4.98***	4.99***	3.88***
	(0.70)	(1.08)	(23.36)	(25.97)	(26.11)	(21.15)
Crisis	14.85	8.19	-25.51***	-7.81***	-7.33***	-9.89***
	(0.26)	(0.14)	(-19.90)	(-8.81)	(-4.75)	(-7.29)
Crash	10.14	13.53	-132.68***	-57.18***	-47.49***	-120.59***
	(0.09)	(0.12)	(-28.19)	(-5.47)	(-3.96)	(-12.55)
Recovery	18.53	4.01	48.61***	56.20***	57.26***	62.65***`
	(0.35)	(0.08)	(8.05)	(12.47)	(10.82)	(13.90)
After-Crisis	-3.69	-10.02	-2.29***	-7.18***	-11.21***	-8.37***
	(-0.32)	(-0.78)	(-8.51)	(-56.44)	(-95.58)	(-64.00)

Table 5. Fund Performance of Passive Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	3.39***	3.38***	5.88***	5.97***	5.98***	5.32***
	(4.25)	(4.25)	(9.43)	(8.97)	(9.02)	(9.42)
Crisis	-5.19	-7.87	-17.91***	-10.18***	-8.63***	-10.95***
	(-0.69)	(-1.07)	(-7.25)	(-6.07)	(-3.65)	(-6.38)
Crash	-8.65	-6.95	-75.95***	-56.50***	-49.50***	-138.49***
	(-0.62)	(-0.51)	(-4.25)	(-5.71)	(-5.12)	(-19.14)
Recovery	-2.35	-8.63	37.57***	50.49***	51.53***	51.12***
	(-0.32)	(-1.16)	(5.48)	(13.01)	(12.33)	(14.00)
After-Crisis	-12.98***	-16.02***	-7.42***	-6.60***	-9.59***	-7.09***
	(-7.76)	(-9.65)	(-6.46)	(-6.43)	(-8.01)	(-6.21)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.42	2.90	5.83***	6.21***	6.22***	5.45***
	(0.80)	(0.50)	(157.62)	(149.97)	(151.17)	(152.47)
Crisis	45.84	44.97	-15.05***	-8.34***	-3.18***	-11.67***
	(1.27)	(1.23)	(-44.51)	(-80.55)	(-12.57)	(-225.11)
Crash	74.39	79.30	-44.40***	-33.70***	-28.89***	-128.44***
	(1.12)	(1.26)	(-90.08)	(-111.03)	(-95.96)	(-449.84)
Recovery	20.85	14.92	37.57***	52.62***	54.37***	50.76***
	(0.50)	(0.36)	(17.01)	(48.23)	(46.04)	(87.71)
After-Crisis	-10.47	-15.51	-8.60***	-7.90***	-11.24***	-8.60***
	(-1.01)	(-1.38)	(-18.28)	(-30.72)	(-38.07)	(-32.17)

Table 6. Fund Performance of Institutional Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3)	(4)	(5)	(6)
			Panel A. Average Fund Performance (%)			
Pre-Crisis	1.79*	2.20**	6.86***	7.10***	7.11***	6.04***
	(1.67)	(1.96)	(6.35)	(7.07)	(7.10)	(7.32)
Crisis	-6.41	-9.07	-26.88***	-12.15***	-9.59***	-12.55***
	(-0.66)	(-0.90)	(-6.52)	(-4.70)	(-3.13)	(-4.82)
Crash	0.59	-2.28	-131.31***	-81.87***	-75.54***	-148.29***
	(0.03)	(-0.13)	(-5.94)	(-6.56)	(-5.78)	(-15.66)
Recovery	-12.17	-14.65	57.68***	68.82***	71.49***	71.86***
	(-1.15)	(-1.35)	(6.12)	(7.63)	(8.10)	(8.34)
After-Crisis	-10.60***	-17.88***	-4.21**	-5.03***	-8.76***	-5.81***
	(-4.78)	(-7.68)	(-2.08)	(-3.53)	(-5.59)	(-4.06)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.877	6.902	11.15***	9.95***	9.94***	8.67***
	(0.75)	(0.88)	(82.13)	(86.48)	(86.94)	(82.27)
Crisis	40.59	21.87	-29.03***	-10.41***	-4.82***	-2.32***
	(0.69)	(0.41)	(-43.96)	(-68.05)	(-30.98)	(-5.16)
Crash	64.14	53.94	-123.77***	-87.18***	-83.02***	-138.77***
	(0.63)	(0.59)	(-20.28)	(-29.83)	(-26.70)	(-238.32)
Recovery	19.99	-6.19	51.24***	64.71***	72.35***	80.54***
	(0.29)	(-0.!0)	(23.44)	(89.84)	(174.13)	(378.73)
After-Crisis	-10.89	-22.80	-9.38***	-8.13***	-12.22***	-9.40***
	(-0.75)	(-1.39)	(-43.14)	(-45.35)	(-52.37)	(-43.75)

Table 7. Fund Performance of Retail Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	0.35	1.81***	6.51***	6.51***	6.53***	5.42***
	(1.24)	(6.14)	(21.58)	(22.91)	(23.02)	(21.38)
Crisis	-5.70**	-3.83	-25.29***	-11.52***	-10.28***	-10.99***
	(-2.12)	(-1.42)	(-21.55)	(-12.92)	(-9.66)	(-10.90)
Crash	8.84*	14.41***	-141.15***	-78.09***	-68.30***	-132.53***
	(1.81)	(2.97)	(-24.10)	(-20.12)	(-17.24)	(-39.94)
Recovery	-17.63***	-18.81***	64.72***	68.49***	71.00***	70.80***
	(-6.25)	(-6.62)	(25.43)	(37.86)	(36.58)	(41.93)
After-Crisis	-9.93***	-16.64***	-1.58***	-5.79***	-8.98***	-6.63***
	(-17.09)	(-28.08)	(-3.07)	(-15.03)	(-22.50)	(-16.99)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.66	5.90	5.17***	4.96***	4.98***	3.89***
	(0.73)	(1.05)	(23.36)	(26.00)	(26.14)	(21.20)
Crisis	14.46	8.32	-25.04***	-7.74***	-7.05***	-10.45***
	(0.27)	(0.15)	(-18.84)	(-8.70)	(-4.49)	(-8.03)
Crash	9.38	12.31	-121.37***	-47.76***	-38.68***	-114.59***
	(0.09)	(0.11)	(-40.90)	(-5.29)	(-3.70)	(-13.74)
Recovery	18.44	5.18	47.14***	55.36***	56.14***	60.52***
	(0.36)	(0.10)	(8.07)	(12.60)	(10.92)	(14.40)
After-Crisis	-3.88	-9.83	-2.70***	-7.29***	-11.30***	-8.46***
	(-0.34)	(-0.78)	(-10.84)	(-54.61)	(-92.82)	(-61.70)

Table 8. Fund Performance of High Sustainable Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	1.62***	3.50***	7.92***	6.65***	6.66***	5.33***
	(3.88)	(8.26)	(20.18)	(15.74)	(15.77)	(14.40)
Crisis	1.95	2.29	-19.34***	-10.49***	-9.79***	-9.71***
	(0.48)	(0.57)	(-12.79)	(-10.18)	(-7.47)	(-8.66)
Crash	31.39***	37.56***	-115.51***	-78.79***	-70.82***	-139.63***
	(4.24)	(5.18)	(-12.58)	(-14.92)	(-13.56)	(-38.41)
Recovery	-22.24***	-26.68***	55.72***	57.25***	59.54***	62.52***
	(-5.24)	(-6.31)	(14.68)	(24.52)	(23.51)	(27.49)
After-Crisis	-11.05***	-17.82***	-2.02***	-6.52***	-9.64***	-7.48***
	(-12.90)	(-20.77)	(-2.79)	(-12.61)	(-17.30)	(-13.92)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.98	9.01	7.14***	5.42***	5.41***	4.14***
	(0.87)	(1.46)	(33.84)	(26.75)	(26.86)	(22.47)
Crisis	11.533	10.376	-11.77***	-3.76***	-3.92**	-3.81***
	(0.19)	(0.17)	(-6.57)	(-4.98)	(-2.55)	(-3.10)
Crash	37.31	50.34	-95.80***	-36.77**	-27.60	-106.86***
	(0.33)	(0.48)	(-5.26)	(-2.22)	(-1.47)	(-9.34)
Recovery	-8.64	-20.90	47.63***	50.82***	50.74***	61.36***
	(-0.13)	(-0.32)	(9.97)	(9.61)	(7.73)	(12.01)
After-Crisis	-3.96	-10.14	-4.31***	-10.82***	-13.97***	-11.80***
	(-0.28)	(-0.68)	(-10.38)	(-30.30)	(-43.58)	(-36.50)

Table 9. Fund Performance of Low Sustainable Mutual Funds

This table describes the mutual funds' performance against both benchmarks and factor models. Panel A reports equal-weighted averages across funds of estimated deltas and alphas, all reported in annualized percentage terms. The delta are average differences between the fund's net return and its benchmark returns. The benchmark consist of the prospectus benchmark and the MSCI World Index. The alphas are estimated intercepts from the regressions of excess net funds returns on factor returns described in the text. Panel B reports the value-weighted averages of estimated deltas and alphas, weighted by each fund's TNA. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
	Panel A. Average Fund Performance (%)					
Pre-Crisis	-1.69***	-0.53	5.01***	6.58***	6.61***	5.88***
	(-2.80)	(-0.79)	(6.72)	(10.34)	(10.44)	(10.17)
Crisis	-15.64***	-11.86**	-32.76***	-12.41***	-11.79***	-12.05***
	(-2.91)	(-2.12)	(-11.29)	(-5.59)	(-4.62)	(-4.65)
Crash	-19.94**	-16.31	-173.24***	-76.49***	-63.51***	-121.18***
	(-2.07)	(-1.62)	(-14.82)	(-8.53)	(-6.78)	(-14.72)
Recovery	-12.12**	-8.20	75.13***	81.68***	83.76***	81.06***
	(-2.12)	(-1.38)	(14.63)	(18.98)	(18.54)	(20.31)
After-Crisis	-7.17***	-14.56***	-0.38	-4.34***	-7.30***	-4.80***
	(-5.85)	(-11.17)	(-0.34)	(-4.85)	(-8.16)	(-5.47)
	Panel B. Value-Weighted Average Fund Performance (%)					
Pre-Crisis	0.49	2.82	2.64***	4.08***	4.11***	3.45***
	(0.01)	(0.47)	(11.74)	(23.30)	(23.51)	(19.70)
Crisis	20.48	16.51	-29.46***	-6.20***	-5.37***	-10.11***
	(0.41)	(0.31)	(-18.78)	(-13.02)	(-5.08)	(-24.56)
Crash	11.09	7.79	-130.26***	-37.98***	-26.71***	-106.38***
	(0.11)	(0.08)	(-126.79)	(-4.47)	(-2.69)	(-10.26)
Recovery	27.83	23.35	52.3***	65.10***	66.23***	67.48***
	(0.58)	(0.47)	(9.84)	(17.69)	(15.89)	(18.18)
After-Crisis	-4.03	-12.03	-2.91***	-7.01***	-11.17***	-7.76***
	(-0.40)	(-1.00)	(-14.21)	(-33.82)	(-61.07)	(-41.41)

Table 10. Determinants of Fund Performance During the Pre-Crisis

This table report slope coefficients estimated from regressions of fund performance in January 1 to January 31, 2020 on fund characteristics and controls. In Panel A, the dependent variable is the mutual funds' prospectus benchmark adjusted performance; in Panel B, it is the Carhart four-factor alpha. Both performance measures are estimated using simple returns and expressed in annualized percentage terms. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Benchmark-Adjusted Performance							
Active	-3.20***					-3.28***	-2.52***	-2.07***
	(-8.16)					(-7.92)	(-5.20)	(-4.19)
Institutional		1.47**				1.69***	2.00***	1.40**
		(-2.33)				(-2.76)	(-3.42)	(-2.34)
High_S			1.89***			1.27***	0.75**	0.63*
			(-5.34)			(-3.42)	(-2.18)	(-1.86)
Conventional_S				0.31				
				(-0.90)				
Low_S					-2.77***	-2.11***	-1.19***	-1.01**
					(-6.22)	(-4.51)	(-2.63)	(-2.24)
Constant	3.39***	0.33*	-0.27	0.29	1.08***	3.43***	-8.15***	-8.42***
	(-9.78)	(-1.80)	(-1.23)	(-1.19)	(-5.86)	(-8.82)	(-2.97)	(-3.16)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.02	0.00	0.02	0.00	0.04	0.06	0.20	0.24
	Panel B. Factor-Adjusted Performance							
Active	0.46					0.32	0.35	0.11
	(-0.64)					(-0.44)	(-0.38)	(-0.12)
Institutional		0.74				0.74	0.88	0.80
		(-0.71)				(-0.72)	(-0.85)	(-0.83)
High_S			0.38			0.57	0.68	0.34
			(-0.70)			(-0.97)	(-1.14)	(-0.59)
Conventional_S				-0.56				
				(-1.06)				
Low_S					0.26	0.51	1.32*	1.31*
					(-0.37)	(-0.68)	(-1.72)	(-1.91)
Constant	5.98***	6.37***	6.27***	6.64***	6.35***	5.74***	-7.77*	-7.42*
	(-9.06)	(-23.00)	(-18.27)	(-18.52)	(-21.99)	(-8.36)	(-1.76)	(-1.80)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.18

Table 11. Determinants of Fund Performance During the Crisis

This table report slope coefficients estimated from regressions of fund performance in February 20 to April 30, 2020 on fund characteristics and controls. In Panel A, the dependent variable is the mutual funds' primary prospectus benchmark adjusted performance; in Panel B, it is the Carhart four-factor alpha. Both performance measures are estimated using simple returns and expressed in annualized percentage terms. The controles include fund-level and industry controls. The fund-level controls inlcude the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry conrols include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-0.37					-1.09	-0.98	-1.97
	(-0.22)					(-0.66)	(-0.46)	(-0.91)
Institutional		-0.93				0.03	2.10	2.19
		(-0.30)				(-0.01)	(-0.97)	(-1.05)
High_S			11.68***			8.14***	5.54***	4.98***
			(-8.26)			(-5.18)	(-3.86)	(-3.43)
Conventional_S				-0.97				
				(-0.64)				
Low_S					-13.36***	-9.46***	-4.78**	-4.56**
					(-6.93)	(-4.45)	(-2.26)	(-2.21)
Constant	-5.19***	-5.48***	-9.74***	-5.15***	-2.29***	-5.15***	-11.35	-7.80
	(-3.52)	(-7.06)	(-9.74)	(-5.25)	(-2.90)	(-3.47)	(-1.04)	(-0.72)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.05	0.00	0.05	0.06	0.22	0.25
				Panel B. Factor-Adjusted Performance				
Active	-1.70					-1.56	-3.37	-1.97
	(-0.66)					(-0.58)	(-1.18)	(-0.91)
Institutional		0.66				0.78	2.84	2.19
		(-0.21)				(-0.24)	(-0.86)	(-1.05)
High_S			0.67			-0.04	-0.94	3.34*
			(-0.35)			(-0.02)	(-0.47)	(-1.76)
Conventional_S				0.96				
				(-0.48)				
Low_S					-2.08	-2.07	-0.18	-2.19
					(-0.76)	(-0.69)	(-0.06)	(-0.86)
Constant	-8.63***	-10.25***	-10.45***	-10.60***	-9.71***	-8.29***	-81.83***	-73.79***
	(-3.67)	(-9.89)	(-7.66)	(-8.20)	(-9.48)	(-3.32)	(-5.38)	(-5.30)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.25

Table 12. Determinants of Fund Performance During the Crash

This table report slope coefficients estimated from regressions of fund performance in February 20 to March 23, 2020 on fund characteristics and controls. In Panel A, the dependent variable is the mutual funds' prospectus benchmark adjusted performance; in Panel B, it is the Carhart four-factor alpha. Both performance measures are estimated using simple returns and expressed in annualized percentage terms. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	18.69***					16.48***	12.72*	5.30
	(-3.13)					(-2.84)	(-1.81)	(-0.74)
Institutional		-8.65				-6.10	-0.91	0.25
		(-0.85)				(-0.61)	(-0.12)	(-0.03)
High_S			35.37***			24.40***	20.43***	16.39***
			(-8.75)			(-5.36)	(-4.64)	(-3.67)
Conventional_S				-4.90				
				(-1.12)				
Low_S					-37.90***	-26.62***	-15.14**	-13.92**
					(-7.17)	(-4.51)	(-2.50)	(-2.44)
Constant	-8.65	9.24***	-3.98	10.69***	17.96***	-8.54	17.51	20.90
	(-1.57)	(-4.21)	(-1.41)	(-3.90)	(-7.80)	(-1.56)	(-0.55)	(-0.66)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.05	0.00	0.05	0.07	0.16	0.24
				Panel B. Factor-Adjusted Performance				
Active	-23.16*					-23.04*	-23.12**	-23.07*
	(-1.88)					(-1.81)	(-2.09)	(-1.80)
Institutional		-11.22				-11.09	-8.47	-2.14
		(-0.62)				(-0.63)	(-0.38)	(-0.11)
High_S			-7.37			-5.23	-8.42	-7.64
			(-0.69)			(-0.29)	(-0.42)	(-0.96)
Conventional_S				3.87				
				(-0.08)				
Low_S					3.22	1.36	-0.89	-4.58
					(-0.54)	(-0.45)	(-0.01)	(-0.43)
Constant	-47.32***	-64.36***	-66.57***	-67.87***	-67.73***	-47.32***	-70.43	-48.61
	(-5.15)	(-17.49)	(-13.25)	(-13.85)	(-17.94)	(-5.08)	(-0.89)	(-0.30)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.13

Table 13. Determinants of Fund Performance During the Recovery

This table report slope coefficients estimated from regressions of fund performance in March 24 to April 30, 2020 on fund characteristics and controls. In Panel A, the dependent variable is the mutual funds' prospectus benchmark adjusted performance; in Panel B, it is the Carhart four-factor alpha. Both performance measures are estimated using simple returns and expressed in annualized percentage terms. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-16.02***					-15.52***	-12.24***	-7.95*
	(-4.33)					(-4.16)	(-2.95)	(-1.84)
Institutional		5.41				5.06	4.57	3.79
		(-1.23)				(-1.14)	(-1.07)	(-0.87)
High_S			-7.77***			-5.21**	-6.69***	-4.39*
			(-3.52)			(-2.07)	(-2.66)	(-1.73)
Conventional_S				2.25				
				(-0.96)				
Low_S					6.80**	4.63	3.73	3.12
					(-2.50)	(-1.51)	(-1.16)	(-0.98)
Constant	-2.35	-17.57***	-14.47***	-18.16***	-18.92***	-2.37	-35.06**	-31.38*
	(-0.67)	(-15.12)	(-9.74)	(-13.05)	(-15.02)	(-0.66)	(-1.98)	(-1.74)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.00	0.01	0.00	0.00	0.02	0.04	0.11
				Panel B. Factor-Adjusted Performance				
Active	22.47***					23.67***	7.81	19.37***
	(-4.41)					(-4.51)	(-1.63)	(-2.83)
Institutional		3.21				2.11	2.89	4.12
		(-0.13)				(-0.05)	(-0.01)	(-0.35)
High_S			-16.43***			-12.57***	-9.52***	-0.39
			(-4.77)			(-3.56)	(-2.69)	(-0.24)
Conventional_S				1.03				
				(-0.71)				
Low_S					17.37***	10.61**	7.94*	6.31
					(-3.60)	(-1.97)	(-1.82)	(-1.45)
Constant	51.32***	70.57***	76.53***	72.77***	64.01***	48.93***	48.22	46.29
	(-12.39)	(-37.30)	(-30.80)	(-28.80)	(-34.05)	(-11.67)	(-0.78)	(-1.22)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.00	0.02	0.00	0.01	0.03	0.06	0.35

Table 14. Determinants of Fund Performance During the After-Crisis

This table report slope coefficients estimated from regressions of fund performance in May 1 to December 31, 2020 on fund characteristics and controls. In Panel A, the dependent variable is the mutual funds' prospectus benchmark adjusted performance; in Panel B, it is the Carhart four-factor alpha. Both performance measures are estimated using simple returns and expressed in annualized percentage terms. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	3.22***					3.08***	1.52	1.10
	(-3.22)					(-3.02)	(-1.18)	(-0.87)
Institutional		-0.73				-0.97	-1.20	-0.36
		(-0.49)				(-0.65)	(-0.87)	(-0.28)
High_S			-1.67**			-0.53	-1.62*	-1.05
			(-2.06)			(-0.62)	(-1.91)	(-1.26)
Conventional_S				-1.26				
				(-1.611)				
Low_S					3.72***	3.40***	2.85***	2.42**
					(-3.73)	(-3.19)	(-2.68)	(-2.37)
Constant	-12.98***	-9.94***	-9.39***	-9.49***	-10.89***	-13.43***	0.37	0.55
	(-14.27)	(-24.43)	(-18.95)	(-17.83)	(-25.55)	(-13.78)	(-0.06)	(-0.10)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.01	0.01	0.11	0.18
				Panel B. Factor-Adjusted Performance				
Active	0.74					0.69	-0.13	-0.98
	(-0.59)					(-0.54)	(-0.09)	(-0.70)
Institutional		0.16				0.03	-0.04	0.35
		(-0.10)				(-0.02)	(-0.03)	(-0.24)
High_S			-1.15			-0.47	-0.90	-1.64**
			(-1.54)			(-0.58)	(-1.11)	(-2.31)
Conventional_S				-0.52				
				(-0.69)				
Low_S					2.11**	1.88*	2.07*	2.22**
					(-2.16)	(-1.76)	(-1.93)	(-2.26)
Constant	-9.59***	-8.91***	-8.49***	-8.70***	-9.42***	-9.83***	10.32*	8.79*
	(-8.05)	(-23.07)	(-17.17)	(-17.67)	(-23.42)	(-7.89)	(-1.86)	(-1.73)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.28

Table 15. ESG Determinants of Fund Performance During the Crisis

This table is identical to Table 11 in the main paper except it focus on the ESG determinants of fund's simple returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Panel A. Benchmark-Adjusted Performance				
Greener_ Environmental	9.08***	9.13***	2.41	2.66
	(-5.52)	(-5.50)	(-1.49)	(-1.44)
Greener_Social	-2.60	-2.57	-1.37	0.09
	(-1.15)	(-1.13)	(-0.65)	(-0.04)
Greener_Governance	2.19	2.24	4.12*	1.74
	(-0.93)	(-0.95)	(-1.90)	(-0.75)
Active		-1.57	-0.96	-2.04
		(-0.90)	(-0.43)	(-0.90)
Institutional		-0.54	2.00	1.91
		(-0.17)	(-0.94)	(-0.91)
Constant	-8.20***	-6.76***	-17.01	-12.16
	(-8.52)	(-4.32)	(-1.50)	(-1.08)
Fund-Level Controls	No	No	Yes	Yes
Industry Controls	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209
Adjusted R^2	0.02	0.02	0.20	0.23
Panel B. Factor-Adjusted Performance				
Greener_ Environmental	7.32***	7.43***	0.10	2.52
	(-3.59)	(-3.62)	(-0.04)	(-1.09)
Greener_Social	-14.14***	-14.03***	-12.01***	-3.99
	(-4.48)	(-4.42)	(-4.15)	(-1.55)
Greener_Governance	13.90***	14.01***	8.19***	3.14
	(-4.06)	(-4.10)	(-2.63)	(-1.09)
Active		-2.74	-2.23	0.10
		(-1.07)	(-0.80)	(-0.04)
Institutional		0.85	2.21	4.43
		(-0.27)	(-0.68)	(-1.43)
Constant	-12.40***	-10.00***	-84.57***	-76.03***
	(-9.91)	(-4.24)	(-5.56)	(-5.45)
Fund-Level Controls	No	No	Yes	Yes
Industry Controls	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209
Adjusted R^2	0.03	0.03	0.11	0.29

Table 16. ESG Determinants of Fund Performance During the Crash

This table is identical to Table 12 in the main paper except it focus on the ESG determinants of fund's simple returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Panel A. Benchmark-Adjusted Performance			
Greener_ Environmental	20.49***	19.76***	7.79*	10.31**
	(-4.73)	(-4.50)	(-1.73)	(-2.07)
Greener_Social	4.07	3.34	6.78	8.66
	(-0.68)	(-0.56)	(-1.19)	(-1.50)
Greener_Governance	-6.04	-6.78	-1.24	-7.84
	(-0.97)	(-1.09)	(-0.20)	(-1.22)
Active		16.68***	13.17*	5.10
		(-2.77)	(-1.79)	(-0.69)
Institutional		-8.20	-1.59	-1.11
		(-0.80)	(-0.22)	(-0.16)
Constant	3.03	-11.38**	6.77	14.47
	(-1.05)	(-2.02)	(-0.21)	(-0.46)
Fund-Level Controls	No	No	Yes	Yes
Industry Controls	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.02	0.13	0.22
	Panel B. Factor-Adjusted Performance			
Greener_ Environmental	12.43*	13.33*	0.39	2.89
	(-1.76)	(-1.88)	(-0.05)	(-0.35)
Greener_Social	-22.08**	-21.44**	-17.22*	2.22
	(-2.12)	(-2.04)	(-1.68)	(-0.23)
Greener_Governance	37.32***	38.20***	21.74**	6.71
	(-3.41)	(-3.49)	(-2.10)	(-0.62)
Active		-27.24***	-26.44**	-23.48*
		(-2.78)	(-2.18)	(-1.88)
Institutional		-7.10	-5.65	2.46
		(-0.59)	(-0.46)	(-0.21)
Constant	-75.84***	-50.73***	-74.92*	-57.27
	(-17.19)	(-5.65)	(-1.70)	(-1.41)
Fund-Level Controls	No	No	Yes	Yes
Industry Controls	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.01	0.03	0.12

Table 17. Fund Flows

This table describes the mutual funds' net flows for the subsamples created based on the funds' characteristics and reports simple averages of net fund flows percentages (%) across funds. The net flow percentages are constructed by summing the weekly net fund flows over the period and dividing by the fund's TNA at the start of the period. The flow percentages are winsorized at the 1% and 99% levels before estimating the simple average. The time periods are: pre-crisis (January 1, 2019 to January 31, 2020); crisis (February 20 to April 30, 2020); crash (February 20 to March 23, 2020); recovery (March 24 to April 30, 2020); after-crisis (May 1 to December 31, 2020). Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Active	Passive	Institutional	Retail	High Sustainability	Low Sustainability
Pre-Crisis	10.62***	24.27***	3.93	11.79***	22.61***	-0.06
	(6.35)	(3.24)	(0.61)	(6.89)	(7.24)	(-0.03)
Crisis	2.10***	2.07*	1.84	2.29***	2.92***	1.00*
	(7.17)	(1.86)	(1.04)	(8.05)	(5.82)	(1.79)
Crash	0.08	0.89*	0.41	0.20	0.28	-0.01
	(0.56)	(1.93)	(0.54)	(1.44)	(1.19)	(-0.03)
Recovery	2.64***	2.25**	2.22*	2.72***	3.21***	1.73***
	(10.22)	(2.22)	(1.69)	(10.57)	(7.32)	(3.60)
After-Crisis	7.25***	6.11	-2.33	7.54***	14.96***	0.13
	(6.48)	(1.54)	(-1.08)	(6.54)	(7.52)	(0.07)

Table 18. Determinants of Fund Flows During the Crisis

This table report slope coefficients estimated from regressions of net fund flows in February 20 to April 30, 2020 on fund characteristics and controls. A fund's net flow is expressed as a percent of the fund's February 19, 2019 TNA. Flows are winsorized at 1% and 99% levels. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	0.03					-0.05	0.56	0.74
	(-0.03)					(-0.04)	(-0.46)	(-0.59)
Institutional		-0.28				-0.17	-0.22	-0.02
		(-0.156)				(-0.10)	(-0.12)	(-0.01)
High_S			1.28**			0.89	0.37	0.77
			(-2.11)			(-1.34)	(-0.57)	(-1.14)
Conventional_S				-0.12				
				(-0.20)				
Low_S					-1.45**	-1.02	-1.08	-1.27*
					(-2.23)	(-1.44)	(-1.44)	(-1.73)
Constant	2.07*	2.12***	1.64***	2.15***	2.45***	2.08*	15.07***	14.26***
	(-1.87)	(-7.53)	(-4.82)	(-5.70)	(-7.49)	(-1.86)	(-3.22)	(-3.03)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04

Table 19. Determinants of Fund Flows During the Crash

This table report slope coefficients estimated from regressions of net fund flows in February 20 to March23, 2020 on fund characteristics and controls. A fund's net flow is expressed as a percent of the fund's February 19, 2020 TNA. Flows are winsorized at 1% and 99% levels. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	-0.81*					-0.85*	-0.39	-0.29
	(-1.69)					(-1.75)	(-0.71)	(-0.52)
Institutional		0.29				0.32	0.20	0.30
		(-0.38)				(-0.42)	(-0.27)	(-0.39)
High_S			0.23			0.26	0.16	0.29
			(-0.80)			(-0.82)	(-0.50)	(-0.92)
Conventional_S				-0.08				
				(-0.29)				
Low_S					-0.19	-0.05	-0.14	-0.24
					(-0.59)	(-0.15)	(-0.38)	(-0.68)
Constant	0.89*	0.12	0.05	0.17	0.18	0.83*	7.33***	6.12***
	(-1.94)	(-0.88)	(-0.32)	(-0.91)	(-1.19)	(-1.79)	(-3.29)	(-2.74)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04

Table 20. Determinants of Fund Flows During the Recovery

This table report slope coefficients estimated from regressions of net fund flows in March 24 to April 30, 2020 on fund characteristics and controls. A fund's net flow is expressed as a percent of the fund's March 23, 2020 TNA. Flows are winsorized at 1% and 99% levels. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	0.38					0.35	0.48	0.72
	(-0.37)					(-0.33)	(-0.43)	(-0.63)
Institutional		-0.41				-0.34	-0.25	-0.18
		(-0.31)				(-0.25)	(-0.19)	(-0.13)
High_S			0.94*			0.58	0.11	0.52
			(-1.77)			(-1.00)	(-0.20)	(-0.87)
Conventional_S				-0.01				
				(-0.03)				
Low_S					-1.16**	-0.89	-0.82	-0.92
					(-2.08)	(-1.44)	(-1.29)	(-1.52)
Constant	2.25**	2.63***	2.27***	2.61***	2.89***	2.31**	9.73**	9.84**
	(-2.23)	(-10.40)	(-7.51)	(-8.01)	(-9.92)	(-2.24)	(-2.35)	(-2.36)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.07

Table 21. Determinants of Fund Flows During the Pre-Crisis

This table report slope coefficients estimated from regressions of net fund flows in January 1, 2019 to January 31, 2020 on fund characteristics and controls. A fund's net flow is expressed as a percent of the fund's January 1, 2019 TNA. Flows are winsorized at 1% and 99% levels. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	-13.65*					-15.57**	-4.26	-4.13
	(-1.79)					(-2.07)	(-0.53)	(-0.50)
Institutional		-8.10				-6.65	-7.83	-9.34
		(-1.21)				(-1.00)	(-1.14)	(-1.37)
High_S			17.25***			14.94***	11.71***	11.01***
			(-4.76)			(-3.78)	(-2.96)	(-2.79)
Conventional_S				-4.78				
				(-1.44)				
Low_S					-15.37***	-7.79**	-7.98**	-7.57**
					(-4.81)	(-2.21)	(-2.20)	(-2.06)
Constant	24.27***	12.03***	5.36***	13.47***	15.31***	22.95***	82.87***	76.20**
	(-3.26)	(-7.09)	(-2.92)	(-6.24)	(-7.64)	(-3.00)	(-2.80)	(-2.56)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.02	0.00	0.01	0.03	0.08	0.09

Table 22. Determinants of Fund Flows During the After-Crisis

This table report slope coefficients estimated from regressions of net fund flows in May 1 to December 31, 2020 to January 31, 2020 on fund characteristics and controls. A fund's net flow is expressed as a percent of the fund's April 30, 2020 TNA. Flows are winsorized at 1% and 99% levels. The controls include fund-level and industry controls. The fund-level controls include the net expense ratio as of January 2020, the Morningstar Category variable, the log of the fund's age in days and the log of the fund's TNA both measured on January 31, 2020. The industry controls include the fund's TNA as a percentage allocated in basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrials, real estate, technology, and utilities. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	1.14					-0.25	-3.79	-2.50
	(-0.28)					(-0.06)	(-0.85)	(-0.55)
Institutional		-10.08***				-9.25***	-9.42***	-10.24***
		(-4.16)				(-3.74)	(-3.62)	(-3.75)
High_S			12.17***			10.47***	8.15***	7.76***
			(-5.20)			(-3.98)	(-3.20)	(-3.06)
Conventional_S				-4.565**				
				(-2.11)				
Low_S					-9.29***	-4.18*	-4.79*	-4.68*
					(-4.14)	(-1.68)	(-1.73)	(-1.70)
Constant	6.11	7.74***	2.79**	8.98***	9.43***	5.18	89.68***	90.93***
	(-1.55)	(-6.83)	(-2.27)	(-6.30)	(-7.33)	(-1.35)	(-4.67)	(-4.66)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.02	0.00	0.01	0.03	0.08	0.09

Table 23. ESG Determinants of Fund Performance During the Crisis

This table is identical to Table 17 in the main paper except it focus on the ESG determinants of fund net flows. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)
Greener_ Environmental	1.19*	1.19*	0.68	1.28
	(-1.87)	(-1.86)	(-0.95)	(-1.55)
Greener_Social	0.40	0.39	0.44	1.01
	(-0.54)	(-0.53)	(-0.58)	(-1.29)
Greener_Governance	-0.61	-0.61	-0.54	-1.38
	(-0.84)	(-0.84)	(-0.66)	(-1.59)
Active		-0.09	0.46	0.59
		(-0.08)	(-0.37)	(-0.47)
Institutional		-0.24	-0.28	-0.14
		(-0.13)	(-0.15)	(-0.08)
Constant	1.79***	1.89*	14.71***	14.09***
	(-4.48)	(-1.71)	(-3.06)	(-2.96)
Fund-Level Controls	No	No	No	No
Industry Controls	No	No	No	No
Observations	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.01	0.04

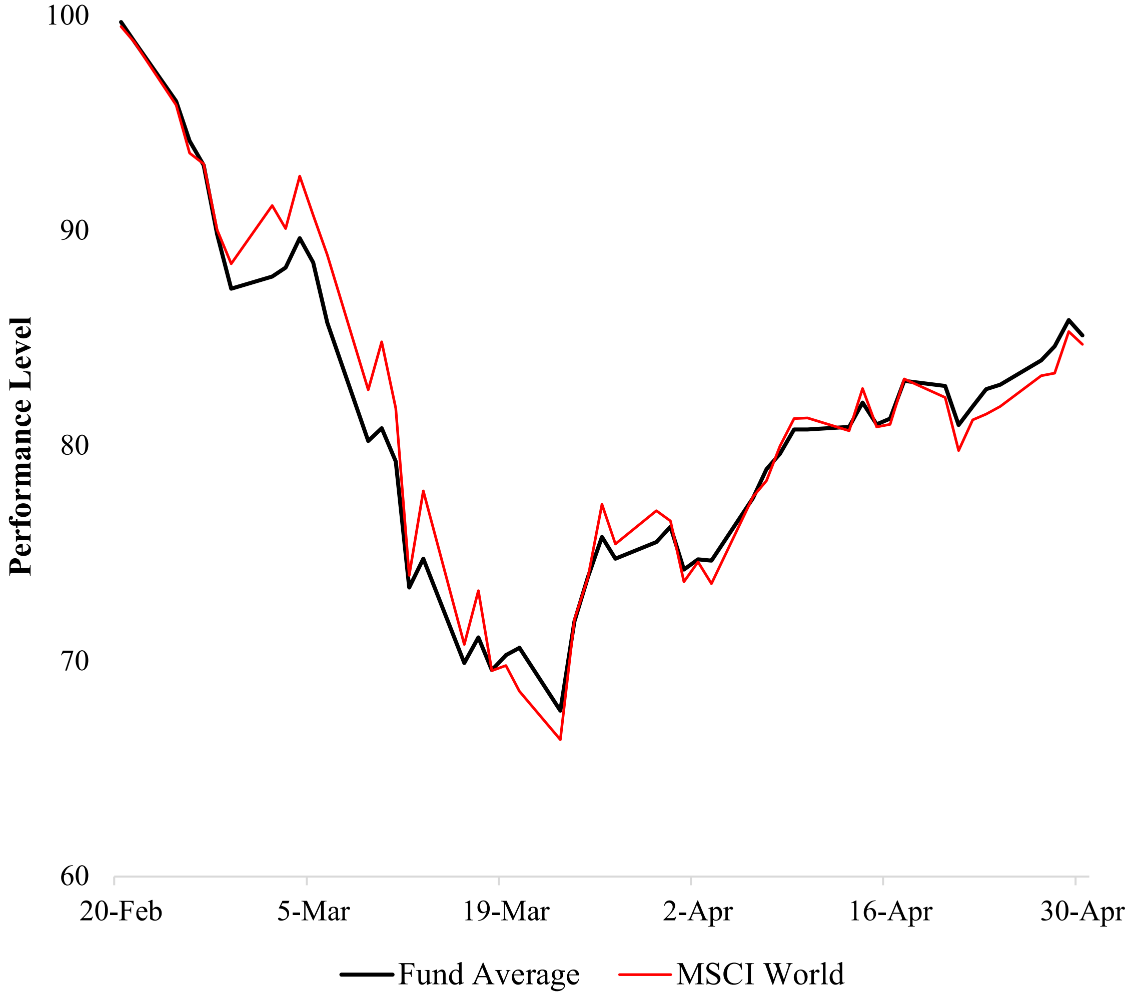


Figure 2. Average Fund Performance vs. the MSCI World Index

This figure plots the performance of the average mutual fund against the MSCI World Index in February 20 through April 30, 2020. Both price indices are initialized at 100 on February 19, 2020 and computed by compounding daily returns. The fund average is computed by taking the average return of the 1209 mutual funds in the main sample on a single day.

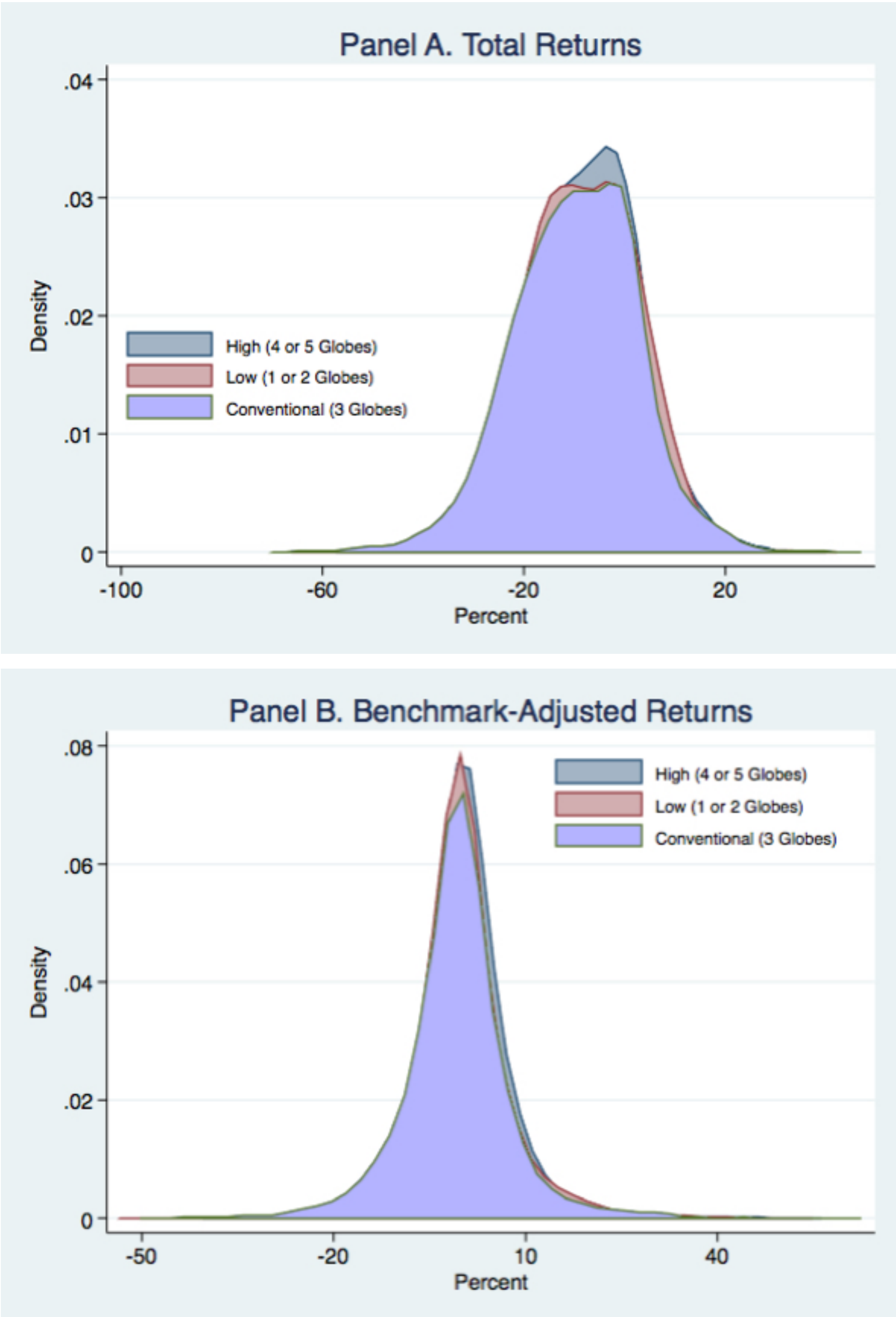
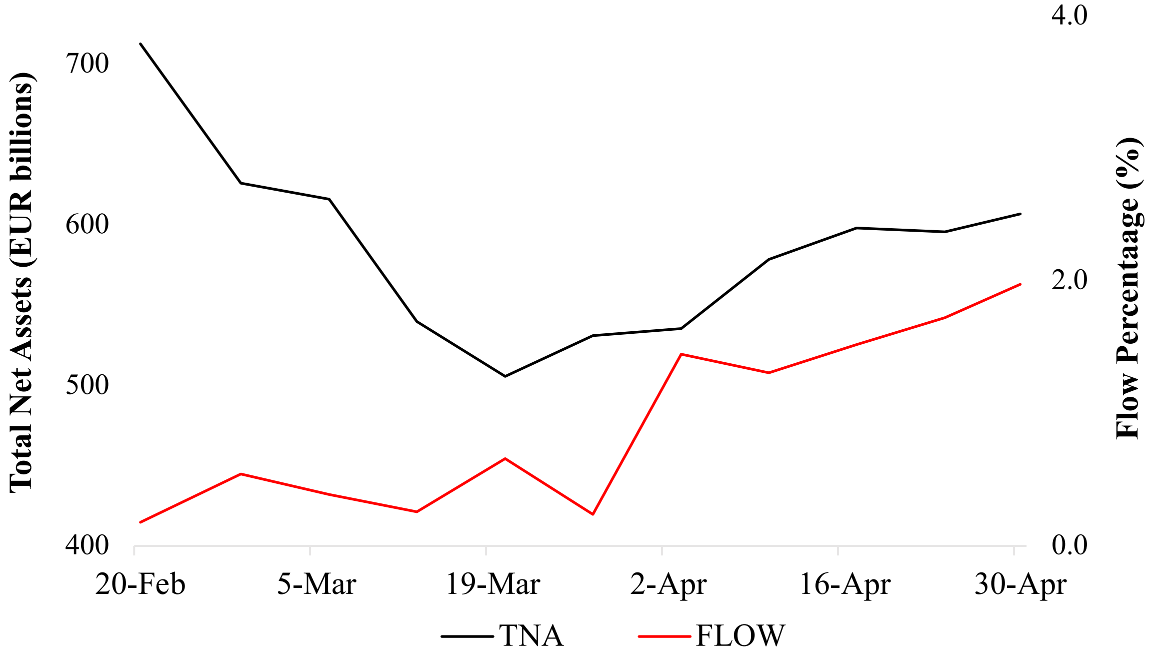


Figure 3. Cumulative Return Densities across Sustainability Categories.

This figure plots densities of funds' cumulative returns from February 20 to April 30, 2020 for three categories of sustainability: high (four or five Morningstar globes), conventional (three Morningstar globes) and low (one or two globes). In Panel A, the total cumulative returns are given by $\log(F_t)$ where $F_t = (1+r_1^F)(1+r_2^F) \dots (1+r_t^F)$. In Panel B, the cumulative returns are benchmark-adjusted, given by $\log(F_t) - \log(B_t)$ where B_t is the cumulative total return of the fund's primary benchmark mentioned in the fund's prospectus.

Panel A. Total Net Assets and Net Fund Flows, February 20 to April 30, 2020



Panel B. Total Net Assets and Net Fund Flows, January 2019 to December 2020

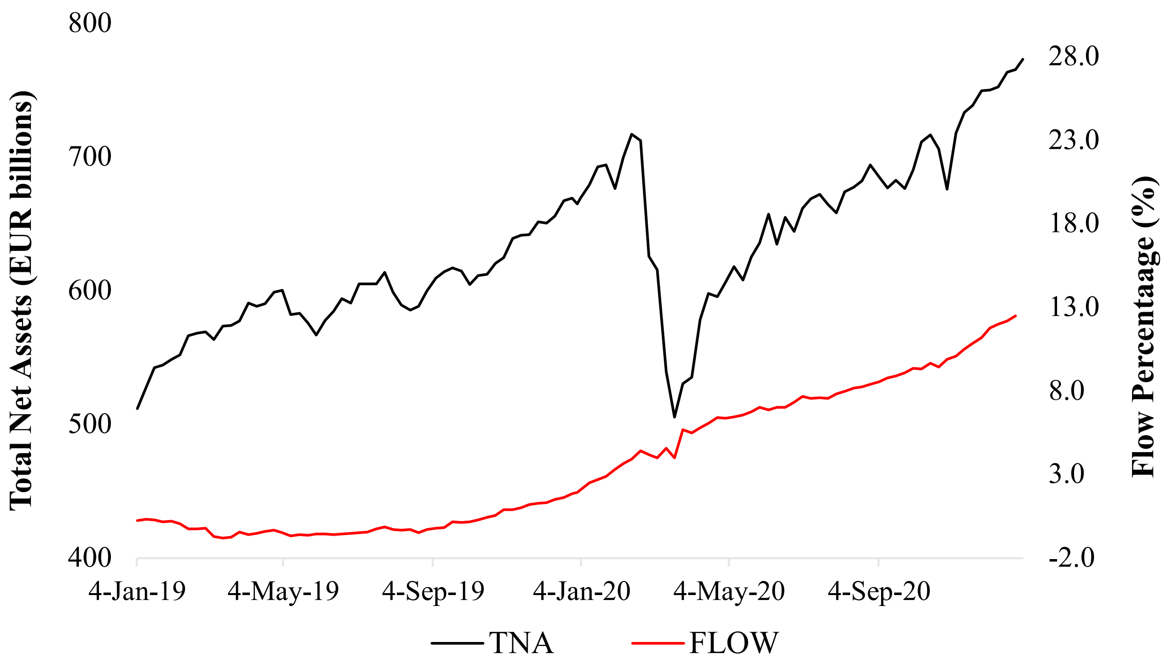


Figure 4. Aggregate Net Fund Flows.

This figure plots aggregate net flows equity mutual funds during the crisis period (Panel A) and over 2019-2021 (Panel B). Specifically, Panel A plots total cumulative net fund flows (in both EUR billions and as a percent of February 19, 2020 aggregate TNA) over the February 20 to April 30, 2020 period. Panel B covers the January 1, 2019 to December 31, 2020 period, and it expresses flows as a percent of January 1, 2019 TNA.

Appendix A – Results from Robustness Checks

Table A1. Fund Performance of Active Mutual Funds using LOG Returns

This table is identical to Table 4 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	-0.29	1.16***	6.04***	6.05***	6.02***	4.97***
	(-1.04)	(3.94)	(20.36)	(21.52)	(21.22)	(20.03)
Crisis	-13.36***	-11.66***	-28.65***	-13.14***	-11.97***	-12.56***
	(-4.99)	(-4.36)	(-23.74)	(-15.30)	(-11.40)	(-12.72)
Crash	-1.45	3.57	-147.40***	-83.90***	-74.04***	-139.07***
	(-0.30)	(0.74)	(-25.04)	(-21.78)	(-18.80)	(-41.95)
Recovery	-23.15***	-24.18***	63.29***	67.74***	70.27***	70.55***
	(-8.20)	(-8.50)	(25.86)	(37.62)	(36.49)	(42.01)
After-Crisis	-11.01***	-18.05***	-2.21***	-6.40***	-11.42***	-7.19***
	(-19.13)	(-30.64)	(-4.36)	(-16.58)	(-27.56)	(-18.47)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.12	5.66	5.05***	4.65***	4.62***	3.57***
	(0.62)	(1.00)	(22.39)	(24.77)	(24.40)	(19.90)
Crisis	8.61	2.39	-27.67***	-8.41***	-8.21***	-10.49***
	(0.15)	(0.04)	(-23.11)	(-10.75)	(-5.66)	(-8.13)
Crash	0.78	4.94	-129.47***	-52.87***	-43.59***	-115.38***
	(0.01)	(0.04)	(-31.74)	(-5.45)	(-3.93)	(-13.65)
Recovery	14.73	0.39	46.97***	54.84***	55.78***	61.19***
	(0.28)	(0.01)	(7.80)	(11.94)	(10.27)	(13.27)
After-Crisis	-4.84	-11.18	-2.95***	-7.86***	-14.16***	-8.98***
	(-0.42)	(-0.87)	(-11.38)	(-61.19)	(-118.32)	(-68.31)

Table A2. Fund Performance of Active Mutual Funds using Full Sample

This table is identical to Table 4 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	0.33	1.76***	6.55***	6.58***	6.59***	5.46***
	(1.24)	(6.34)	(23.34)	(24.81)	(24.93)	(23.07)
Crisis	-5.21**	-3.77	-25.51***	-11.01***	-9.20***	-10.76***
	(-2.10)	(-1.52)	(-23.35)	(-13.39)	(-9.40)	(-11.71)
Crash	9.24**	14.02***	-143.37***	-78.54***	-69.10***	-132.65***
	(2.06)	(3.15)	(-27.08)	(-22.46)	(-19.28)	(-44.84)
Recovery	-17.08***	-18.38***	66.60***	70.52***	73.39***	72.92***
	(-6.55)	(-6.99)	(28.60)	(41.030	(39.99)	(45.82)
After-Crisis	-9.31***	-17.13***	-0.96**	-5.44***	-8.78***	-6.29***
	(-16.49)	(-29.81)	(-1.99)	(-15.35)	(-23.82)	(-17.48)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.65	6.07	5.39***	4.99***	5.00***	3.89***
	(0.73)	(1.07)	(23.18)	(25.79)	(25.93)	(21.10)
Crisis	15.72	8.03	-25.46***	-7.84***	-7.36***	-9.85***
	(0.28)	(0.14)	(-20.35)	(-8.97)	(-4.81)	(-7.39)
Crash	9.48	13.60	-129.22***	-52.81***	-43.58***	-115.32***
	(0.08)	(0.12)	(-31.70)	(-5.50)	(-3.96)	(-13.62)
Recovery	20.60	3.68	48.44***	56.00***	57.03***	62.49***
	(0.40)	(0.07)	(8.11)	(12.47)	(10.82)	(13.98)
After-Crisis	-3.63	-9.93	-2.33***	-7.17***	-11.19***	-8.35***
	(-0.31)	(-0.77)	(-8.65)	(-56.65)	(-95.78)	(-63.79)

Table A3. Fund Performance of Passive Mutual Funds using LOG Returns

This table is identical to Table 5 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
	Panel A. Average Fund Performance (%)					
Pre-Crisis	1.21***	3.08***	7.60***	6.32***	6.32***	5.03***
	(2.90)	(7.26)	(19.59)	(14.94)	(14.87)	(13.54)
Crisis	-5.15	-4.58	-21.62***	-11.75***	-11.36***	-10.83***
	(-1.26)	(-1.134)	(-13.39)	(-11.15)	(-8.39)	(-9.18)
Crash	20.83***	27.49***	-120.63***	-84.70***	-76.75***	-146.73***
	(2.80)	(3.78)	(-12.91)	(-15.87)	(-14.54)	(-39.75)
Recovery	-26.50***	-30.90***	54.28***	56.08***	58.34***	61.40***
	(-6.18)	(-7.24)	(14.69)	(24.05)	(22.97)	(27.12)
After-Crisis	-12.12***	-18.89***	-2.55***	-7.12***	-11.99***	-8.02***
	(-14.15)	(-22.03)	(-3.58)	(-13.86)	(-20.35)	(-15.00)
	Panel B. Value-Weighted Average Fund Performance (%)					
Pre-Crisis	4.57	8.60	6.85***	5.09***	5.11***	3.84***
	(0.80)	(1.40)	(33.18)	(25.42)	(25.15)	(21.03)
Crisis	6.06	5.31	-12.98***	-3.73***	-4.26***	-3.75***
	(0.10)	(0.09)	(-6.43)	(-6.55)	(-3.15)	(-3.36)
Crash	29.46	43.16	-99.24***	-42.15**	-32.71*	-113.20***
	(0.27)	(0.41)	(-5.31)	(-2.48)	(-1.70)	(-9.23)
Recovery	-12.26	-24.31	46.24***	49.37***	49.27***	59.60***
	(-0.18)	(-0.37)	(9.77)	(9.11)	(7.34)	(11.31)
After-Crisis	-5.10	-11.28	-4.80***	-11.43***	-16.37***	-12.37***
	(-0.36)	(-0.76)	(-11.90)	(-32.62)	(-53.79)	(-38.27)

Table A4. Fund Performance of Passive Mutual Funds using Full Sample

This table is identical to Table 5 in the main paper except it uses the full sample of … equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	3.31***	3.34***	5.61***	5.73***	5.75***	5.07***
	(4.49)	(4.51)	(9.70)	(9.43)	(9.48)	(9.74)
Crisis	-4.49	-7.64	-16.80***	-9.97***	-8.66***	-10.45***
	(-0.65)	(-1.12)	(-7.37)	(-6.40)	(-4.01)	(-6.42)
Crash	-7.29	-6.88	-69.94***	-53.60***	-46.44***	-136.44***
	(-0.56)	(-0.55)	(-4.23)	(-5.86)	(-5.16)	(-19.87)
Recovery	-2.18	-8.26	34.19***	48.51***	49.50***	48.74***
	(-0.32)	(-1.21)	(5.44)	(13.45)	(12.79)	(14.12)
After-Crisis	-12.72***	-15.80***	-7.56***	-6.35***	-9.27***	-6.84***
	(-8.15)	(-10.20)	(-7.17)	(-6.65)	(-8.28)	(-6.44)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.41	2.97	5.82***	6.17***	6.19***	5.43***
	(0.81)	(0.52)	(161.75)	(151.20)	(152.39)	(153.12)
Crisis	43.41	42.45	-14.27***	-8.39***	-3.44***	-11.58***
	(1.26)	(1.21)	(-39.63)	(-81.39)	(-13.38)	(-239.98)
Crash	72.24	76.75	-39.70***	-32.88***	-27.95***	-125.84***
	(1.22)	(1.27)	(-82.73)	(-113.82)	(-97.28)	(-446.78)
Recovery	18.19	12.44	35.55***	51.25***	52.96***	49.56***
	(0.46)	(0.31)	(15.36)	(44.14)	(42.26)	(77.16)
After-Crisis	-10.19	-15.12	-8.63***	-7.57***	-10.79***	-8.21***
	(-1.01)	(-1.38)	(-18.35)	(-29.36)	(-36.32)	(-30.46)

Table A5. Fund Performance of Institutional Mutual Funds using LOG Returns

This table is identical to Table 6 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	1.37	1.73	6.50***	6.76***	6.73***	5.73***
	(1.27)	(1.54)	(5.97)	(6.68)	(6.59)	(6.86)
Crisis	-12.87	-16.02	-29.95***	-14.04***	-11.57***	-14.44***
	(-1.31)	(-1.57)	(-6.65)	(-5.63)	(-3.78)	(-5.28)
Crash	-8.69	-12.32	-136.51***	-87.13***	-80.71***	-154.80***
	(-0.50)	(-0.67)	(-6.12)	(-6.87)	(-6.04)	(-15.93)
Recovery	-16.32	-19.06*	55.76***	66.97***	69.583***	70.16***
	(-1.54)	(-1.74)	(6.07)	(7.74)	(8.20)	(8.51)
After-Crisis	-11.83***	-19.14***	-4.96**	-5.79***	-11.60***	-6.52***
	(-5.30)	(-8.23)	(-2.42)	(-4.01)	(-6.77)	(-4.49)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.44	6.42	10.82***	9.60***	9.65***	8.35***
	(0.69)	(0.82)	(80.70)	(84.66)	(83.48)	(80.25)
Crisis	34.84	16.92	-32.14***	-12.50***	-7.07***	-3.71***
	(0.59)	(0.32)	(-45.00)	(-68.22)	(-41.17)	(-7.76)
Crash	56.67	47.55	-129.76***	-94.25***	-90.20***	-147.62***
	(0.56)	(0.52)	(-20.76)	(-30.65)	(-27.62)	(-212.87)
Recovery	15.73	-9.89	48.66***	62.68***	70.56***	78.17***
	(0.23)	(-0.16)	(22.06)	(77.97)	(145.66)	(728.94)
After-Crisis	-12.10	-24.05	-10.05***	-8.84***	-15.27***	-9.97***
	(-0.84)	(-1.47)	(-45.72)	(-48.77)	(-57.14)	(-46.29)

Table A6. Fund Performance of Institutional Mutual Funds using Full Sample

This table is identical to Table 6 in the main paper except it uses the full sample of … equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	2.24*	2.76*	7.77***	7.90***	7.91***	6.66***
	(2.17)	(2.54)	(7.55)	(8.21)	(8.24)	(8.38)
Crisis	-5.95	-7.78	-27.20***	-9.91***	-6.37**	-10.34***
	(-0.63)	(-0.80)	(-7.23)	(-3.88)	(-2.05)	(-4.10)
Crash	-0.76	-0.43	-141.70***	-82.54***	-76.42***	-144.27***
	(-0.05)	(-0.03)	(-7.00)	(-7.29)	(-6.48)	(-16.43)
Recovery	-10.22	-13.83	64.26***	72.57***	76.18***	75.08***
	(-1.00)	(-1.31)	(7.16)	(8.95)	(9.50)	(9.60)
After-Crisis	-10.42***	-17.03***	-2.16	-4.45***	-8.42***	-5.38***
	(-4.87)	(-7.65)	(-1.08)	(-3.40)	(-5.96)	(-4.11)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.87	6.89	11.18***	9.95***	9.93***	8.68***
	(0.75)	(0.88)	(82.85)	(87.30)	(87.76)	(83.00)
Crisis	40.14	21.64	-28.96***	-10.25***	-4.67***	-2.29***
	(0.68)	(0.41)	(-44.05)	(-67.69)	(-30.88)	(-5.17)
Crash	63.07	53.16	-123.51***	-86.88***	-82.82***	-138.93***
	(0.62)	(0.59)	(-20.24)	(-29.79)	(-26.76)	(-250.83)
Recovery	20.07	-5.94	50.98***	64.71***	72.30***	80.57***
	(0.29)	(-0.09)	(23.19)	(87.36)	(164.44)	(432.26)
After-Crisis	-10.67	-22.50	-9.26***	-8.06***	-12.17***	-9.30***
	(-0.74)	(-1.38)	(-42.77)	(-46.47)	(-53.60)	(-44.82)

Table A7. Fund Performance of Retail Mutual Funds using LOG Returns

This table is identical to Table 7 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	-0.12	1.30***	6.10***	6.14***	6.11***	5.07***
	(-0.43)	(4.39)	(20.591)	(21.82)	(21.521)	(20.26)
Crisis	-13.49***	-11.59***	-28.39***	-12.97***	-11.92***	-12.27***
	(-4.98)	(-4.29)	(-23.52)	(-14.90)	(-11.19)	(-12.26)
Crash	-2.71	3.02	-146.62***	-83.33***	-73.40***	-138.32***
	(-0.55)	(0.62)	(-24.54)	(-21.25)	(-18.36)	(-41.12)
Recovery	-22.34***	-23.59***	62.90***	67.11***	69.55***	69.62***
	(-7.86)	(-8.24)	(25.42)	(37.71)	(36.26)	(41.92)
After-Crisis	-11.16***	-17.93***	-2.34***	-6.54***	-11.51***	-7.34***
	(-19.22)	(-30.26)	(-4.60)	(-16.73)	(-27.35)	(-18.53)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.24	5.48	4.85***	4.65***	4.62***	3.60***
	(0.65)	(0.98)	(22.36)	(24.80)	(24.43)	(19.97)
Crisis	0.54	4.12	-27.14***	-8.41***	-7.94***	-11.18***
	[(0.01)	(0.04)	(-21.70)	(-10.77)	(-5.39)	(-9.15)
Crash	8.54	2.76	-124.47***	-52.02***	-42.59***	-119.81***
	(0.16)	(0.05)	(-34.71)	(-5.32)	(-3.75)	(-12.62)
Recovery	14.80	1.70	45.63***	54.10***	54.75***	59.21***
	(0.29)	(0.03)	(7.80)	(12.04)	(10.35)	(13.68)
After-Crisis	-4.98	-10.94	-3.34***	-7.94***	-14.21***	-9.04***
	(-0.44)	(-0.87)	(-13.89)	(-59.12)	(-115.54)	(-65.76)

Table A8. Fund Performance of Retail Mutual Funds using Full Sample

This table is identical to Table 7 in the main paper except it uses the full sample of … equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Prospectus Benchmark	Δ MSCI World	α^{CAPM}	α^{FF3}	α^{Car4}	α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	0.42	1.82***	6.51***	6.56***	6.58***	5.46***
	(1.57)	(6.53)	(23.10)	(24.67)	(24.80)	(22.86)
Crisis	-5.35**	-3.84	-25.22***	-11.04***	-9.42***	-10.67***
	(-2.14)	(-1.54)	(-22.97)	(-13.29)	(-9.53)	(-11.44)
Crash	8.32	13.39***	-141.57***	-77.71***	-68.15***	-132.04***
	(1.83)	(2.97)	(-26.32)	(-21.80)	(-18.69)	(-43.89)
Recovery	-16.58***	-18.01***	65.45***	69.41***	72.14***	71.49***
	(-6.32)	(-6.82)	(27.79)	(40.70)	(39.38)	(45.32)
After-Crisis	-9.51***	-16.43***	-1.25***	-5.61***	-8.90***	-6.46***
	(-17.35)	(-29.57)	(-2.58)	(-15.62)	(-23.76)	(-17.64)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	3.78	5.89	5.15***	4.95***	4.96***	3.89***
	(0.76)	(1.05)	(23.18)	(25.82)	(25.97)	(21.14)
Crisis	14.75	7.49	-24.84***	-7.82***	-7.15***	-10.43***
	(0.28)	(0.14)	(-18.93)	(-8.94)	(-4.61)	(-8.18)
Crash	8.12	11.57	-119.77***	-47.36***	-38.29***	-114.07***
	(0.08)	(0.11)	(-43.00)	(-5.33)	(-3.71)	(-13.75)
Recovery	19.93	4.30	46.50***	54.85***	55.59***	60.05***
	(0.40)	(0.09)	(8.13)	(12.66)	(10.96)	(14.57)
After-Crisis	-3.82	-9.71	-2.80***	-7.24***	-11.23***	-8.39***
	(-0.34)	(-0.78)	(-11.42)	(-54.76)	(-92.39)	(-61.40)

Table A9. Fund Performance of High Sustainable Mutual Funds using LOG Returns

This table is identical to Table 8 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	1.21***	3.08***	7.60***	6.32***	6.32***	5.03***
	(2.90)	(7.26)	(19.59)	(14.94)	(14.87)	(13.54)
Crisis	-5.15	-4.58	-21.62***	-11.75***	-11.36***	-10.83***
	(-1.26)	(-1.134)	(-13.39)	(-11.15)	(-8.39)	(-9.18)
Crash	20.83***	27.49***	-120.63***	-84.70***	-76.75***	-146.73***
	(2.80)	(3.78)	(-12.91)	(-15.87)	(-14.54)	(-39.75)
Recovery	-26.50***	-30.90***	54.28***	56.08***	58.34***	61.40***
	(-6.18)	(-7.24)	(14.69)	(24.05)	(22.97)	(27.12)
After-Crisis	-12.12***	-18.89***	-2.55***	-7.12***	-11.99***	-8.02***
	(-14.15)	(-22.03)	(-3.58)	(-13.86)	(-20.35)	(-15.00)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	4.57	8.60	6.85***	5.09***	5.11***	3.84***
	(0.80)	(1.40)	(33.18)	(25.42)	(25.15)	(21.03)
Crisis	6.06	5.31	-12.98***	-3.73***	-4.26***	-3.75***
	(0.10)	(0.09)	(-6.43)	(-6.55)	(-3.15)	(-3.36)
Crash	29.46	43.16	-99.24***	-42.15**	-32.71*	-113.20***
	(0.27)	(0.41)	(-5.31)	(-2.48)	(-1.70)	(-9.23)
Recovery	-12.26	-24.31	46.24***	49.37***	49.27***	59.60***
	(-0.18)	(-0.37)	(9.77)	(9.11)	(7.34)	(11.31)
After-Crisis	-5.10	-11.28	-4.80***	-11.43***	-16.37***	-12.37***
	(-0.36)	(-0.76)	(-11.90)	(-32.62)	(-53.79)	(-38.27)

Table A10. Fund Performance of High Sustainable Mutual Funds using Full Sample

This table is identical to Table 8 in the main paper except it uses the full sample of … equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3) α^{CAPM}	(4) α^{FF3}	(5) α^{Car4}	(6) α^{FF5}
			Panel A. Average Fund Performance (%)			
Pre-Crisis	1.72***	3.53***	7.95***	6.77***	6.78***	5.41***
	(4.32)	(8.74)	(21.22)	(16.76)	(16.79)	(15.36)
Crisis	2.20	2.23	-19.65***	-10.17***	-9.26***	-9.58***
	(0.57)	(0.59)	(-13.85)	(-10.56)	(-7.49)	(-9.21)
Crash	31.19***	37.45***	-117.48***	-78.67***	-70.86***	-138.48***
	(4.44)	(5.46)	(-13.63)	(-15.80)	(-14.34)	(-40.70)
Recovery	-21.61***	-26.71***	56.58***	57.80***	60.19***	62.526***
	(-5.37)	(-6.67)	(15.80)	(25.63)	(24.56)	(28.65)
After-Crisis	-10.79***	-17.36***	-1.478**	-6.29***	-9.48***	-7.28***
	(-13.24)	(-21.29)	(-2.16)	(-12.72)	(-17.70)	(-14.06)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	5.03	9.04	7.12***	5.41***	5.41***	4.12***
	(0.88)	(1.46)	(33.86)	(26.76)	(26.87)	(22.47)
Crisis	11.55	0.19	-11.74***	-3.83***	-3.98***	-3.91***
	(10.43)	(0.18)	(-6.56)	(-5.10)	(-2.60)	(-3.22)
Crash	37.38	50.58	-95.28***	-36.53**	-27.35	-106.96***
	(0.34)	(0.48)	(-5.25)	(-2.20)	(-1.46)	(-9.34)
Recovery	-8.668	-21	47.50***	50.67***	50.55***	61.12***
	(-0.13)	(-0.32)	(9.98)	(9.62)	(7.74)	-12.04
After-Crisis	-3.833	-9.994	-4.30***	-10.80***	-13.95***	-11.78***
	(-0.27)	(-0.67)	(-10.39)	(-30.24)	(-43.55)	(-36.45)

Table A11. Fund Performance of Low Sustainable Mutual Funds using LOG Returns

This table is identical to Table 9 in the main paper except it uses log returns instead of simple returns. This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3)	(4)	(5)	(6)
			Panel A. Average Fund Performance (%)			
Pre-Crisis	-2.26***	-1.24*	4.44***	6.09***	6.03***	5.41***
	(-3.76)	(-1.86)	(6.09)	(9.79)	(9.54)	(9.63)
Crisis	-24.00***	-20.91***	-37.13***	-14.22***	-13.60***	-13.65***
	(-4.43)	(-3.71)	(-12.82)	(-6.68)	(-5.40)	(-5.42)
Crash	-32.14***	-29.59***	-179.63***	-80.93***	-67.61***	-125.23***
	(-3.30)	(-2.91)	(-15.01)	(-8.97)	(-7.17)	(-15.10)
Recovery	-17.32***	-13.78**	72.67***	79.95***	81.93***	79.67***
	(-3.00)	(-2.31)	(14.57)	(19.13)	(18.59)	(20.59)
After-Crisis	-8.65***	-16.23***	-1.54	-5.39***	-10.00***	-5.87***
	(-7.05)	(-12.46)	(-1.36)	(-5.81)	(-10.57)	(-6.44)
			Panel B. Value-Weighted Average Fund Performance (%)			
Pre-Crisis	0.04	2.31	2.23***	3.74***	3.67***	3.12***
	(0.01)	(0.39)	(10.33)	(22.25)	(21.69)	(18.57)
Crisis	14.35	10.69	-32.26***	-7.27***	-6.49***	-11.35***
	(0.29)	(0.20)	(-21.92)	(-21.33)	(-6.86)	(-42.58)
Crash	2.12	-0.53	-133.04***	-40.94***	-29.22***	-109.82***
	(0.02)	(-0.01)	(-83.71)	(-4.30)	(-2.62)	(-9.25)
Recovery	23.93	19.48	50.70***	63.87***	64.81***	66.33***
	(0.50)	(0.39)	(9.55)	(16.98)	(15.05)	(17.42)
After-Crisis	-5.13	-13.20	-3.72***	-7.69***	-14.19***	-8.45***
	(-0.50)	(-1.10)	(-18.66)	(-34.10)	(-75.63)	(-41.18)

Table A12. Fund Performance of Low Sustainable Mutual Funds using Full Sample

This table is identical to Table 9 in the main paper except it uses the full sample of … equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 1. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Δ Prospectus Benchmark	(2) Δ MSCI World	(3)	(4)	(5)	(6)
		Panel A. Average Fund Performance (%)				
Pre-Crisis	-1.53***	-0.36	5.23***	6.80***	6.82***	5.99***
	(-2.77)	(-0.60)	(7.92)	(12.01)	(12.11)	(11.72)
Crisis	-14.25***	-11.07***	-32.18***	-11.19***	-9.74***	-11.02***
	(-2.88)	(-2.18)	(-12.35)	(-5.58)	(-4.23)	(-4.74)
Crash	-20.30**	-15.86*	-174.05***	-78.13***	-65.90***	-122.88***
	(-2.28)	(-1.73)	(-16.81)	(-9.91)	(-7.99)	(-17.26)
Recovery	-9.27*	-7.14	77.27***	83.75***	86.54***	83.02***
	(-1.77)	(-1.32)	(16.58)	(21.59)	(21.12)	(23.39)
After-Crisis	-6.38***	-14.30***	0.50	-3.88***	-7.12***	-4.47***
	(-5.58)	(-11.95)	(0.46)	(-4.76)	(-8.65)	(-5.51)
		Panel B. Value-Weighted Average Fund Performance (%)				
Pre-Crisis	0.77	2.67	2.59***	4.04***	4.07***	3.39***
	(0.15)	(0.45)	(11.49)	(22.94)	(23.15)	(19.43)
Crisis	22.13	15.94	-29.32***	-6.40***	-5.57***	-10.12***
	(0.45)	(0.30)	(-18.97)	(-13.29)	(-5.22)	(-24.16)
Crash	9.52	8.21	-128.99***	-37.82***	-26.60***	-106.22***
	(0.10)	(0.08)	(-128.06)	(-4.51)	(-2.72)	(-10.30)
Recovery	31.99	21.98	51.59***	64.70***	65.78***	67.20***
	(0.69)	(0.44)	(9.71)	(17.38)	(15.57)	(17.95)
After-Crisis	-3.87	-11.84	-2.96***	-6.94***	-11.07***	-7.68***
	(-0.39)	(-0.99)	(-14.54)	(-33.96)	(-61.05)	(-41.39)

Table A13. Determinants of Fund Performance During the Crisis using LOG returns

This table is identical to Table 11 in the main paper except it uses log returns instead of simple returns. This difference This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-3.53**					-4.33**	-2.04	-3.30
	(-2.11)					(-2.51)	(-0.93)	(-1.49)
Institutional		0.256				1.33	3.31	3.37
		(-0.08)				(-0.41)	(-1.40)	(-1.45)
High_S			12.44***			8.82***	5.84***	5.28***
			(-8.39)			(-5.37)	(-3.89)	(-3.46)
Conventional_S				-0.909				
				(-0.57)				
Low_S					-14.39***	-10.10***	-5.63**	-5.36**
					(-7.06)	(-4.50)	(-2.55)	(-2.46)
Constant	-9.84***	-13.13***	-17.59***	-12.76***	-9.62***	-9.88***	-9.04	-6.76
	(-6.81)	(-16.06)	(-16.65)	(-12.35)	(-11.65)	(-6.27)	(-0.82)	(-0.61)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.05	0.00	0.05	0.07	0.22	0.25
				Panel B. Factor-Adjusted Performance				
Active	-1.39					-1.24	-2.20	0.30
	(-0.508)					(-0.44)	(-0.73)	(-0.10)
Institutional		0.32				0.45	2.52	4.63
		(-0.10)				(-0.14)	(-0.76)	(-1.45)
High_S			0.80			0.01	-0.90	2.96
			(-0.42)			(-0.01)	(-0.44)	(-1.53)
Conventional_S				0.98				
				(-0.49)				
Low_S					-2.29	-2.26	-0.19	-2.12
					(-0.84)	(-0.76)	(-0.06)	(-0.83)
Constant	-10.59***	-11.89***	-12.16***	-12.26***	-11.32***	-10.21***	-83.19***	-76.89***
	(-4.21)	(-11.47)	(-9.00)	(-9.453)	(-10.97)	(-3.85)	(-5.40)	(-5.37)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.27

Table A14. Determinants of Fund Performance During the Crisis using Full Sample

This table is identical to Table 11 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 11.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-0.72					-1.03	-0.71	-1.90
	(-0.45)					(-0.67)	(-0.37)	(-0.95)
Institutional		-0.84				0.21	1.03	1.21
		(-0.29)				(-0.07)	(-0.50)	(-0.60)
High_S			11.29***			8.04***	5.11***	4.84***
			(-8.49)			(-5.51)	(-3.83)	(-3.53)
Conventional_S				-1.02				
				(-0.72)				
Low_S					-12.19***	-8.41***	-4.35**	-4.08**
					(-6.73)	(-4.22)	(-2.23)	(-2.16)
Constant	-4.49***	-5.11***	-9.09***	-4.76***	-2.05***	-4.87***	7.83	12.83
	(-3.18)	(-7.02)	(-9.77)	(-5.10)	(-2.80)	(-3.53)	(-0.96)	(-1.57)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.04	0.00	0.04	0.05	0.22	0.25
				Panel B. Factor-Adjusted Performance				
Active	-0.53					-0.40	-3.24	0.50
	(-0.23)					(-0.17)	(-1.20)	(-0.18)
Institutional		2.96				3.01	3.82	6.03*
		(-0.92)				(-0.92)	(-1.16)	(-1.89)
High_S			-0.14			-0.49	-1.84	2.57
			(-0.08)			(-0.25)	(-0.96)	(-1.43)
Conventional_S				0.75				
				(-0.40)				
Low_S					-0.77	-1.04	0.04	-1.86
					(-0.31)	(-0.38)	(-0.01)	(-0.79)
Constant	-8.66***	-9.33***	-9.11***	-9.46***	-8.97***	-8.52***	-20.29*	-16.26
	(-4.03)	(-9.7-)	(-7.26)	(-7.84)	(-9.34)	(-3.75)	(-1.66)	(-1.46)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.27

Table A15. Determinants of Fund Performance During the Crash using LOG returns

This table is identical to Table 12 in the main paper except it uses log returns instead of simple returns. This difference This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Panel A. Benchmark-Adjusted Performance					
Active	14.48**					12.14**	11.53	3.70
	(-2.47)					(-2.11)	(-1.64)	(-0.52)
Institutional		-6.61				-3.91	1.14	2.22
		(-0.65)				(-0.39)	(-0.15)	(-0.30)
High_S			36.37***			25.32***	20.76***	16.82***
			(-8.99)			(-5.59)	(-4.74)	(-3.81)
Conventional_S				-4.84				
				(-1.10)				
Low_S					-39.22***	-27.42***	-16.33***	-15.04***
					(-7.37)	(-4.62)	(-2.71)	(-2.63)
Constant	-15.93***	-2.08	-15.54***	-0.53	7.08***	-15.97***	19.66	20.68
	(-2.94)	(-0.94)	(-5.48)	(-0.19)	(-3.08)	(-2.89)	(-0.63)	(-0.66)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.05	0.00	0.05	0.07	0.16	0.24
			Panel B. Factor-Adjusted Performance					
Active	-18.45*					-18.20*	-26.78*	-23.75*
	(-1.75)					(-1.67)	(-1.96)	(-1.69)
Institutional		-8.44				-8.70	-5.93	0.83
		(-0.61)				(-0.63)	(-0.42)	(-0.06)
High_S			-6.24			-3.30	-4.13	7.10
			(-0.86)			(-0.41)	(-0.51)	(-0.88)
Conventional_S				0.78				
				(-0.10)				
Low_S					6.79	5.80	-0.05	-4.57
					(-0.67)	(-0.53)	(0.00)	(-0.43)
Constant	-55.59***	-72.27***	-70.51***	-73.07***	-74.41***	-55.54***	-45.25	-15.14
	(-5.68)	(-18.66)	(-14.06)	(-14.80)	(-19.13)	(-5.62)	(-0.76)	(-0.26)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.11

Table A16. Determinants of Fund Performance During the Crash using Full Sample

This table is identical to Table 12 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	16.53***					15.98***	14.94**	6.32
	(-3.03)					(-3.03)	(-2.37)	(-0.97)
Institutional		-9.44				-6.48	-3.81	-3.28
		(-1.04)				(-0.72)	(-0.54)	(-0.48)
High_S			35.33***			23.90***	18.84***	15.43***
			(-9.37)			(-5.68)	(-4.63)	(-3.80)
Conventional_S				-3.19				
				(-0.78)				
Low_S					-38.18***	-27.42***	-17.18***	-15.42***
					(-7.75)	(-4.99)	(-3.10)	(-2.95)
Constant	-7.29	8.68***	-4.15	9.41***	17.88***	-7.73	12.57	23.53
	(-1.45)	(-4.22)	(-1.58)	(-3.62)	(-8.36)	(-1.56)	(-0.53)	(-1.03)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.05	0.00	0.05	0.07	0.17	0.24
				Panel B. Factor-Adjusted Performance				
Active	-22.67**					-22.15**	-25.56**	-22.08*
	(-2.35)					(-2.23)	(-2.11)	(-1.76)
Institutional		-9.35				-9.30	-6.01	1.91
		(-0.76)				(-0.76)	(-0.48)	(-0.16)
High_S			-5.00			-3.71	-6.37	5.47
			(-0.75)			(-0.51)	(-0.86)	(-0.74)
Conventional_S				2.93				
				(-0.43)				
Low_S					2.28	1.44	-0.48	-5.20
					(-0.25)	(-0.15)	(-0.05)	(-0.56)
Constant	-46.44***	-67.07***	-65.86***	-68.76***	-68.18***	-45.47***	-69.99	-49.09
	(-5.19)	(-18.96)	(-14.63)	(-15.27)	(-18.98)	(-5.02)	(-1.58)	(-1.20)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.12

Table A17. Determinants of Fund Performance During the Recovery using LOG returns

This table is identical to Table 13 in the main paper except it uses log returns instead of simple returns. This difference This difference materializes in two ways. First, the deltas are estimated as the average difference between the fund log returns and the log benchmark returns. Second, the alphas are estimated by regressing the fund's excess log returns on the factor log returns. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-18.32***					-17.86***	-13.18***	-9.04**
	(-4.90)					(-4.73)	(-3.14)	(-2.07)
Institutional		5.90				5.63	5.09	4.31
		(-1.32)				(-1.26)	(-1.17)	(-0.97)
High_S			-7.22***			-4.73*	-6.42**	-4.19
			(-3.18)			(-1.82)	(-2.48)	(-1.60)
Conventional_S				2.32				
				(-0.97)				
Low_S					6.01**	4.12	3.16	2.59
					(-2.16)	(-1.32)	(-0.96)	(-0.80)
Constant	-4.83	-22.21***	-19.28***	-22.80***	-23.34***	-4.88	-32.61*	-29.29
	(-1.37)	(-18.62)	(-12.67)	(-15.98)	(-18.01)	(-1.35)	(-1.79)	(-1.58)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.00	0.01	0.00	0.00	0.02	0.05	0.11
				Panel B. Factor-Adjusted Performance				
Active	19.78***					21.38***	10.22*	16.29***
	(-4.29)					(-4.41)	(-1.76)	(-2.87)
Institutional		0.73				-0.84	-0.38	2.00
		(-0.08)				(-0.10)	(-0.05)	(-0.30)
High_S			-16.50***			-13.64***	-10.38***	-1.26
			(-4.69)			(-3.51)	(-2.66)	(-0.35)
Conventional_S				2.63				
				(-0.71)				
Low_S					17.22***	10.23*	9.45*	6.14
					(-3.58)	(-1.96)	(-1.88)	(-1.51)
Constant	50.50***	68.86***	74.83***	67.85***	64.71***	51.47***	-24.28	-34.06
	(-12.06)	(-36.95)	(-30.72)	(-28.59)	(-33.59)	(-11.41)	(-0.85)	(-1.31)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,209	1,209	1,209	1,209	1,209	1,209	1,209	1,209
Adjusted R^2	0.01	0.00	0.01	0.00	0.01	0.02	0.06	0.33

Table A18. Determinants of Fund Performance During the Recovery using Full Sample

This table is identical to Table 13 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 13.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Benchmark-Adjusted Performance				
Active	-14.90***					-14.99***	-13.57***	-8.65**
	(-4.33)					(-4.31)	(-3.53)	(-2.14)
Institutional		6.22				5.71	5.01	4.89
		(-1.50)				(-1.36)	(-1.23)	(-1.19)
High_S			-8.46***			-4.98**	-6.16**	-3.87
			(-3.99)			(-2.11)	(-2.57)	(-1.62)
Conventional_S				0.76				
				(-0.35)				
Low_S					9.15***	7.21**	6.20**	5.23*
					(-3.47)	(-2.47)	(-2.06)	(-1.79)
Constant	-2.18	-16.44***	-13.15***	-16.39***	-18.42***	-2.52	3.93	4.04
	(-0.67)	(-14.83)	(-9.44)	(-11.91)	(-15.61)	(-0.76)	(-0.29)	(-0.30)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.01	0.00	0.01	0.00	0.01	0.02	0.04	0.11
				Panel B. Factor-Adjusted Performance				
Active	23.89***					24.58***	9.77*	18.07***
	(-5.60)					(-5.50)	(-1.84)	(-3.36)
Institutional		4.64				2.58	2.65	4.22
		(-0.57)				(-0.32)	(-0.35)	(-0.67)
High_S			-17.81***			-13.87***	-10.28***	-0.70
			(-5.30)			(-3.75)	(-2.78)	(-0.20)
Conventional_S				1.19				
				(-0.34)				
Low_S					19.78***	12.45**	9.93**	7.05*
					(-4.41)	(-2.55)	(-2.11)	(-1.82)
Constant	49.50***	71.55***	78.00***	71.34***	66.76***	50.36***	50.33**	49.65**
	(-12.85)	(-40.17)	(-33.91)	(-31.29)	(-36.23)	(-12.21)	(-2.31)	(-2.40)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.01	0.00	0.02	0.00	0.02	0.03	0.08	0.33

Table A19. Fund Flows using Full Sample

This table is identical to Table 17 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table 15. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1) Active	(2) Passive	(3) Institutional	(4) Retail	(5) High Sustainability	(6) Low Sustainability
Pre-Crisis	28.32***	41.40***	21.52	29.24***	42.47***	21.83***
	(7.58)	(3.68)	(1.45)	(7.88)	(6.52)	(2.80)
Crisis	2.83***	1.68	2.61	2.92***	3.84***	1.30**
	(8.27)	(1.50)	(1.36)	(8.69)	(6.46)	(2.15)
Crash	0.32**	0.65	0.96	0.38**	0.70**	0.28
	(2.10)	(1.31)	(1.10)	(2.50)	(2.57)	(0.95)
Recovery	3.08***	1.98**	1.85	3.17***	3.60***	1.69***
	(9.91)	(1.96)	(1.17)	(10.26)	(6.92)	(3.21)
After-Crisis	13.92***	7.82**	9.24	13.63***	20.62***	7.43**
	(7.85)	(2.05)	(1.33)	(7.73)	(7.50)	(2.20)

Table A20. Determinants of Fund Flows During the Crisis using Full Sample

This table is identical to Table 18 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table X. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	1.15					1.16	0.88	0.88
	(-0.99)					(-0.98)	(-0.66)	(-0.66)
Institutional		-0.15				-0.01	-0.14	-0.14
		(-0.08)				(-0.01)	(-0.07)	(-0.07)
High_S			1.66**			1.03	0.51	0.83
			(-2.34)			(-1.31)	(-0.65)	(-1.06)
Conventional_S				-0.03				
				(-0.04)				
Low_S					-1.95***	-1.51*	-1.54*	-1.62
					(-2.70)	(-1.88)	(-1.80)	(-1.92)
Constant	1.68	2.76***	2.18***	2.77***	3.25***	1.70	20.11***	20.29***
	(-1.51)	(-8.41)	(-5.59)	(-6.43)	(-8.40)	(-1.49)	(-3.80)	(-3.79)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.05

Table A21. Determinants of Fund Flows During the Crash using Full Sample

This table is identical to Table 19 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table X. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	-0.33					-0.45	-0.19	-0.02
	(-0.63)					(-0.88)	(-0.33)	(-0.04)
Institutional		0.66				0.69	0.58	0.67
		(-0.74)				(-0.78)	(-0.66)	(-0.75)
High_S			0.55*			0.67*	0.58	0.69*
			(-1.70)			(-1.91)	(-1.64)	(-1.94)
Conventional_S				-0.45				
				(-1.56)				
Low_S					-0.08	0.23	0.20	0.12
					(-0.25)	(-0.63)	(-0.50)	(-0.31)
Constant	0.65	0.31**	0.15	0.53***	0.37**	0.44	6.44***	5.58**
	(-1.32)	(-2.09)	(-0.90)	(-2.60)	(-2.16)	(-0.88)	(-2.91)	(-2.48)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03

Table A22. Determinants of Fund Flows During the Recovery using Full Sample

This table is identical to Table 20 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table X. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	1.10					1.26	0.77	0.74
	(-1.05)					(-1.19)	(-0.67)	(-0.63)
Institutional		-1.22				-1.12	-1.33	-1.36
		(-0.76)				(-0.69)	(-0.81)	(-0.80)
High_S			0.91			0.18	-0.30	0.17
			(-1.44)			(-0.26)	(-0.41)	(-0.24)
Conventional_S				0.53				
				-0.87				
Low_S					-1.76***	-1.70**	-1.71**	-1.71**
					(-2.77)	(-2.34)	(-2.21)	(-2.32)
Constant	1.98**	3.07***	2.69***	2.79***	3.45***	2.26**	13.99***	15.12***
	(-1.97)	(-10.21)	(-7.42)	(-7.45)	(-9.71)	(-2.17)	(-2.93)	(-3.18)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.07

Table A23. Determinants of Fund Flows During the Pre-Crisis using Full Sample

This table is identical to Table 21 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table X. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	-13.08					-16.05	0.13	-0.83
	(-1.11)					(-1.37)	(-0.01)	(-0.07)
Institutional		-8.13				-6.63	-11.89	-12.81
		(-0.54)				(-0.44)	(-0.81)	(-0.88)
High_S			20.37***			21.14***	14.79*	13.45*
			(-2.63)			(-2.61)	(-1.92)	(-1.69)
Conventional_S				-11.45*				
				(-1.66)				
Low_S					-9.89	0.63	-4.71	-4.03
					(-1.13)	(-0.07)	(-0.52)	(-0.45)
Constant	41.40***	29.65***	22.11***	33.74***	31.71***	37.04***	369.07***	367.49***
	(-3.69)	(-8.06)	(-5.25)	(-6.74)	(-7.97)	(-3.25)	(-5.88)	(-5.74)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.13

Table A24. Determinants of Fund Flows During the After-Crisis using Full Sample

This table is identical to Table 22 in the main paper except it uses the full sample of 1400 equity mutual funds. This sample does not include the screening on fund size (>€10m TNA) and age (>24 months) applied to the subsample in Table X. Robust t-statistics are in brackets and the *,** and *** indicate significance at 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	6.10					5.27	-8.41*	-6.23
	(-1.46)					(-1.23)	(-1.75)	(-1.26)
Institutional		-4.53				-3.81	-6.78	-8.24
		(-0.63)				(-0.53)	(-1.07)	(-1.28)
High_S			10.91***			9.07**	7.84**	8.22**
			(-3.15)			(-2.31)	(-2.00)	(-2.14)
Conventional_S				-3.86				
				(-1.12)				
Low_S					-8.16**	-4.03	-5.92	-5.78
					(-2.10)	(-0.93)	(-1.29)	(-1.24)
Constant	7.86**	13.77***	9.72***	15.04***	15.59***	6.68*	219.17***	220.89***
	(-2.06)	(-7.97)	(-4.63)	(-7.01)	(-8.01)	(-1.74)	(-5.82)	(-5.84)
Fund-Level Controls	No	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	No	Yes
Observations	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
Adjusted R^2	0.00	0.00	0.01	0.00	0.00	0.01	0.10	0.11