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The War in Ukraine: A Turning Point for Sustainable Investing?

An empirical study of investor preferences, performance and downside risk in the European mutual fund market

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Abstract

This thesis examines the impact of the war in Ukraine on sustainability-related investor preferences, performance, and exposure to downside risk in the European mutual fund market. We analyse a sample of 1,952 actively managed global equity mutual funds registered for sale in Europe using data from February 2021 to February 2023.

We do not find evidence of statistically significant differences in relative flows between high sustainability funds and their conventional peers in response to the war. However, investigating specific sustainability strategies, we find climate action-themed funds to experience higher relative flows and funds applying exclusion of either military contracting or fossil fuels to experience lower relative flows after the outbreak of the war, reflecting changes in public opinion and energy demand. Examining these effects, we observe no statistically significant difference in relative flows between institutional and retail investors. We find high sustainability funds and climate action-themed funds to perform better relative to their peers during the war, but we find no evidence of a relationship between sustainability and downside risk exposure. Overall, our findings suggest that sustainability remains a source of resilience through the war and that some investors have increased their sustainability focus, despite increased acceptance of controversial industries like fossil fuels and military contracting.

Keywords – Sustainable Investing, Mutual Funds, Difference-in-Differences, War in Ukraine

Contents

List of Figures

List of Tables

1 Introduction

The purpose of this thesis is to analyse how the Russian invasion of Ukraine has impacted sustainability-related investor preferences, performance and downside risk in the European mutual fund market. As the focus on sustainability keeps increasing and becoming an ever-more integrated part of the decision-making process of investors, so is the literature on the topic expanding. Prior research indicates that sustainability may positively impact fund resilience in times of market distress. Considering this, we examine how high sustainability funds have fared relative to their conventional peers. Furthermore, we argue that the war has caused a shift in public opinion and demand for the green transition, but also for the military and fossil fuel industries. We therefore specifically analyse the war's impact on funds with a thematic focus on Sustainable Development Goal 13 (climate action) and on funds applying exclusion of either military contracting or fossil fuels, through employing relative fund flows as a proxy for investor preferences. Furthermore, we analyse the potential differences between retail and institutional investors on these topics.

We collect data on actively managed global equity mutual funds registered for sale in Europe from Morningstar Direct and Refinitiv Eikon. After cleaning the sample, we arrive at a total of 1,952 mutual funds which we analyse through difference-in-differences and triple difference-in-differences frameworks. We employ propensity score matching to ensure that our samples satisfy the requirements for a difference-in-differences estimation. We estimate alpha derived from the Fama-French five-factor model, the Sharpe ratio and the Sortino ratio to assess fund performance, and value at risk and expected shortfall to assess downside risk.

Our findings suggest that there is no statistically significant difference in relative fund flows or exposure to downside risk between high sustainability funds and conventional funds, but that high sustainability funds perform better during the war, supporting the argument that sustainability increases resilience. We further find that climate action-themed funds experience higher relative flows and that funds applying exclusion of either military contracting or fossil fuels experience lower relative flows due to the war. We find no statistically significant difference in relative fund flows between retail and institutional investors. The overall picture indicates that sustainability remains a source of resilience during the war and that some investors have increased their sustainability focus, despite increased acceptance of controversial industries like military contracting and fossil fuels.

1.1 Background and Motivation

With sustainability becoming an increasingly relevant topic in society over the past decades, the market for sustainable mutual funds has grown rapidly (UNCTAD, 2021). Incorporating sustainability-related metrics in investment decisions has become standard practice. The reasons behind this can be manyfold. In addition to contributing positively to society, many prior studies indicate that sustainability factors may impact performance positively during crises (Fang and Parida, 2022; Tampakoudis et al., 2023; Becchetti et al., 2015). Furthermore, several studies have found sustainable funds to have lower exposure to downside risk, increasing their attractiveness in times of market distress (Hoepner et al., 2022; Durán-Santomil et al., 2019).

The Russian invasion of Ukraine in February 2022 provides a new opportunity to investigate how sustainable investing is impacted by crisis periods. The war continues to have global consequences, with high inflation, soaring energy prices and increased food insecurity across the world, which is bound to impact investors' preferences and priorities. Although the consequences of the war are felt globally, Europe remains more directly involved in the conflict, for instance through military and humanitarian aid to Ukraine and housing of Ukrainian refugees, as well as the geographic proximity. It is therefore particularly interesting to investigate how the war has impacted sustainable investing in Europe.

As war rages close to home, many Europeans have become more accepting of increased military spending. While it is true that military spending in Europe has been rising since Russia's illegal annexation of Crimea in 2014, the invasion in February 2022 has accelerated this trend further. A survey conducted by the European Parliament's Public Opinion Monitoring Unit (2022), revealed that 52% of European respondents were positive to increased military spending. The shift in public opinion can also be seen through the historic change of attitude to NATO membership in Sweden and Finland, with the subsequent submission of membership applications. Whereas military-related activities may have previously been considered unsustainable, investors may now accept it as a necessary evil.

Additionally, the energy sector has been highly impacted, with soaring prices following the West's decision to rid itself of reliance on Russian oil and gas. As many European countries were highly dependent on Russian oil and gas supplies before the war, the need to develop alternative energy sources has been amplified. Despite suggestions that the war has caused Europe to increase its consumption of fossil fuels, data show that consumption fell in the second half of 2022 (Myllyvirta, 2023). Rather, European countries have increased renewable energy production to record levels (Ellerbeck, 2023). At the same time, large Western oil and gas companies doubled their profits in 2022 following a surge in energy prices (Buosso, 2023). While the crisis may provide an opportunity to accelerate the green transition, policymakers also recognise the need to secure short-term energy needs. This can for instance be seen in the EUs response plan REPowerEU, which both includes initiating new partnerships for the delivery of gas and the development of renewable energy sources (European Commission, 2022). Additionally, a study conducted in Switzerland demonstrated increased public support for clean energy policies following the outbreak of the war (Steffen and Patt, 2022).

The crisis caused by the war in Ukraine holds certain unique characteristics which may result in different impacts on sustainable investing than what has been found during other crises. Firstly, changes in public opinion and demand for the green transition, military contracting and fossil fuels may have impacted investor preferences for these sectors specifically, as well as sustainable mutual funds as a whole. Secondly, suggestions of an accelerated green transition on the one side and high returns in the oil and gas industry on the other provide an ambiguous picture of how the war would impact sustainable mutual fund performance. Lastly, prior research has found sustainable funds to be less exposed to downside risk as a consequence of stronger long-term orientation. However, a crisis marked by pressing short-term needs for controversial sectors like fossil fuels and military contracting may contrast those findings. By exploiting the unique situation created by the war, we may add to the current literature and deepen the understanding of sustainable investing under market distress.

This thesis therefore aims to answer the following research question: *How has the war in Ukraine affected sustainability-related investor preferences, sustainable mutual fund performance and downside risk exposure?*

2 Literature Review

Our literature review aims to summarise the existing evidence on sustainable mutual fund flows, performance and downside risk exposure relevant to the current market situation caused by the war in Ukraine. The review begins by examining the determinants of mutual fund flows before elaborating on the sustainable mutual fund industry overall. Next, we investigate some of the key characteristics and strategies of sustainable mutual funds, as well as the distinction between the two main investor groups. Although the literature is expanding quickly, evidence is still inconclusive on several topics, providing us with an opportunity to contribute to the literature through this thesis. Finally, this chapter provides the foundation from which we build our hypotheses.

2.1 Mutual Fund Flows

Similarly to the works of Döttling and Kim (2022) and Pastor and Vorsatz (2020), we employ mutual fund flows as a proxy for investor preferences. Understanding the dynamics which affect fund flows is therefore critical to analyse the effects of the war in Ukraine on sustainability-related investor preferences. Several studies examining mutual fund flows have found macroeconomic variables to be important determinants (Jank, 2012; Kopsch et al., 2015). Kopsch et al. (2015) specifically identified volatility and inflation expectations as important determinants of fund flows. Furthermore, variables such as past performance and Morningstar star rating, which is an overall rating for fund performance, have been found to impact fund flows (Del Guercio and Tkac, 2008; Pastor and Vorsatz, 2020). In addition, Döttling and Kim (2022) and Pastor and Vorsatz (2020) identify net assets, expense ratio and fund age as key variables. Although mutual fund flows are considered an efficient indicator of investor preferences (Amdouni, 2021; Ben-Rephael et al., 2012; Indro, 2004), we acknowledge that several other variables are involved in driving fund flows. To disentangle the effect stemming from investor preferences, one should therefore control for the above-mentioned variables.

2.2 Sustainable Mutual Funds

While the sustainable mutual fund sector has been growing significantly over the past years, studies on its performance compared to conventional peers during normal market conditions remain inconclusive. Within the current literature, some studies have found sustainable funds to outperform conventional peers (Gil-Bazo et al., 2010; Reddy et al., 2017), some have found them to underperform (Dong et al., 2019; Nofsinger and Varma, 2013), and some have found no statistically significant difference in performance (Bauer et al., 2005). From a growing pool of research, meta-analyses have found the majority of the existing research to report no statistical difference in performance between sustainable and conventional mutual funds (Atz et al., 2023; AitElMekki, 2020). Some earlier studies may have been limited by a smaller pool of sustainable funds to draw from, but as the sector and sustainability-related metrics keep growing, the literature may provide more substantial evidence and a more comprehensive understanding of the characteristics of sustainable mutual funds. This thesis contributes modestly to that aim.

2.3 Sustainable Mutual Fund Strategies

Despite sustainable mutual funds often being referred to as one category, there is significant variation within this group (Carlsson Hauff and Nilsson, 2022). The variation can be seen through varying levels of sustainability commitment, differing focus within the sustainability universe, and different investment strategies. The most common sustainability-related investment strategy is exclusionary screening (Eurosif, 2018). Mutual funds applying such a strategy are typically restricted from investing more than a given share of the fund's assets, or completely restricted from investing, in an industry deemed not to be sustainable. Other common strategies include positive screening, where funds actively seek to invest in firms which stand out positively from a sustainability point of view, and engagement, where funds actively seek to promote positive change within the firms they invest in (Carlsson Hauff and Nilsson, 2022). Sustainable thematic investing is a less common strategy which is related to positive screening, but one which may be particularly relevant in the current context. The strategy involves the fund selecting assets based on a particular sustainability-related theme (Eurosif, 2018). With a wide spectre of sustainability strategies, the choice of which to focus on in this thesis comes down to relevance and data availability. Firstly, we argue that exclusionary screening is the easiest strategy to identify for the average investor. Two of the most notable industries typically excluded are fossil fuels and military-related activities. These are particularly relevant when considering a war-induced crisis, and this thesis therefore examines the effects of these two exclusion policies. Secondly, considering the suggestions that the war may have accelerated the green transition, it is particularly interesting to consider funds with a thematic approach reflecting this transition.

Funds which apply exclusionary screening as an investment strategy, effectively limit their investment universe, meaning they reduce their pool of possible investments. As such, a fund which applies exclusionary screening should theoretically at best achieve an equally optimal portfolio composition as a fund applying no restrictions to the investment universe. In line with this, Leite and Cortez (2015) found that funds applying exclusion criteria significantly underperformed their conventional peers during normal market conditions, but matched the performance of their conventional peers during crisis periods. Similarly, Pastor and Vorsatz (2020) found no significant relationship between applying exclusion criteria and performance during the Covid-19 pandemic. They did however find that funds applying exclusion criteria experienced higher flows during the pandemic. The research indicates that applying exclusion criteria does not necessarily hold negative implications, but that the effects are dependent on the characteristics and state of the market. To the best of our knowledge, prior studies have not examined the effect of negative screening strategies on exposure to downside risk.

The literature on sustainability-themed investing is limited. However, following a rise in popularity, some studies have emerged. These studies indicate that sustainability-themed funds perform similarly to other sustainable funds, as measured by risk-adjusted returns (Ielasi et al., 2018; Ielasi and Rossolini, 2019). While some thematic funds may have a higher risk exposure due to the thematic approach limiting their ability to diversify their portfolio, Ielasi and Rossolini (2019) found that sustainability-themed funds in general achieve a sufficiently diverse portfolio owing to themes like environment and energy being present in several sectors.

2.4 Sustainability Ratings

As sustainability as a whole could be perceived as a rather abstract and subjective metric, investors may rely on ratings, labels and categorisations provided by third parties when assessing and comparing sustainable mutual funds (Koellner et al., 2005). The most commonly used rating system is the Morningstar Sustainability Rating which evaluates funds' sustainability performance and awards them one to five globes based on their relative performance, with five globes being awarded to the most sustainable funds (Dolvin et al., 2019). The existing body of research on the relationship between sustainability rating and fund flows suggests that a higher sustainability rating leads to larger relative net inflows (Dolvin et al., 2019; Durán-Santomil et al., 2019; Becker et al., 2022). However, on the relationship between sustainability ratings and risk-adjusted returns, the research appears to be less in alignment. With some studies indicating no significant relationship (Dolvin et al., 2019) and others finding a positive relationship (Durán-Santomil et al., 2019), the evidence remains inconclusive. Finally, Durán-Santomil et al. (2019) found higher sustainability ratings to be negatively correlated with downside risk measured by value at risk, indicating that sustainable funds are less exposed to downside risk than their conventional peers.

Among other relevant sustainability categorisations is the EU SFDR regulation requiring the classification of financial products as either article 6, 8 or 9 depending on the level of ESG integration in the investment mandate (European Parliament, 2019). Funds without a sustainability scope report under article 6. Funds reporting under Article 8 consider sustainability aspects in the investment process, but it is not an objective of the fund, whereas funds reporting under Article 9 hold sustainability as a main objective of the fund. Although this regulatory framework is self-assessed and intended to dictate the funds' reporting requirements, it may also serve as a useful categorisation of the level of commitment to sustainability shown by a fund. With the SFDR regulation implemented in 2021, there is limited research on the relationship between classification and fund flows, performance and downside risk. Becker et al. (2022) found funds reporting under article 8 or 9 to attract larger relative inflows than a control group made up of funds not affected by the EU regulation. Similarly, Ferriani (2022) found article 9 funds to attract greater relative inflows and higher returns than their peers, but did not find article 8 to be relevant in explaining flow heterogeneity. The studies, however, did not examine a potential link between SFDR articles and exposure to downside risk.

2.5 Sustainability During Crisis

One of the main upsides associated with sustainable mutual funds is the idea that they may be more resilient than their conventional peers during times of market distress. This quality is partly driven by a stronger long-term orientation and lower sensitivity to short-term negative performance (Capotă et al., 2022). The literature on sustainable mutual fund flows during crisis periods provides mixed evidence. While some studies from the Covid-19 pandemic found sustainable funds to experience higher flows than their conventional peers (Pastor and Vorsatz, 2020; Fang and Parida, 2022), others found sustainable funds to experience sharper declines in fund flows (Döttling and Kim, 2022). Fang and Parida (2022) argue that investors associate sustainability with quality and therefore pour more money into sustainable funds during times of market distress. Having found evidence of the opposite, Döttling and Kim (2022) argue that demand for sustainable funds is fragile to economic shocks, largely driven by retail investors affected by negative income shocks.

While the relationship between sustainability score and fund returns is inconclusive in non-crisis periods, many prior studies indicate that high sustainability funds perform better than their conventional peers in crisis periods, such as the Covid-19 pandemic (Pastor and Vorsatz, 2020; Fang and Parida, 2022; Tampakoudis et al., 2023) and the financial crisis of 2008 (Becchetti et al., 2015). On the other hand, Belghitar et al. (2017) found SRI funds to underperform their conventional peers during the 2008 financial crisis, and Leite and Cortez (2015) found no statistical difference in performance when comparing SRI funds with conventional peers during crisis periods in the French market.

The pattern of sustainable mutual fund returns in crisis and non-crisis periods can be seen in relation to protection against downside risk. The potential cost of underperforming compared to conventional funds in non-crisis periods may be compensated for by protection against downside risk in crisis periods, as measured by superior risk-adjusted returns during market downturns (Nofsinger and Varma, 2013). This is partially explained by socially responsible firms having better governance standards, which make them better equipped to successfully manage challenges in crisis periods. Similarly, several papers have found evidence that engagement on ESG issues systematically reduced firms' exposure to downside risk, as measured by value at risk (Durán-Santomil et al., 2019; Hoepner et al., 2022; Viviani et al., 2019).

Given that the Russian invasion of Ukraine is still a relatively recent event, there is limited research done on its impacts on sustainable investing as of yet. Chen et al. (2022) investigated the war's impacts on U.S. sustainable equity funds. They found that sustainable funds did not achieve lower returns than their conventional peers when accounting for fossil fuel and weapons exposure, but they did attract lower flows. Furthermore, they found that mutual funds overall increased their exposure to fossil fuels and weapons. These findings are interesting, as we may expect to see investors reconsidering which degree of exposure to controversial industries is acceptable within the scope of sustainability.

2.6 Institutional Investors and Retail Investors

We distinguish between the two main categories of investors: institutional investors and retail investors. Institutional investors and retail investors differ significantly through different strategies, priorities, liquidity constraints and action room, which could impact the way they are affected by shocks to the market (Döttling and Kim, 2022). It is therefore reasonable to assume that the two groups may also be differently affected by the market shock caused by the war in Ukraine. While institutional investors may be freer in regard to liquidity constraints, they may be more restricted in regard to investment mandates. At the same time, certain factors associated with this particular crisis may cause these effects to be less significant compared to previous crises. Evidently, several effects related to the fundamental differences between institutional and retail investors are present in this crisis, motivating the inclusion of this distinction in our thesis.

Previous research from the Covid-19 pandemic has shown that the decline in retail SRI flows can be sharper than that of institutional flows during times of market distress, indicating that institutional sustainable funds may be more resilient (Döttling and Kim, 2022). On the other hand, Pastor and Vorsatz (2020) found that institutional funds experienced lower flows overall during the pandemic, but found no statistical significance with respect to sustainability. Döttling and Kim (2022) explained the steeper decline in retail flows in part by retail investors being more affected by the cost-of-living crisis, and thus not being able to prioritise long-term investments to the same extent. Whereas unemployment rates in Europe rose rapidly after the outbreak of the Covid-19 pandemic, rates remained fairly constant after the outbreak of the war in Ukraine (Eurostat, 2022). Considering this, we may expect this effect to be weaker during the war in Ukraine than during the Covid-19 pandemic.

Furthermore, institutional investors are often bound by investment mandates. As a result, they may be unable to increase their exposure to a certain industry even if a particular market shock would make it desirable to do so. Retail investors, on the other hand, are to a larger degree driven by pro-social preferences (Riedl and Smeets, 2017). As a result, one could expect a change in net flows to reflect changing social preferences in the retail mutual fund market. At the same time, we have seen some institutional investors loosen mandates and alter investment priorities to respond effectively to the consequences of the war. BlackRock announced in May 2022 that they would reduce their climate-related shareholder resolutions and increase investments in fossil fuels in the short term (Murray, 2022). Meanwhile, Swedish financial group SEB decided to remove some of the mandates restricting its funds from investing in arms manufacturers and defence companies (SEB, 2022). Following this, the effect of mandates restricting outflows from institutional funds may have decreased due to the war.

2.7 Hypotheses

This thesis aims to add to the discussion on sustainable mutual funds during times of crisis by exploiting the unique market situation created by the war in Ukraine. Consistent with prior research on sustainable mutual funds during crises, we expect to find a nuanced picture of sustainability as a source of resilience overall. Following evidence from the Covid-19 pandemic (Döttling and Kim, 2022) and early evidence from the war in Ukraine (Chen et al., 2022), we expect to see lower relative fund flows to high sustainability mutual funds when compared to conventional mutual funds. In line with prior research (Pastor and Vorsatz, 2020; Hoepner et al., 2022), we nonetheless expect high sustainability funds to show resilience through better performance and lower exposure to downside risk. As such, lower relative flows would not be driven by past performance in the sustainable mutual fund sector as a whole, but rather by a change of preferences towards more controversial sectors. We expect European investors to be affected by the war, and consequently, we expect to see changes in investor preferences. Specifically, we expect to see an increased appetite for climate action-themed funds and a decreased appetite for funds excluding military contracting and fossil fuel. The negative effects of applying these screening strategies, could to some degree counter the positive effects of climate action-themed funds when considering the sustainable mutual fund sector as a whole.

The existing body of research on sustainable mutual fund flows during crises provides mixed evidence. Some studies have found high sustainability funds to experience higher flows during the Covid-19 pandemic (Pastor and Vorsatz, 2020), arguing that investors associate sustainable funds with quality, while others have found sustainable funds to experience sharper declines during the pandemic (Döttling and Kim, 2022). Considering the perceived increased acceptance and appeal of industries like military contracting and fossil fuels, one could expect to see an outflow from high sustainability funds which are generally less exposed to these industries. This would be in line with early evidence from the war in Ukraine (Chen et al., 2022). On the other hand, we recognise that the supposed accelerated green transition in Europe may pull in the other direction. We nonetheless hypothesise that high sustainability funds experience lower relative flows compared to their conventional peers due to the war, in line with Chen et al. (2022).

$H1_0$: High sustainability funds experience lower relative flows compared to their conventional peers due to the war.

Furthermore, we examine the war's impact on investor preferences for climate action, military contracting and fossil fuels. While the war may be an opportunity to accelerate the green transition, it has also impacted public opinion on military contracting and demand for fossil fuels. Consequentially, it is reasonable to assume that investor preferences have been impacted both regarding climate action-themed funds and funds with exclusion policies for controversial industries like military contracting and fossil fuels. Whereas most investors tend to view fossil fuels as less sustainable, the labelling of the military as unsustainable may be less obvious. Military-related activities nonetheless remain among the most common sustainability-linked exclusion criteria and must therefore be considered relevant. While Pastor and Vorsatz (2020) found investors to favour funds applying exclusion strategies during the Covid-19 pandemic, we argue that the substantial shift in public opinion and demand for military- and fossil fuel-related industries should cause an outflow from funds holding exclusion policies for these industries. On the other hand, we argue that the accelerated green transition may have increased the attractiveness of climate action-themed funds in the eyes of investors. We therefore hypothesise that funds with a climate action-themed approach experience higher relative flows, while funds which hold a military contracting or fossil fuel exclusion policy experience lower relative flows due to the war compared to control groups without these strategies.

$H2_0$: A climate action-themed strategy has a positive effect on relative fund flows during the war.

$H3_0$: Military contracting exclusion has a negative effect on relative fund flows during the war.

$H4_0$: Fossil fuel exclusion has a negative effect on relative fund flows during the war.

To further examine the war's impact on sustainable mutual funds, we introduce the distinction between institutional and retail investors. The literature on this distinction in times of market distress is limited. We therefore build on the work of Döttling and Kim (2022) from the Covid-19 pandemic and aim to add to this part of the literature. As discussed, the two investor groups differ significantly in many ways. Retail investors are generally more affected by the cost-of-living crisis, which could cause them to rethink and reduce their investments. Secondly, institutional investors may be bound by mandates, forcing them to stay put, rather than shift to more controversial industries like fossil fuels and military contracting. On the other hand, we have not seen the same spike in unemployment as during the pandemic and some institutional investors have loosened certain mandates, indicating that these effects may be less prominent compared to during the pandemic. We nonetheless hypothesise that sustainable retail funds experience lower relative flows compared to their institutional counterparts due to the war in Ukraine, in line with Döttling and Kim (2022).

$H5_0$: Sustainable retail funds experience lower relative flows compared to sustainable institutional funds due to the war.

Lastly, we examine how the war has affected the performance and downside risk of sustainable mutual funds. Following the existing evidence of sustainable mutual funds being more resilient, performing better and having lower exposure to downside risk than their conventional peers in times of market distress (Pastor and Vorsatz, 2020; Hoepner et al., 2022), we may expect to see similar trends during the war in Ukraine. On the other hand, the unique characteristics of the war, particularly its effect on the military and fossil fuel industries, could cause results to differ from previous crises. We nonetheless hypothesise that sustainable mutual funds, in line with existing evidence, perform better and exhibit lower exposure to downside risk than their conventional peers due to the war in Ukraine.

$H6_0$: Sustainable funds perform better and exhibit lower exposure to downside risk compared to their conventional peers due to the war.

3 Data

Our main sources for collecting data on mutual funds are Refinitiv Eikon and Morningstar Direct. We use Kenneth R. French's website and the European Central Bank's Statistical Data Warehouse for other relevant variables such as factor returns and the risk-free rate. In the following, we present the general selection criteria, variable identification and the processing of this data to arrive at our final sample.

3.1 Selection Criteria

We employ a series of selection criteria to create a suitable sample of mutual funds to answer the research question at hand. Firstly, we require the mutual funds to operate with a minimum of 80% asset allocation to equities, in order to avoid balanced funds. We also require them to be open-ended and be registered for sale in Europe. For what concerns the available investment universe, we require the scope of the fund's investments to be global equities. We also require that all mutual funds follow an active management approach.

In addition to these criteria, we should address the issue of incubation bias when working with mutual funds. Incubation bias is the result of an incubation strategy where several new funds are started privately, where those that exhibit superior performance are opened to the public (Evans, 2010). Conducting a similar study Döttling and Kim (2022) filter on fund size in order to remove incubation bias. However, Evans (2010) argues that this does not remove the bias, but may rather result in additional bias in returns. He further suggests one can remove incubation bias by employing a ticker creation date filter. However, this method was based on the date at which the ticker was assigned by NASD (today known as FINRA) and applies to U.S. domestic mutual funds. Considering that we analyse mutual funds listed for sale in Europe, this approach is not applicable. An alternative approach is to include an age filter or remove return data for a given fund until the fund reaches three years of age, as Evans (2010) found this to eliminate the bias. The drawback of using an age filter is that it also excludes funds that are not subject to this bias and thereby excludes valid information. Furthermore, to the best of our knowledge, the research on incubation bias in European mutual funds is limited. Therefore, we cannot assert that the bias is also prominent amongst mutual funds offered for sale in Europe. Nonetheless, we employ a precautionary approach and find it appropriate to address the issue of incubation bias through a compromise where we exclude funds that were launched after 31 December 2018, i.e. around two years prior to the beginning of the time period selected for the analysis.

3.2 Variable Selection

Applying these selection criteria, we initially gather a survivorship-bias-free sample of mutual fund share classes from the Morningstar Direct database. We obtain daily flows, share class net assets, weekly returns in euros and U.S. dollars along with other baseline fund characteristics such as inception date. We also obtain an institutional indicator variable, time series data on sustainability ratings, star ratings, investment style, investment strategies and product involvement for ESG-related variables. We supplement this data with SFDR classification, total expense ratio and an institutional indicator from Refinitiv Eikon.

We also gather daily factor returns for the Fama-French five-factor model from Kenneth R. French's online data library which we convert to weekly returns. The factor returns should reflect the factor returns of the asset universe available to the funds in our sample. As we have defined the available investment universe of the funds to be global equities we use the broadest available dataset which is factor returns for developed markets. Although other studies employing empirical asset pricing models often refer to this dataset as global research factors (Norges Bank Investment Management, 2020; Otero and Reboredo, 2018), we acknowledge that this dataset is limited to developed markets and thereby does not include factor returns for emerging markets. We therefore consider the robustness of the results using an alternative benchmark in Section 5.5. To proxy for inflation expectations we gather weekly data on the Federal Funds Effective Rate from the Federal Reserve Economic Data database. We use the MSCI World Index as a proxy for the global market. As a proxy for volatility expectations, we collect weekly observations from CBOE Volatility Index, also known as the VIX. Lastly, we obtain data on the risk-free rate. Given that a risk-free asset is a theoretical concept as all assets carry some amount of risk, we also need a proxy for this variable. Considering that we primarily use returns in euros and that the mutual funds are sold to European investors we choose a proxy suitable for the European market. In 2018 the ECB, ESMA, the Belgian FSMA and the European Commission established a working group on euro risk-free rates (ESMA, 2022). In the same year, the group recommended the use of the euro short-term rate (€STR) as the risk-free rate for the euro area. Considering that the euro area encompasses large parts of Europe, we follow the group's recommendation. We use weekly data for the €STR derived from the compounded €STR average rate with a 1-week tenor. More precisely we proxy the weekly return of the risk-free rate in week t (R_{ft}) by employing the following transformation:

$$R_{ft} = ((1 + \frac{€STR_{cwt}}{100})^{\frac{1}{52}} - 1) * 100, \tag{3.1}$$

where $€STR_{cwt}$ is the annualised €STR compounded from a 1-week tenor in week t.

3.3 Time Period and Data Granularity

When selecting the time period for the analysis we want to ensure that we have comparable data prior to and following the war. Limited by the available data following the war, the time period for the analysis ranges from one year prior to and one year following its outbreak. Given that we consider a relatively short time period, it could be of interest to look at daily time series. However, in doing so, we risk including a considerable amount of noise in our analysis. On the other hand, using a lower granularity such as monthly time series could exclude important variations in the data. In order to find a satisfactory balance between noise and signal, we therefore use weekly data. This choice is also supported by similar studies which look at mutual fund performance and flows in periods of crisis (Otero and Reboredo, 2018; Döttling and Kim, 2022).

3.4 Data Cleaning and Share Class Aggregation

Mutual funds are often offered as different share classes (Morgan Stanley, 2015). Share classes differ in cost structure and load charges, but hold the same investment portfolio. As a result, the different share classes may yield different returns, despite holding the same portfolio. Some share classes are typically offered to institutional investors rather than retail investors, and this is reflected in the cost structure.

Following Döttling and Kim (2022) we combine and aggregate the share classes to fund level. The process starts by verifying that there are no missing weekly return observations for the entire time period for each share class. Share classes that do not meet this requirement are removed from the sample. Share classes that do not have at least one daily flow observation for any given week of the time period are also dropped from the sample. We acknowledge that imposing these criteria will potentially induce survivorship bias as these criteria exclude share classes that are discontinued. However, as we are performing a comparative study where the relative outcomes between groups are of importance, the relevance of this bias is mitigated under the assumption that the bias is equal in all groups.

For the remaining share classes, we tally daily flows by week. Our main dependent variable, relative percentage net flows (Relative Flow), is calculated as:

$$Relative\ Flow_{it} = (\frac{Flow_{it}}{TNA_{it-1}}) * 100, \tag{3.2}$$

where $Flow_{it}$ is the aggregated daily flows for share class i in week t, and TNA_{it-1} is the total net assets for share class i at the end of the previous week. We further identify relative flows that are so extreme that they are unlikely to represent normal relative fund flow behaviour but rather be related to substantial idiosyncratic events. Similar studies have previously used thresholds which exclude share classes that have any relative flow observations greater or equal to 10 (1000%) or less than or equal to -0.9 (-90%) (Bollen, 2007; Omori and Kitamura, 2022). As these thresholds have been used for both monthly and annual observations we find it reasonable to also employ them at a higher granularity of weekly observations.

Our final cleaned sample consists of 4,569 share classes where each share class is tied to a fund Id. Döttling and Kim (2022) identify whether a share class is offered to institutional investors by using an indicator variable offered by Morningstar. The identification method used for this indicator variable differs depending on whether the fund is based in the U.S. market or not. For the U.S. market the identification method is based both on the share class I[1] and the minimum investment amount (>$100,000). For non-U.S. markets,

[1]These are share classes with large minimum investment amounts, low expenses and are typically purchased by institutional investors (Morningstar, 2018)

Morningstar determines the indicator value based on whether the share class is intended for institutional investors as defined by the fund's provider. From a visual inspection of the data we find that this indicator variable fails to capture several class I shares. We therefore also consider the indicator provided by Refinitiv Eikon which states that a share class is institutional if it is "primarily or exclusively offered to institutions, corporations, pension plans, banks, etc." (Refinitiv Eikon, personal communication, 30 March, 2023). This indicator variable seems to capture those class I shares that are not accounted for by Morningstar's indicator. As we consider the European market, the indicator provided by Morningstar, and to some degree the indicator provided by Refinitiv Eikon fail to account for those share classes that are not identified as institutional but whose initial investment amount is far beyond what the average retail investor is able to invest. We therefore include an additional criterion, stating that share classes with a minimum investment amount of more than a $100 000 equivalent are classified as institutional.

Share classes are aggregated to fund level by fund Id and the institutional indicator. This entails that a fund with retail and institutional share classes is separated into two individual funds, aggregated by the number of share classes within the respective investor type category. For the aggregation procedure, fund flows and net assets are simply added, and the relative flow is then calculated in the same way as for the individual share classes. The age of the fund is defined by the age of the oldest share class in months. The return of the fund is the net asset value-weighted average for a given week. We also compute the net asset value-weighted average for the total expense ratio based on the average net asset value for the entire time period. For variables such as sustainability ratings which are determined at the fund level, we replace missing values for one share class with available values from the other share classes within the same fund. For overall star ratings which are based on variables that can differ across share classes within the same fund, we use the rounded net asset-weighted average which is calculated based on those share classes with available ratings. Finally, all fund-specific continuous variables are winsorized at the 99% level to mitigate the effect of extreme outliers.

4 Methodology

This section starts by defining the dependent variables used in the analysis before expanding on the general research design which consists of a quasi-experimental approach where we define several difference-in-differences model specifications. We further present the main prerequisites for the method and define the period and groups which we analyse through the presented difference-in-differences framework.

4.1 Dependent Variables

4.1.1 Investor Preference Measure

In order to address the war's impact on sustainability-related investor preferences, we need a measure that reflects investor preference. Similar studies have employed mutual fund flows as a proxy for investor preferences, as mutual fund flows are a well-documented sentiment indicator (Amdouni, 2021; Ben-Rephael et al., 2012; Indro, 2004). However, as depicted in the literature review there are several other variables that affect mutual fund flows which might not directly be related to investor preferences. As for most proxies, mutual fund flows are therefore an imperfect measure of the variable of interest. Acknowledging these shortcomings we find mutual fund flows, as defined in Equation 3.2, to be the best available alternative to proxy for investor preferences.

4.1.2 Performance Measures

In addition to investor preferences, we aim to answer whether high sustainability funds and funds that employ the relevant strategies display a significant difference in performance. To provide a comprehensive analysis that captures some of the many aspects of performance evaluation, we consider several measures. In particular, we consider traditional performance measures as well as a performance measure that emphasises downside risk. In the following, we present the selected measures used to evaluate performance following the outbreak of the war.

For the traditional risk-adjusted performance measures we estimate alpha and Sharpe ratio. Alpha can be interpreted as the residual excess return of an asset after subtracting the expected return derived from a theoretical asset pricing model (Barillas and Shanken, 2016). We have selected the Fama-French five-factor model as the theoretical asset pricing model. This choice is partly based on the empirical evidence of the factors' relevance in explaining returns (Fama and French, 2014). Furthermore, as the returns of open-end mutual funds are primarily determined by the value of the underlying securities, we can use the factor coefficients from the asset pricing model to determine the risk profiles for the different mutual funds. This idea was implemented by Otero and Reboredo (2018) who looked at the impact of precious metal screening on the financial and risk performance of mutual funds in crisis periods. In order to match precious metal screening mutual funds to conventional mutual funds, they use i.a. betas and corresponding adjusted R^2 derived from regressing each fund's excess return on the five factors of the Fama-French five-factor model. We elaborate more on this matching procedure in Section 4.2.3. We estimate alpha and factor coefficients for all mutual funds in the two subperiods (pre- and post-period) as follows:

$$\begin{aligned} R_{itp} - R_{ftp} = \alpha_{ip} + \beta_{ipM}(R_{Mtp} - R_{ftp}) + \beta_{ips} SMB_{tp} + \beta_{iph} HML_{tp} + \\ \beta_{ipr} RMW_{tp} + \beta_{ipc} CMA_{tp} + \epsilon_{itp}, \end{aligned} \tag{4.1}$$

where $R_{itp} - R_{ftp}$ and $R_{Mtp} - R_{ftp}$ are the excess returns of mutual fund i and the market respectively in week t of subperiod p. SMB_{tp} is the return of an equally weighted portfolio made up of nine small stock portfolios minus the return of an equivalent portfolio constructed of big stocks (Kenneth R. French - Data Library, 2023). HML_{tp} is the return of a value portfolio subtracted by a growth portfolio. RMW_{tp} denotes the return of the robust minus weak operating portfolio and CMA_{tp} is the return of a conservative investment portfolio minus the return of an aggressive investment portfolio. Finally, α_{ip} is the intercept and the estimated alpha for fund i in subperiod p and ϵ_{itp} is the error term. The factor returns provided by Kenneth R. French's online data library are all in U.S. dollars. Accordingly, we use the U.S. dollar returns for each mutual fund to achieve appropriate alpha and beta estimations.

While the alpha derived from the Fama-French five-factor model accounts for systematic risk, we also include a performance measure that incorporates the total risk of the investment. Thus we include the Sharpe ratio. The Sharpe ratio is defined as:

$$Sharpe\ Ratio_{ip} = \frac{\overline{R}_{ip} - \overline{R}_{fp}}{\sigma_{ip}}, \tag{4.2}$$

where $\overline{R}_{ip}$ and $\overline{R}_{fp}$ is the average return of fund i and the risk-free asset respectively in subperiod p, while σ_{ip} is the standard deviation of the portfolio's excess returns in period p.

Finally, we include the Sortino ratio as a performance measure that emphasises downside risk. The Sortino ratio can be considered an improvement to the Sharpe Ratio as the latter penalizes positively skewed return distributions (Rollinger and Hoffman, 2014). By specifying a desired target return, the Sortino ratio only accounts for the volatility derived from returns that fall below this threshold. We use the weekly €STR which is our risk-free rate estimate as this threshold. We calculate the downside sigma as follows:

$$\sigma_{ip}^{-} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(Min(0, R_{itp} - R_{ftp}))^2}, \tag{4.3}$$

where σ_{ip}^{-} is the target downside deviation for fund i in subperiod p, R_{itp} is the return for fund i in week t of subperiod p and R_{ftp} is the risk-free rate of return in week t of subperiod p. The Sortino ratio is then given as follows and represents the downside risk-adjusted performance measure:

$$Sortino\ Ratio_{ip} = \frac{\overline{R}_{ip} - \overline{R}_{fp}}{\sigma_{ip}^{-}} \tag{4.4}$$

4.1.3 Downside Risk Measures

Considering previous findings regarding sustainable funds' alleged resilience in crisis periods we include measures that specifically estimate downside risk in addition to the performance measures. Studies on ESG engagement and mutual funds in crisis periods have used measures such as value at risk (VaR) and expected shortfall (ES) to estimate downside risk (Otero and Reboredo, 2018; Hoepner et al., 2022). These measures account for related aspects of tail risk and we include both to provide a comprehensive overview of the downside risk profiles. Value at risk provides an estimate of the greatest potential loss within a time period for a given confidence interval while the expected shortfall captures the expected value of the loss given that the VaR threshold has been exceeded. When estimating VaR and ES, there are several methods that can be applied. Primarily the choice depends on the selection of a parametric or a non-parametric estimation method. Contrary to a non-parametric method, parametric methods make assumptions about the theoretical distribution of the variable (Ben Salem et al., 2022). A commonly used distribution for the parametric method is the Gaussian distribution for which the mean and standard deviation are estimated from the sample data. However, it is well documented in the financial literature that financial returns tend to have fat tails and therefore do not follow a normal distribution (Eom et al., 2019). We also find this to be the case when considering the returns in our pooled data sample. In order to address this issue, Favre and Galeano (2002) proposed a modified VaR measure (mVaR) that accounts for the third and fourth moments (skewness and kurtosis) of statistical distributions using a Cornish Fisher expansion as can be seen in Equation 4.5 and 4.6.

$$mVaR_{ip} = -(\overline{R}_{ip}) - \sqrt{\sigma_{ip}^2} * z_{cfip} \tag{4.5}$$

$$z_{cfip} = z_c + \frac{(z_c^2 - 1)\, S_{ip}}{6} + \frac{(z_c^3 - 3z_c)\, K_{ip}}{24} - \frac{(2z_c^3 - 5z_c)\, S_{ip}^2}{36}, \tag{4.6}$$

where $mVaR_{ip}$ is the modified value at risk for fund i in subperiod p and σ_{ip} is the standard deviation of the returns of fund i in period p. z_c is the z-score of a standard normal distribution corresponding to the critical value for the selected probability (5%) and z_{cfip} is the adjusted z-score for fund i in subperiod p which accounts for skewness (S) and kurtosis (K) of the return distribution. Considering the fat tails of the returns, using the modified VaR seems appropriate for this analysis. However, as we make assumptions about the theoretical distribution of the returns, a small sample might provide inaccurate estimations for the true distribution parameters. Furthermore, there might be some individual funds whose return distributions cannot be accurately captured using the parametric method in Equation 4.5. We therefore also use historical simulation, which is a non-parametric method that simply estimates VaR based on the empirical quantiles of the returns. In estimating the expected shortfall we also use a modified parametric method (Boudt et al., 2008) and a non-parametric method where ES is estimated as the average value of returns given that the VaR threshold using historical simulation is exceeded.

4.2 Research Design

4.2.1 Difference-in-Differences

Following a similar study done on the Covid-19 pandemic (Döttling and Kim, 2022), we employ a difference-in-differences framework to estimate the impact of different sustainability treatments on relative fund flows, performance and downside risk after the outbreak of the war. The difference-in-differences method is a common approach used to compare a treated and an untreated population, or two populations with different degrees of treatment, over time, as it facilitates causal inference when randomisation is not possible. The general regression model used for the difference-in-differences estimations when considering relative flows can be formulated as follows:

$$\begin{gathered} Relative\ Flow_{it} = \gamma_i + \lambda_t + \beta_0 + \beta_1 * Treatment_i + \beta_2 * Post_t + \\ \beta_3 * Post_t * Treatment_i + \theta C_{it} + \epsilon_i, \end{gathered} \tag{4.7}$$

where $Relative\ Flow_{it}$ is the relative fund flows for fund i in week t, $Treatment_i$ is a dummy variable indicating whether fund i possesses a specific feature (high sustainability label, a thematic investment strategy targeted at climate change or a military contracting or fossil fuel exclusion policy) (1) or not (0) and $Post_t$ is a dummy variable indicating whether the observation is in the post-period (1) or pre-period (0). C_{it} represents the vector of fund-level control variables and ϵ_{it} is the error term. We also include entity fixed effects at the fund level (γ_i) and time fixed effects at the week level (λ_t) to account for unobserved heterogeneity. Finally, the coefficient of the interaction term (β_3) is our difference-in-differences estimator and captures the relative effect of possessing the specific feature following the breakout of the war compared to the counterfactual outcome. The counterfactual outcome is interpreted as how the relative flows would have developed had the fund not possessed the specific feature. We account for heteroskedastic errors and the often plausible autocorrelation within entities by using heteroskedasticity robust standard errors clustered at the fund level. To assess the implementation of two-way fixed effects we also conduct a pooled regression model as a comparison where we include several fund-invariant control variables denoted by X_t. Control variables are selected on the basis of previous research as presented in the literature review. These include past performance, Morningstar's overall rating (OR), logged total net assets, expense ratio, fund age and proxies for macroeconomic variables such as volatility and inflation expectations and global market movements.

We also employ a difference-in-differences estimation when considering the performance and downside risk evaluation. Contrary to relative flows for which we have weekly observations, these measures are all estimated for each subperiod. Consequently, the difference-in-differences estimation is practically a two-period model. The regression model is defined as:

$$Y_{ip} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_p + \beta_3 Post_p * Treatment_i + \theta C_{ip} + \epsilon_{ip}, \qquad (4.8)$$

where Y_{ip} is a collective term for the observations in period p for fund i of the measures: alpha, Sharpe ratio, Sortino ratio and 5% modified (m) and historical (h) VaR and ES. For the control variables denoted by C_{ip} we include logged average total net assets, average fund flow, expense ratio and fund age.

4.2.2 Triple Difference-in-Differences

In order to investigate if the effect on relative flows of having sustainability features during the war differs between the two investor types, we also include a triple difference-in-differences estimation:

$$\begin{aligned} Relative\ Flow_{it} = {} & \gamma_i + \lambda_t + \beta_0 + \beta_1 Treatment_i + \beta_2 Institutional_i + \beta_3 Post_t + \\ & \beta_4 Treatment_i * Institutional_t + \beta_5 * Treatment_i * Post_t + \\ & \beta_6 Institutional * Post_t + \beta_7 Treatment_i * Institutional_i * Post_t + \\ & \theta C_{it} + \epsilon_{it}, \end{aligned} \qquad (4.9)$$

where the coefficient of the triple interaction term β_7 is the estimate of interest. The coefficient estimates the difference between two difference-in-differences. Each difference-in-differences estimates the effect on relative flows of having a sustainability feature during the war when separately considering the two investor types in the treatment and control groups. A positive estimate implies greater relative flows as a result of having the sustainability feature during the war for an institutional fund compared to that of a retail fund. Other model specifications such as controls and clustering of standard errors are equivalent to those specified in Equation 4.7

4.2.3 Propensity Score Matching

In order to draw causal inferences from the quasi-experiment outlined above, we rely on the simulation of a randomized controlled trial. Treatment selection in observational studies tends to be influenced by subject characteristics (Austin, 2011). In our case, funds choose their investment strategies and the treatment is therefore not randomly allocated. Consequentially, we risk systematic differences in baseline characteristics of the treated group and the control group which in turn could lead to confounding variables. To address this issue we employ a method of propensity score matching. The propensity score is defined as the probability of treatment assignment conditional on a vector of observable covariates (Rosenbaum and Rubin, 1983). These covariates should be related to the self-selection of the treatment and to the outcome variables of interest (Harris and Horst, 2016). We therefore use the beta coefficients and adjusted R^2 derived from the Fama-French five-factor model in Equation 4.1 in addition to other fund characteristics such as the age of the oldest share class, total expense ratio, investor type, average fund return, average Morningstar overall rating and average total net assets (log) in the pre-period.

In order to estimate the propensity score we use a logistic regression model which is one of the most common estimation methods for the propensity score (Austin, 2011). Once estimated, the propensity scores are used for matching each treated unit with one or several control units that have a similar score. There are numerous matching algorithms, and one of the most commonly used is greedy nearest-neighbour matching (Thoemmes and Kim, 2011). The algorithm gets its name from the procedure which entails sequentially matching a treated unit with the control unit whose propensity score is closest, without considering whether the control unit would be a better match for another treated unit. Other methods such as optimal matching account for this by minimizing the overall distance across all groups (Harris and Horst, 2016). Nevertheless, studies on the efficiency of matching algorithms have found that the resulting balance in baseline covariates is similar for both methods (Austin, 2014). We therefore choose a greedy nearest-neighbour algorithm with a 1:1 matching ratio.

4.2.4 Balance Assessment

In order to evaluate the quality of the matches we assess the balance by performing statistical hypothesis tests on the covariates which is a widely applied practice for balance evaluation (Imai et al., 2008). More precisely, we perform a two-sided t-test to test for statistically significant differences in means for the continuous variables, a two-sample z-test of proportions for the binary variable, and a Wilcoxon rank sum test for the ordinal variable. We then compare the p-values before and after the matching to see if the overall balance was improved. While these tests could provide indications of good balance, we should also recognise that the sample sizes are fairly reduced once we discard the control funds that are not matched to a treated fund. Consequently, the tests have less power to detect imbalances in the covariates (Imai et al., 2008). We therefore also include alternative statistics which do not rely on hypothesis testing for assessing balance. The most common statistic is the standardised mean distance (Zhang et al., 2019) which is calculated as follows for continuous and dichotomous variables respectively:

$$SMD = \frac{\overline{X}_T - \overline{X}_C}{\sqrt{\frac{(S_T^2 + S_C^2)}{2}}} \tag{4.10}$$

$$SMD = \frac{\hat{p}_T - \hat{p}_C}{\sqrt{\frac{\hat{p}_T(1-\hat{p}_T) + \hat{p}_C(1-\hat{p}_C)}{2}}}, \tag{4.11}$$

where $\overline{X}_T$ and $\overline{X}_C$ are the means of the continuous covariate in the treatment and control group respectively, while S_T^2 and S_C^2 are the respective sample variances in the two groups. For the dichotomous variables, $\hat{p}_T$ and $\hat{p}_C$ represent the proportion of the variable in the treatment and control group respectively. A popular feature of the standardised mean difference (SMD) which can be seen from Equation 4.10 and 4.11 is that it is independent of the unit of measurement (Zhang et al., 2019). This is practical as it allows comparison between covariates and facilitates visualisation of overall balance. In addition to SMD, the variance of the covariates in the full and matched sample should also be compared. The variance ratio of the continuous covariates in the treatment and control groups is used for this comparison. A perfectly balanced sample will have SMD values equal to 0 and variance ratios equal to 1. While one should strive to reach such levels, conventional thresholds for adequate balance used in the literature are [-0.1, 0.1] and [0.5, 2] for SMDs and variance ratios respectively (Zhang et al., 2019).

4.2.5 Parallel Trend Assumption

A key prerequisite of the difference-in-differences method is the parallel trend assumption. The assumption posits that the difference in the average outcome between the treated and control groups would remain constant in the absence of the treatment (Marcus and Sant'Anna, 2021). In order to assess the parallel trend assumption we rely on a visual inspection of the movement of the relative flows in the pre-period. Relative flows measured on a weekly basis is a rather volatile measure. In order to better visualise the underlying trends in the data, we therefore use loess regression which is a non-parametric technique often used to visualise trends (Wilke, 2019). For the performance and downside risk measures we only have one observation in the pre-period, making a visual inspection of trends infeasible. Therefore, similarly to (Otero and Reboredo, 2018), we rely on the assumption that the control groups change from the pre-period to the post-period as the treatment groups would have changed had they not possessed the respective features.

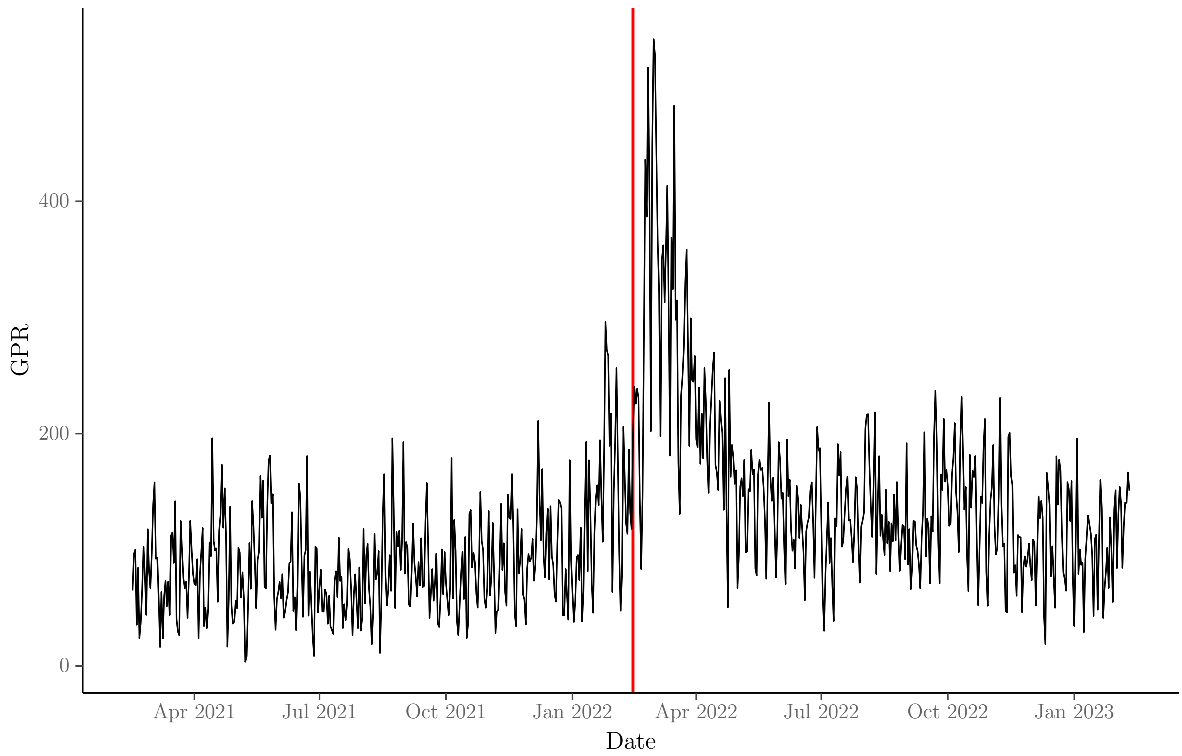
4.2.6 Defining the Treatment Period

The treatment period is defined by the Russian invasion of Ukraine, for which the official date is 24 February 2022. Even though Russian government officials denied any allegations of an impending attack until the day of the invasion, Russian troops were gathering at the Ukrainian border as early as April 2021 (Bielieskov, 2021). This prompts the question of when the Russian-Ukrainian tensions might have substantially affected investors' perception of geopolitical risk.

To address this question, we rely on the geopolitical risk index constructed by Caldara and Iacoviello (2022). The index is based on newspaper coverage of geopolitical tensions, which is an information channel we can reasonably assume investors have access to. Figure 4.1 shows the development of the index for the time period we are considering.

Figure 4.1: Geopolitical Risk Index

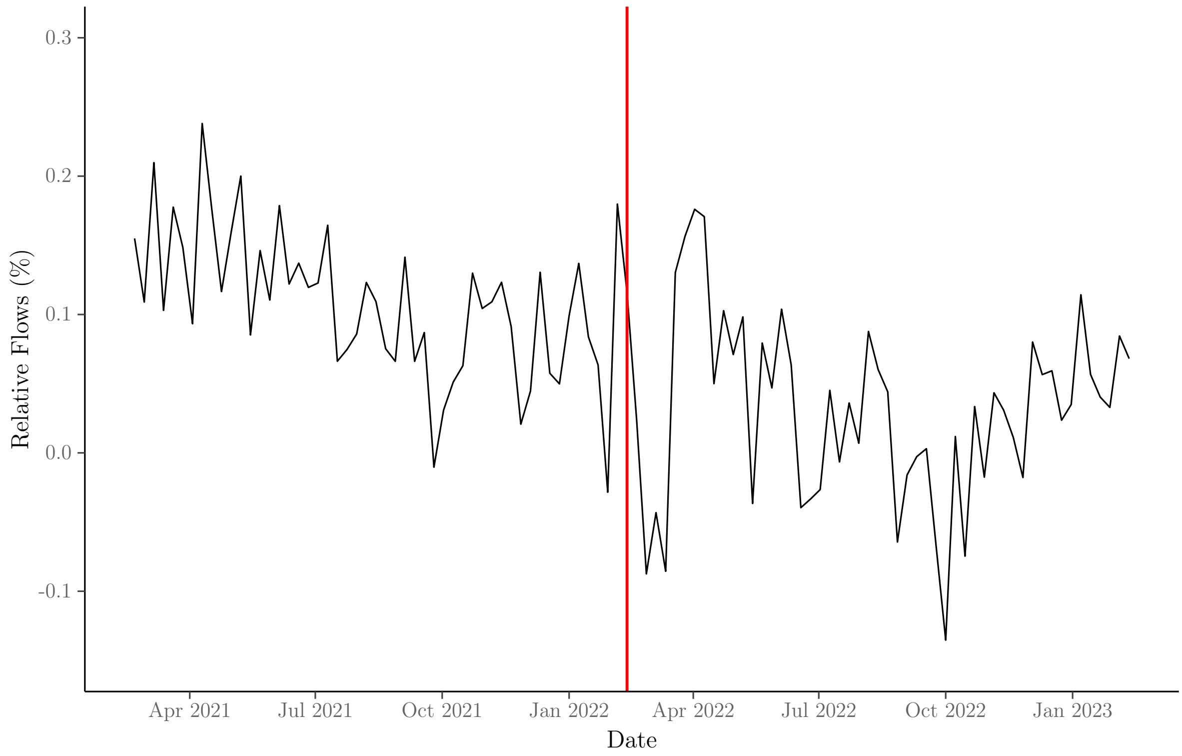
This figure shows the development of the geopolitical risk (GPR) index from February 2021 to February 2023. The red vertical line marks the division between the pre- and post-period.



The most conspicuous change occurs following 21 February 2022, which was the day when Russian President Vladimir Putin recognised the Ukrainian regions of Donetsk and Luhansk as independent states. However, we observe that there is a gradual upward trend starting already in January 2022. The US gradually stepped up their warnings and intelligence sharing, warning that the invasion could happen any day now on 11 February, announcing the evacuation of most of its embassy staff on 12 February (Lee, 2022), and labelling the threat of invasion as very high on 17 February (Dallison and McLeary, 2022). This could entail that investors were already concerned with the outbreak of a potential war which could have impacted their investment decisions before the official date of the invasion. To delve deeper into this, we consider the aggregated relative flow of all funds in our sample as shown in Figure 4.2.

Figure 4.2: Aggregated Relative Flows: All Funds

This figure shows the aggregated relative flows for all funds in the sample. The red vertical line marks the division between the pre- and post-period.



The graph exhibits a sharp decline starting around the first week of February. While the graph displays an alternating pattern and the decline is succeeding a peak, it is of a notably greater magnitude than the preceding fluctuations. In light of these considerations, we define the post-treatment period as all data points including and subsequent to one week prior to the outbreak of the war on 24 February 2022.

4.2.7 Defining Treatment and Control Groups

Through our analysis, we perform several difference-in-differences estimations, and must therefore identify several pairs of treatment and control groups.

We compare a treatment group of high-sustainability funds with a control group of conventional funds. Previous studies have primarily relied on Morningstar Sustainability Ratings to define these groups (Döttling and Kim, 2022; Chen et al., 2022; Pastor and Vorsatz, 2020). We apply a combination of the Morningstar Sustainability Rating and SFDR Articles when defining what constitutes a high sustainability or conventional mutual fund, thereby narrowing the definition as compared to previous studies. The Morningstar Sustainability Rating provides a third-party evaluation of a fund's financially material ESG risk exposure (Nordic Info Team, 2020), whereas SFDR is a self-reported evaluation of the integration of sustainability in the fund's investment strategy (European Parliament, 2019). Additionally, SFDR is an EU regulation, making it more relevant in our study than in comparable ones which have focused on the U.S. market. By combining the two, we arrive at a thorough definition of fund sustainability. We define high sustainability funds as being classed as either four or five on the Morningstar Sustainability Rating, meaning negligible or low ESG risk, and SFDR Article 9, meaning sustainability is a core objective of the fund. We define conventional funds as being classed as one, two or three on the Morningstar Sustainability Rating, meaning medium to severe ESG risk, and SFDR "0-EET", "Not Reported" or "Article 6", meaning having no sustainability scope. We also include funds that do not have a Morningstar Sustainability Rating as long as they fall within one of the SFDR categories.

Next, we compare a treatment group of funds that practice a thematic investment strategy targeted at climate action, with a control group that does not practice this investment strategy. To define these groups we use an indicator variable provided by Morningstar. In particular, the variable refers to investments directed at the transition to a low-carbon economy, renewable energies and climate change mitigation. Additionally, we require that the percentage of assets involved in carbon solutions be less than 10% for mutual funds in the control group. This is done to ensure that funds in the control group are not actively following a similar investment strategy that is not captured by the climate action indicator variable.

Finally, we separately compare treatment groups of mutual funds with fossil fuel exclusion and mutual funds with military contracting exclusion policies with control groups of funds without such policies. Because mutual funds can change their policies, we consider time series of indicator variables for the exclusion policies provided by Morningstar. To avoid cross-contamination between the treatment and control groups we limit the samples to mutual funds that have not changed policy throughout the time period of available data. As a robustness check for the exclusion policy indicator, we verify the degree of involvement related to the industries. Among mutual funds that exclude fossil fuels, we find that some had an average product involvement in fossil fuels of more than a remarkable 50%. We inquired Morningstar on how exactly these measurements are determined and how such a discrepancy can occur. They responded that the logic of the two measurements differs. More precisely, the exclusion indicator can be triggered if the fund "mentions that they exclude fossil fuels in their prospectus/fund-supplement/esg policy/exclusion policy" (Calista D., Morningstar Direct Support, personal communication, 6 April, 2023). On the other hand, the involvement variable is derived from the funds' detailed portfolio holdings. This means that a fund could be categorised as fossil fuel excluding even if it holds a portfolio that has more than 50% exposure to fossil fuels, as long as it reports employing an exclusion policy. By looking at the prospectus of some of the funds in question we find that they are typically funds investing in global infrastructure and the green energy transition. The high exposure to fossil fuels can be explained by a policy that allows the fund to invest in companies with high fossil fuel exposure as long as they provide a credible transition strategy (Nordea Asset Management, 2022). For the validity of the analysis, we need a measure that captures the investor's perception of the fund's policy toward fossil fuels. Different investors might have different perceptions of whether these funds do exclude fossil fuels. Therefore, we find it appropriate to remove funds that report a fossil fuel exclusion policy, yet whose fossil fuel involvement is greater or equal to 10%. We choose 10% as this is a typical bound for exclusion policies (Sandberg and Nilsson, 2015). We do not find similar behaviour for funds that report a military contracting exclusion policy. Therefore, when considering the military contracting exclusion policy, we define the treatment group as funds that have reported military contracting exclusion for the entire period of available data, while the control group consist of funds that have not employed this policy. The same will apply to the fossil fuel exclusion sample with the addition of the requirement of an average fossil fuel involvement of less than 10% in the time period of consideration.

5 Results

The following section first presents an assessment of the matching procedure and the parallel trend assumption before presenting the results from the difference-in-differences estimations with relative flows, the performance measures and the downside risk measures as dependent variables.

5.1 Assessing Balance

As an initial assessment, we assess the balance by considering the statistical hypothesis tests. Tables B.1 to B.4 show the results. When considering the full samples we observe that there are highly significant differences between the groups with respect to several covariates. We further observe that matching removes all statistical significance across all covariates in all feature samples. However, we do find indications of reduced statistical power as a consequence of smaller sample sizes for the matched groups. For instance, in Table B.3 when considering the Fama-French five-factor adjusted R^2, we find that a marginal reduction in the differences in means of 0.008 between the control and treatment group leads to an increase in P-value of 42.8% (51.2% - 8.4%). We should note that this reduction could also be a result of increased sample variance in the matched sample. Yet, if we assume the same variances in the matched sample as those measured in the full samples, this still leads to an increase in p-value of 35.6%. Taking this into account, we consider the balance assessed by p-value with caution and emphasise more on the observed means for which we find a substantial improvement for most covariates across all feature samples.

Finally, we visually inspect the covariate balance with respect to statistics that are not hypothesis tests. Figures B.1 to B.4 show the covariate balance assessed by SMD and variance ratios for the different feature samples. For all samples, we note that matching substantially increases the overall covariate balance with respect to SMD. For the variance ratios, the improvement is less noticeable, yet most covariates are within the thresholds, which is also the case when considering SMD. However, we do observe a particular difficulty with balancing the variance ratio for the SMB factor and the FF5 adjusted R^2.

The overall assessment suggests that we have achieved adequate balance for most covariates.

However, we find some signs of imbalance in the visual inspection of SMD and variance ratios with respect to the style covariates. In Section 5.5 we test the robustness of our findings with other model specifications where alternative style covariates are employed in the matching procedure.

5.2 Assessing Parallel Trends

Figures C.1 to C.4 display the trend developments for the different feature samples and their respective control groups in the pre- and post-period. To assess the parallel trends assumption we consider the trends of the pre-period whose end is marked by the fully-drawn vertical line. We find a similar pattern when considering the high sustainability and climate action samples in Figure C.1 and C.2. While there seems to be a slight deviation in the gradients of the slopes for the first half of the pre-period, the trends look highly similar in the second half. The trends also seem to be fairly parallel when considering the military exclusion policy sample in Figure C.3. Finally, in Figure C.4 we observe the trends in the sample for the fossil fuel exclusion policy. While the trends look adequately parallel at the beginning of the pre-period, the trends seem to diverge to some extent towards the end of 2021 and the beginning of 2022. Collectively for all samples we conclude that while the trends exhibit similar behaviour for the most part, the trends are not perfectly parallel. We address the implications of these results in the limitations section.

5.3 Difference-in-Differences Estimation: Relative Flows

The following sections present the results for the difference-in-differences estimations when considering relative flows as the dependent variable. For each feature sample, we present five regression specifications. Column 1 presents the results for the pooled model specification. Columns 2-4 gradually account for fixed effects by first introducing time fixed effects at the week level and entity fixed effects at the fund level before using both in a two-way fixed effect specification. Finally, column 5 presents the results from the triple difference-in-differences estimation with two-way fixed effects.

5.3.1 High Sustainability Funds and Conventional Funds

Table 5.1 presents the results for the matched sample of high sustainability and conventional funds. The High Sust.×Post interaction term is negative and statistically significant at the 1% level in the pooled specification. Introducing time fixed effects does not significantly affect the results. This suggests that there are few unobserved time-invariant confounders. However, once we control for fund fixed effects the coefficient for the difference-in-differences interaction term is no longer statistically significant. This could imply that the pooled regression estimate is biased as a result of omitted variable bias originating from unobserved heterogeneity across funds. Expectedly, the same is found when accounting for both effects in column 4. Based on these results, we cannot conclude that high sustainability funds had significantly lower relative flows contrary to what they would have had if they had been conventional following the war. Finally, in column 5 we consider the triple difference-in-differences estimation. Although the triple interaction term High Sust.×Institutional×Post is positive and points in the direction of higher relative flows for an institutional high sustainability fund in response to the outbreak of the war, the estimate is not statistically significant.

Furthermore, we find strong evidence that high sustainability funds on average experienced higher relative flows when considering our sample period as a whole, significant at the 1% level. This finding is therefore in line with the strand of literature which indicates that higher sustainability ratings attract higher relative fund flows (Dolvin et al., 2019; Durán-Santomil et al., 2019; Becker et al., 2022). However, we cannot conclude whether this relationship holds true after the outbreak of the war.

5.3.2 Effect of Climate Action-Themed Investment Strategy

Table 5.2 presents the results for the matched sample of funds employing a thematic investment strategy targeted at climate action and their controls. The Climate Action×Post interaction term is negative, though statistically insignificant in the pooled specification. Introducing time fixed effects does not significantly affect the results. Including fund fixed effects largely impacts the results, yielding a positive and statistically significant coefficient for the difference-in-differences interaction term at the 5% level. This coefficient remains statistically significant at the 5% level when we account for both fixed effects in column 4. Based on these results, funds that employ a climate action-themed investment strategy experienced 0.22 percentage points greater relative flows than they would have done had they not employed this strategy during the war. Döttling and Kim (2022) argue that a 0.2 percentage point difference in relative flows measured on weekly intervals is an economically large effect. Given our similar research design, we regard this effect as both statistically and economically significant.

Finally, in column 5 we consider the triple difference-in-differences estimation. Similar to Table 5.1 the triple interaction term Climate Action×Institutional×Post is positive yet statistically insignificant. Therefore there does not appear to be any differences between institutional and retail investors with respect to the impact on relative flows of employing a climate action investment strategy during the war.

5.3.3 Effect of Military Contracting Exclusion Policy

Table 5.3 presents the results for the matched sample of funds excluding military contracting and their controls. The coefficient MC Exclusion×Post is negative and statistically significant at the 1% level in the pooled specification in column 1. Similar to Table 5.1 and Table 5.2 we find that introducing time fixed effects have little impact on the results, while introducing fund fixed effects notably reduces the difference-in-differences coefficient estimate and its significance. However, the coefficient of -0.17 percentage points can be considered economically significant and is still statistically significant at the 5% level even when accounting for both fixed effects in column 4. The findings indicate that funds which exclude military contracting have experienced lower relative flows as a result of employing this policy after the outbreak of the war. Lastly, we find a positive, yet statistically insignificant estimate for the triple interaction term MC Exclusion×Institutional×Post in column 5.

5.3.4 Effect of Fossil Fuel Exclusion Policy

Table 5.4 presents the results for the matched sample of funds excluding fossil fuels and their controls. We find a negative coefficient for the FF Exclusion×Post interaction, significant at the 1% level in the pooled specification. Similar to the results in Tables 5.1 to 5.3 we find that time fixed effects have little impact on the results, while including fund fixed effects significantly impacts the coefficient estimate for the difference-in-differences interaction term. Still, the coefficient of -0.077 percentage points is statistically significant at the 5% level even when accounting for both fixed effects in column 4. While the effect is statistically significant, its economic significance is weaker compared to those in Table 5.2 and Table 5.3. Nonetheless, the effect is not negligible and indicates that funds which excluded fossil fuels experienced lower relative flows in response to the outbreak of the war compared to what they would have done had they not employed this policy. Similarly to the high sustainability, climate action and military exclusion samples, we find a positive yet statistically insignificant coefficient estimate for the triple interaction term FF Exclusion×Institutional×Post in column 5.

5.4 Performance and Downside Risk Evaluation

Table 5.5 shows the results from the regressions described in Equation 4.8. Panel A presents the results for the matched sample of high sustainability and conventional funds. For the traditional risk-adjusted performance measures (alpha and Sharpe ratio) we find that high sustainability funds perform better relative to their conventional peers during the war. This is in line with the previous findings for sustainable funds in periods of crisis by Pastor and Vorsatz (2020) and Becchetti et al. (2015). Conversely, we do not find support for the findings of Hoepner et al. (2022) regarding reduced exposure to downside risk as measured by value at risk. However, when considering the Sortino ratio we observe a statistically significant difference-in-differences estimate at the 1% level implying a greater downside risk-adjusted performance. In summary, these findings suggest that although high sustainability funds do not seem to exhibit superior tail risk in response to the war, they do provide better risk- and downside risk-adjusted performance.

Next, in Panel B we observe the results for the sample of mutual funds that employ a thematic investment strategy targeted at climate action. The results are similar to those exhibited in Panel A when considering the performance measures. We also observe a positive and statistically significant coefficient estimate at the 5% level for the modified value at risk indicating that a climate action-themed investment strategy provided better downside risk protection following the outbreak of the war. Admittedly, the result is not robust when also considering the historical estimates. The overall findings suggest that mutual funds that employed a climate action-themed investment strategy during the war provided better risk- and downside risk-adjusted performance compared to what they would have done had they not employed this strategy. The results are inconclusive when considering downside risk measured by value at risk and statistically insignificant when measured by expected shortfall.

In Panel C we observe the results for the sample with military contracting excluding funds. While the estimates for all measures are negative, none are statistically significant even when considering a less stringent significance level of 10%. Consequently, we can not conclude that funds excluding military contracting during the war in Ukraine performed worse, nor exhibit greater downside risk than they would have done had they not employed this policy. Similar results are found when considering the fossil fuel exclusion in Panel D. We observe positive estimates for alpha, Sharpe- and Sortino ratio, yet none are statistically significant. We further note that the modified VaR and ES estimates are statistically significant at the 10% and 5% levels respectively and could indicate a better tail-risk performance. However, as for the climate action sample, we conclude that these results are inconclusive when also taking the historical estimates into account. Overall, we do not find evidence of statistically significant differences in performance and downside risk for funds employing a military contracting or fossil fuel exclusion policy compared to the counterfactual outcome.

5.5 Robustness Tests

The analysis infers a causal link between the sustainability strategies and a change in relative fund flows, performance and downside risk after the outbreak of the war. However, we must acknowledge the possibility of funds applying one strategy, also applying the other strategies. Furthermore, when considering one strategy there might be an uneven distribution of the other strategies between the treatment and control groups. Consequently, the effect of applying one strategy may in fact influence our analysis of the others and vice versa. To account for the possibility of the effects of one strategy being captured in the analysis of another, we ensure an even distribution of funds employing the other strategies in the treatment and control groups by including these strategies in the matching criteria. Additionally, as noted in Section 3.2 the data set for estimating the coefficients from the Fama-French five-factor model only covers developed markets. Considering that we allow for a broader investment horizon in the fund selection criteria, we risk not adequately capturing the investment style of certain funds. Therefore, we also consider a less nuanced but broader measure for capturing the investment style of the funds. In particular, we use a categorical variable of the Morningstar Style Box (MSB). The Morningstar Style Box is a nine-grid square that categorises investment portfolios based on two dimensions (size and investment style) as shown in Figure D.1. In the following, we present the results when correcting for the other strategies and assess whether these results are robust to our initial findings and to using an alternative investment style for which we have also applied this correction.

When correcting for the other strategies in the climate action sample in Panel A of Table D.1 we find the same directional result for the two-way fixed effect difference-in-differences estimation in column 1 as in Table 5.2. However, the coefficient is reduced from 0.22 to 0.15 percentage points and is only significant at the 10% level. There are no differences with respect to the statistical significance of the triple difference-in-differences coefficient. When considering the sample matched using the Morningstar Style Box in column 2, we observe a similar result as in column 1. We also observe similar directional coefficient estimates for the triple difference-in-differences coefficient in the MSB-matched sample being significant at the 10% level. When considering the performance measures in Panel A of Table D.2, we observe that the initial results in Panel B of Table 5.5 are robust even when correcting for the other strategies and using the alternative benchmark. For the downside risk measure, we find a weakened tendency towards a positive effect on modified value at risk, now only significant at the 10% level with the original benchmark and statistically insignificant when considering the alternative benchmark.

Next, we consider the military contracting exclusion policy. The effect of the policy on relative flows is still significant at the 5% level in the two-way fixed effect specification when accounting for the other strategies in column 1 of Panel B in Table D.1. However, the coefficient is increased to -0.16 percentage points. We find a similar result when matching on MSB in column 2. For the triple interaction term, we now find an effect of 0.3 percentage points significant at the 5% level. However, unlike the original sample, we observe an imbalance with respect to the investor type with there being a higher percentage of institutional investors in the treatment group. We also note that this effect is not present when considering the MSB-matched sample in column 4 for which the proportion of institutional investors in both groups is balanced. When considering the performance and downside risk measures in Panel B of Table D.2 there are no significant differences to the initial results in Panel C of Table 5.5 when correcting for the other strategies regardless of the benchmark.

Finally, we consider the fossil fuel exclusion policy. The coefficient for the effect of the policy on relative flows is practically unchanged with an increase of 0.01 percentage points when comparing the estimate in column 1 of Panel C in Table D.1 to that of column 4 Table 5.4. While the estimate is now only significant at the 10% level, the t-statistics corresponds to a p-value of 5.4%. Furthermore, we see that the effect is greater and still significant at the 5% level when matching on MSB as can be seen in column 2 of Panel C of Table D.1. In the triple-difference-in-differences specification, there are no significant changes for either benchmark when compared to the initial result in column 5 of Table 5.4. When considering the performance measures in Panel C of Table D.2 we find that the coefficient for the Sortino ratio is positive and statistically significant at the 5% level when correcting for the other strategies using the original benchmark in column 1. However, we do not observe any statistical significance for this coefficient when matching on MSB. For the downside risk measures we obtain similar results to the initial findings in Panel D of Table 5.5 when correcting for the other strategies using the original benchmark, yet only modified expected shortfall is significant at the 10% level in the sample matched on MSB. This implies that the proclivity of an improved tail risk for funds excluding fossil fuels is not robust.

Overall these findings suggest that there could be some confounding effects between strategies in our initial results. Correcting for this primarily leads to the same directional findings with somewhat smaller effect sizes. Finally, we find that most results are robust when considering an alternative style benchmark. As a whole, we find our main results to be robust to the alternative model specifications. However, the robustness of the effect of a climate action-themed strategy on relative fund flows decreases but remains significant at the 10% level.

Table 5.1: Impact on Relative Flows: High Sustainability

This table presents the difference-in-differences and triple difference-in-differences estimations in Equation 4.7 and 4.9. The treatment variable is high sustainability (High Sust.) and the dependent variable is relative percentage net flow (Relative Flow). All continuous independent variables have been scaled except for TNA which has been logged.

	Dependent variable:				
	Relative Flow				
	(1)	(2)	(3)	(4)	(5)
High Sust.×Institutional×Post					0.057
					[0.429]
High Sust.×Post	−0.186***	−0.187***	−0.074	−0.077	−0.100
	[−2.708]	[−2.715]	[−1.201]	[−1.236]	[−1.295]
Institutional×Post					−0.198**
					[−2.142]
Post	−0.117**		−0.160***		
	[−2.148]		[−2.865]		
High Sust.	0.294***	0.294***			
	[4.334]	[4.341]			
Institutional	−0.118**	−0.118**			
	[−2.002]	[−1.999]			
1-week lagged return	0.038***	0.053***	0.037***	0.048***	0.048***
	[3.662]	[3.026]	[3.652]	[2.907]	[2.915]
Log(TNA)	−0.012	−0.012	−0.642***	−0.630***	−0.644***
	[−0.914]	[−0.862]	[−6.657]	[−6.450]	[−6.824]
OR ⋆⋆	−0.050	−0.060	0.061	0.046	0.058
	[−0.361]	[−0.437]	[0.765]	[0.588]	[0.767]
OR ⋆⋆⋆	−0.036	−0.040	0.139	0.130	0.148
	[−0.277]	[−0.308]	[1.438]	[1.344]	[1.534]
OR ⋆⋆⋆⋆	0.097	0.091	0.180*	0.172	0.189*
	[0.693]	[0.651]	[1.679]	[1.600]	[1.765]
OR ⋆⋆⋆⋆⋆	0.205	0.200	0.309**	0.302**	0.316***
	[1.411]	[1.386]	[2.520]	[2.474]	[2.605]
Fed Rate	−0.018		−0.054***		
	[−1.038]		[−3.020]		
MSCI Return	0.010		−0.002		
	[0.860]		[−0.161]		
VIX	−0.032**		−0.044***		
	[−2.039]		[−2.740]		
Fund Age	−0.038	−0.038			
	[−1.582]	[−1.604]			
Expense Ratio	0.007	0.007			
	[0.198]	[0.220]			
Constant	0.114				
	[0.765]				
Specification	Pooled	Week FE	Fund FE	Two-way FE	Two-way FE
Interaction	Double	Double	Double	Double	Triple
Observations	21,630	21,630	21,630	21,630	21,630
R^2	0.026	0.013	0.032	0.017	0.018
Adjusted R^2	0.025	0.008	0.022	0.002	0.003

Notes: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

Table 5.2: Impact on Relative Flows: Climate Action

This table presents the difference-in-differences and triple difference-in-differences estimations in Equation 4.7 and 4.9. The treatment variable is climate action and the dependent variable is relative percentage net flow (Relative Flow). All continuous independent variables have been scaled except for TNA which has been logged.

	Dependent variable:				
	Relative Flow				
	(1)	(2)	(3)	(4)	(5)
Climate Action×Institutional×Post					0.086
					[0.356]
Climate Action×Post	−0.004	−0.006	0.214**	0.218**	0.188
	[−0.040]	[−0.058]	[2.052]	[2.083]	[1.628]
Institutional×Post					−0.023
					[−0.136]
Post	−0.011		−0.134		
	[−0.122]		[−1.414]		
Climate Action	0.326***	0.326***			
	[3.682]	[3.687]			
Institutional	−0.154**	−0.154**			
	[−2.334]	[−2.339]			
1-week lagged return	0.019	0.035	0.019	0.031	0.031
	[1.313]	[1.486]	[1.374]	[1.455]	[1.450]
Log(TNA)	−0.005	−0.004	−0.758***	−0.791***	−0.793***
	[−0.331]	[−0.310]	[−3.879]	[−3.990]	[−4.002]
OR ⋆⋆	0.019	0.019	0.110	0.124	0.131
	[0.134]	[0.129]	[0.515]	[0.578]	[0.618]
OR ⋆⋆⋆	−0.002	−0.002	0.180	0.198	0.200
	[−0.018]	[−0.018]	[0.830]	[0.917]	[0.939]
OR ⋆⋆⋆⋆	0.158	0.158	0.216	0.236	0.240
	[1.518]	[1.519]	[0.956]	[1.050]	[1.091]
OR ⋆⋆⋆⋆⋆	0.215*	0.215*	0.414*	0.447*	0.449**
	[1.700]	[1.710]	[1.794]	[1.931]	[1.981]
Fed Rate	−0.058**		−0.089***		
	[−2.171]		[−3.750]		
MSCI Return	−0.010		−0.025		
	[−0.631]		[−1.522]		
VIX	−0.068***		−0.087***		
	[−2.610]		[−3.411]		
Fund Age	−0.015	−0.016			
	[−0.404]	[−0.417]			
Expense Ratio	−0.028	−0.027			
	[−0.800]	[−0.786]			
Constant	−0.092				
	[−0.795]				
Specification	Pooled	Week FE	Fund FE	Two-way FE	Two-way FE
Interaction	Double	Double	Double	Double	Triple
Observations	11,742	11,742	11,742	11,742	11,742
R^2	0.026	0.019	0.025	0.018	0.018
Adjusted R^2	0.025	0.010	0.015	−0.001	−0.001

Notes: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

Table 5.3: Impact on Relative Flows: Military Contracting Exclusion

This table presents the difference-in-differences and triple difference-in-differences estimations in Equation 4.7 and 4.9. The treatment variable is military exclusion policy (MC Exclusion) and the dependent variable is relative percentage net flow (Relative Flow). All continuous independent variables have been scaled except for TNA which has been logged.

	Dependent variable:				
	Relative Flow				
	(1)	(2)	(3)	(4)	(5)
MC Exclusion×Institutional*Post					0.001 [0.005]
MC Exclusion×Post	−0.229*** [−3.192]	−0.229*** [−3.188]	−0.173** [−2.188]	−0.171** [−2.124]	−0.171* [−1.949]
Institutional×Post					0.028 [0.244]
Post	−0.101 [−1.471]		−0.079 [−1.092]		
MC Exclusion	0.243*** [3.729]	0.242*** [3.722]			
Institutional	−0.074 [−1.186]	−0.074 [−1.190]			
1-week lagged return	0.034** [2.208]	0.048* [1.810]	0.034** [2.283]	0.049* [1.878]	0.049* [1.876]
Log(TNA)	0.006 [0.426]	0.006 [0.452]	−0.665*** [−4.556]	−0.684*** [−4.289]	−0.685*** [−4.403]
OR ⋆⋆	−0.180 [−1.104]	−0.179 [−1.087]	0.180* [1.914]	0.187** [2.007]	0.189** [2.075]
OR ⋆⋆⋆	−0.129 [−0.789]	−0.130 [−0.789]	0.253** [2.576]	0.262*** [2.654]	0.262*** [2.780]
OR ⋆⋆⋆⋆	−0.052 [−0.315]	−0.051 [−0.307]	0.332*** [3.259]	0.347*** [3.355]	0.348*** [3.504]
OR ⋆⋆⋆⋆⋆	−0.018 [−0.104]	−0.012 [−0.071]	0.435*** [3.827]	0.453*** [4.020]	0.455*** [4.140]
Fed Rate	−0.015 [−0.632]		−0.038* [−1.676]		
MSCI Return	0.004 [0.355]		−0.008 [−0.651]		
VIX	−0.012 [−0.628]		−0.022 [−1.158]		
Fund Age	−0.070*** [−2.878]	−0.070*** [−2.885]			
Expense Ratio	0.038 [1.312]	0.039 [1.337]			
Constant	0.183 [1.084]				
Specification	Pooled	Week FE	Fund FE	Two-way FE	Two-way FE
Interaction	Double	Double	Double	Double	Triple
Observations	14,420	14,420	14,420	14,420	14,420
R^2	0.024	0.012	0.025	0.012	0.012
Adjusted R^2	0.023	0.005	0.015	−0.005	−0.005

Notes: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

Table 5.4: Impact on Relative Flows: Fossil Fuel Exclusion

This table presents the difference-in-differences and triple difference-in-differences estimations in Equation 4.7 and 4.9. The treatment variable is fossil fuel exclusion policy (FF Exclusion) and the dependent variable is relative percentage net flow (Relative Flow). All continuous independent variables have been scaled except for TNA which has been logged.

	Dependent variable:				
	Relative Flow				
	(1)	(2)	(3)	(4)	(5)
FF Exclusion×Institutional×Post					0.091 [1.168]
FF Exclusion×Post	−0.117*** [−3.100]	−0.118*** [−3.102]	−0.078** [−2.047]	−0.077** [−2.020]	−0.116** [−2.486]
Institutional×Post					−0.130** [−2.280]
Post	−0.106*** [−3.300]		−0.104*** [−3.209]		
FF Exclusion	0.126*** [3.386]	0.126*** [3.386]			
Institutional	−0.072** [−2.005]	−0.072** [−2.003]			
1-week lagged return	0.016** [2.354]	0.020* [1.874]	0.015** [2.335]	0.019* [1.838]	0.019* [1.845]
Log(TNA)	−0.013 [−1.552]	−0.012 [−1.508]	−0.506*** [−10.423]	−0.517*** [−10.016]	−0.526*** [−10.241]
OR ⋆⋆	0.050 [0.500]	0.049 [0.490]	0.222*** [3.844]	0.225*** [3.849]	0.236*** [4.076]
OR ⋆⋆⋆	0.151 [1.550]	0.150 [1.542]	0.382*** [5.394]	0.387*** [5.414]	0.399*** [5.625]
OR ⋆⋆⋆⋆	0.240** [2.467]	0.240** [2.461]	0.501*** [6.598]	0.506*** [6.602]	0.517*** [6.778]
OR ⋆⋆⋆⋆⋆	0.257** [2.567]	0.257** [2.567]	0.583*** [6.773]	0.588*** [6.781]	0.597*** [6.976]
Fed Rate	−0.011 [−0.999]		−0.030*** [−2.634]		
MSCI Return	0.004 [0.654]		−0.005 [−0.767]		
VIX	−0.033*** [−3.259]		−0.041*** [−4.035]		
Fund Age	−0.055*** [−4.536]	−0.056*** [−4.561]			
Expense Ratio	0.037* [1.769]	0.037* [1.787]			
Constant	0.010 [0.097]				
Specification	Pooled	Week FE	Fund FE	Two-way FE	Two-way FE
Interaction	Double	Double	Double	Double	Triple
Observations	55,414	55,414	55,414	55,414	55,414
R^2	0.016	0.007	0.021	0.012	0.012
Adjusted R^2	0.016	0.005	0.011	0.000	0.000

Notes: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

Table 5.5: Performance and Downside Risk Evaluation

This table presents the difference-in-differences estimations in Equation 4.8. Each panel presents seven regressions for each of the dependent variables: Fama-French five-factor (FF5) derived alpha, Sharpe ratio, Sortino ratio and modified (m) and historical (h) value at risk (VaR) and expected shortfall (ES). VaR and ES are internally consistent with the quantile (5%) of the distribution and are thereby given as negative numbers. Positive estimates therefore imply lower downside risk as measured by these variables. Control variables are included in all model specifications.

Panel A: High Sustainability

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
High Sust.×Post	0.116***	0.042***	0.063***	0.016	0.099	0.066	−0.014
	[4.816]	[2.901]	[2.936]	[0.174]	[0.951]	[0.651]	[−0.122]
High Sust.	−0.018	−0.028**	−0.043**	−0.061	−0.134	−0.100	−0.098
	[−1.149]	[−2.032]	[−2.086]	[−0.403]	[−0.859]	[−0.622]	[−0.674]
Post	−0.101***	−0.100***	−0.152***	−1.008***	−0.679***	−1.053***	−0.804***
	[−6.741]	[−9.805]	[−9.878]	[−14.889]	[−8.939]	[−13.477]	[−9.207]
Observations	420	420	420	420	420	420	420
Adjusted R^2	0.111	0.278	0.280	0.248	0.119	0.237	0.187

Panel B: Climate Action

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
Climate Action×Post	0.176***	0.079***	0.118***	0.284**	0.006	0.179	−0.176
	[4.746]	[3.832]	[3.970]	[2.349]	[0.043]	[1.409]	[−1.336]
Climate Action	−0.018	−0.014	−0.027	0.361	0.386*	0.391	0.362*
	[−0.659]	[−0.663]	[−0.911]	[1.485]	[1.710]	[1.583]	[1.858]
Post	−0.055**	−0.071***	−0.109***	−1.046***	−0.566***	−0.948***	−0.524***
	[−1.976]	[−4.739]	[−5.056]	[−11.759]	[−5.642]	[−10.358]	[−5.602]
Observations	228	228	228	228	228	228	228
Adjusted R^2	0.146	0.156	0.164	0.251	0.147	0.224	0.175

Panel C: Military Contracting Exclusion

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
MC Exclusion×Post	−0.012	−0.017	−0.036	−0.021	−0.102	−0.043	−0.136
	[−0.435]	[−0.951]	[−1.241]	[−0.223]	[−0.796]	[−0.387]	[−1.011]
MC Exclusion	−0.001	0.017	0.035	0.377*	0.352*	0.394*	0.341*
	[−0.066]	[0.901]	[1.168]	[1.804]	[1.702]	[1.771]	[1.721]
Post	−0.112***	−0.126***	−0.191***	−1.204***	−0.910***	−1.263***	−1.076***
	[−5.883]	[−10.645]	[−10.198]	[−16.603]	[−9.258]	[−15.987]	[−11.503]
Observations	280	280	280	280	280	280	280
Adjusted R^2	0.181	0.398	0.384	0.268	0.181	0.265	0.268

Panel D: Fossil Fuel Exclusion

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
FF Exclusion×Post	0.008	0.006	0.014	0.096*	−0.013	0.136**	0.084
	[0.492]	[0.708]	[0.934]	[1.861]	[−0.205]	[2.154]	[1.164]
FF Exclusion	−0.005	−0.004	−0.010	0.069	0.057	0.035	0.026
	[−0.473]	[−0.477]	[−0.675]	[0.828]	[0.670]	[0.385]	[0.297]
Post	−0.111***	−0.138***	−0.215***	−1.310***	−0.975***	−1.400***	−1.211***
	[−10.138]	[−22.003]	[−20.778]	[−33.510]	[−20.716]	[−29.588]	[−21.935]
Observations	1,076	1,076	1,076	1,076	1,076	1,076	1,076
Adjusted R^2	0.182	0.427	0.409	0.362	0.240	0.353	0.317

Notes: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

6 Discussion

Following the presentation of our results, we discuss how the results relate to our hypotheses. Seen in context with the existing body of research, we contribute to the understanding of the dynamics of sustainable investing in times of crisis. Contrasting our hypothesis, we do not find evidence of significant differences in relative flows between high sustainability funds and their conventional peers. We do however find a positive effect on relative flows of applying a thematic climate action strategy, in line with our hypothesis. At the same time, we find a negative effect on relative flows from applying a military contracting or fossil fuel exclusion policy during the war, also in line with our hypotheses. In contrast to our hypothesis, we do not find any significant differences between institutional and retail investors with respect to the aforementioned impacts on relative flows during the war. Lastly, we find high sustainability funds and climate action-themed funds to perform better relative to their peers, but we do not find a statistically significant relationship between exclusion strategies and performance, partially supporting our hypothesis that sustainable funds perform better due to the war. On the other hand, we do not find evidence of sustainable funds holding lower exposure to downside risk through our downside risk measures, in contrast to our hypothesis.

Our findings regarding investor preferences are particularly interesting, as the war has caused a shift in public opinion on both the green transition and military contracting, as well as heightened demand for alternative energy sources, both renewable and fossil fuels. Despite this change, we find no statistically significant difference in relative flows to high sustainability funds compared to conventional funds. Our findings therefore contrast the findings of Chen et al. (2022) from the first months of the war and the findings of Döttling and Kim (2022) from the Covid-19 pandemic which both found evidence similar to our original hypothesis. On the other hand, Pastor and Vorsatz (2020) found evidence of greater relative flows to sustainable funds during the Covid-19 pandemic, contrasting our results as well, but in the opposite direction. While Chen et al. (2022) also examined the impact of the war in Ukraine on sustainable mutual funds, our analysis covers a longer time period after the outbreak of the war and looks specifically at European mutual funds which could explain differences in results. As some evidence points towards the green transition in Europe being accelerated by the war in Ukraine, it may be reasonable that investors have not abandoned high sustainability funds, despite increased acceptance of fossil fuels and military spending.

Considering the suggestions that the war may have accelerated the green transition, we examine whether the war has impacted investor preferences for climate action-themed funds. Although the positive effect of this strategy is less robust when considering an alternative style benchmark, the findings indicate that the war has increased investor appetite for funds with a thematic strategy focused on climate action. Interestingly, but perhaps unsurprisingly, the change in investor preferences resembles the shift in the EU energy policy response to the war, which emphasises increased support for the development of renewable energy sources. Naturally, increased government support for the green transition may be one of the causes behind the increased investor preference for climate action-themed funds.

At the same time, we consider the prominent role of military contracting and fossil fuels, as we specifically investigate the war's impact on funds with exclusion policies for these two industries. In line with our hypotheses, we find applying a military contracting or fossil fuel exclusion policy to have a negative effect on fund flows during the war. This suggests that investors have become more accepting of military contracting and fossil fuels after the outbreak of the war, and these results are also robust when controlling for the possibility of funds applying several strategies and when using an alternative style benchmark.

Despite fundamental differences between institutional and retail investors, we do not find statistically significant differences in relative fund flows to high sustainability funds for the two investor groups. The same is true when considering the climate action sample and the two exclusion samples. Our findings therefore contrast our original hypothesis and the findings of Döttling and Kim (2022) which suggest a sharper decline in retail flows during crises. On the other hand, Pastor and Vorsatz (2020) did not find statistically significant differences between the two investor groups with respect to sustainability, which is in line with our findings. Possible mechanisms which may cause our results to deviate from the findings of Döttling and Kim (2022) could be that retail investors have not experienced the same spike in unemployment after the outbreak of the war as compared to the start of the pandemic and that some institutional investors have seen a loosening of investment mandates. Evidently, different effects could pull in opposite directions, meaning we can not claim that the two investor groups' preferences are equally affected by the war. We leave the in-depth exploration of these particular effects for future research.

In line with our hypothesis and similar studies from the Covid-19 pandemic (Fang and Parida, 2022; Tampakoudis et al., 2023), we find high sustainability funds and climate action-themed funds to perform better relative to their peers, as measured by alpha, Sharpe ratio and Sortino ratio. Similar to some previous studies (Nofsinger and Varma, 2013), we find high sustainability funds to underperform relative to their conventional peers when considering the full sample period, yet they outperform them when we introduce the effect of the war. These findings are therefore consistent with the idea that sustainability may be beneficial with respect to performance during crisis periods. A possible explanation for this could be that public support and interest in the green transition has increased demand and thereby particularly increased the profitability of climate action-themed funds. This could in turn be one of the drivers behind the superior performance of high sustainability funds. On the other hand, we do not find a statistically significant relationship between applying either of the exclusion policies and any of the performance measures after the outbreak of the war, in line with the findings of Leite and Cortez (2015). Considering the heightened demand for fossil fuels and military contracting in the short term, it may not be surprising that funds excluding these industries have not outperformed their peers during the crisis.

Contrary to our original hypothesis and several similar studies (Hoepner et al., 2022; Viviani et al., 2019), we do not find evidence of high sustainability funds having lower exposure to downside risk, as measured by value at risk and expected shortfall, during the war. Overall, we find the same to be true for the climate action and both exclusion samples. While the findings contradict our original hypothesis, we see evidence more in line with our expectations when considering a broader definition of downside risk. Firstly, the Sortino ratio may be seen in relation to downside risk, as it considers the downside standard deviation. Secondly, some previous studies (Nofsinger and Varma, 2013) have considered superior returns during market crises as a form of protection against downside risk. Following this definition, we also find high sustainability funds to be better protected against downside risk. Overall, we do not find evidence of a relationship between sustainability and exposure to downside risk during the war, but considering the broader picture, we may argue that investors in high sustainability funds are better protected during the war through higher risk- and downside risk-adjusted returns.

Our findings provide evidence of how the war in Ukraine has impacted sustainability-related preferences, performance and downside risk exposure in the European mutual fund market. While we do not find differences in relative flows between high sustainability and conventional funds, we find evidence of investors increasingly preferring funds focused on the green transition, but also decreased preference for funds excluding military contracting and fossil fuels. Within the high sustainability sample, we may consider the possibility of the positive effect of climate action-themed funds and the negative effects of fossil fuels and military contracting to some degree equalising each other. We cannot conclude that this constitutes a permanent shift in investor preferences, but we argue that it indicates greater support for the green transition, as well as greater investor acceptance for these industries in the shorter term. Simultaneous shifts towards climate action-themed funds and away from fossil fuel-excluding funds can be seen in context with the need to develop alternative energy sources in both the short and long term. In line with similar studies, we find high sustainability funds and climate action-themed funds to outperform their conventional peers during the war. This strengthens the claim that sustainability can be a source of resilience during market crises, even though we do not find evidence of a relationship between sustainability and downside risk. Although it is too early to conclude about the war's long-term implications on sustainable investing and despite the increased acceptance of fossil fuels in the short term, it appears that investors may seize this opportunity to accelerate the green transition through the channelling of funds towards climate action initiatives.

6.1 Limitations

We must acknowledge the limitations of our study and their implications on our ability to answer the research question at hand. The validity of the parallel trend assumption, the accuracy of the preference proxy and the data limitation due to the recency of the invasion are of particular importance. Using a difference-in-differences framework we rely on the critical assumption of parallel trends. As we are not able to assess this assumption when considering the performance and downside risk measures, the causal interpretation might be fallacious if the unobserved counterfactual outcome is not accurately estimated through the control group. However, we are able to make this assessment for relative flows and find that the trends are similar, yet not perfectly parallel. Consequentially, this might draw from the credibility of the results as we cannot assert internal validity with absolute certainty. Having selected this quantitative methodology we use relative flows as a proxy for investor preferences. The accuracy of this proxy relies on the degree to which preferences are expressed through financial behaviour. Furthermore, we acknowledge that flows are not only determined by investor preferences. While we control for most of the well-documented determinants, we are unable to control for other factors that could affect fund flows such as financial constraints at the investor level. This is mainly due to the quantitative inaccessibility of individual financial data for the investors in our sample of European mutual funds and lack of adequate proxies. Finally, limited by the time elapsed since the war, the empirical results are only based on one year's worth of data following its outbreak. Our ability to assess long-term changes in preferences is therefore limited. Considering this we cannot assert if the results are a consequence of permanent changes in sustainability-related investor preferences or merely a pragmatic change in response to a short-term necessity. In light of these limitations, future research might expand on our findings by also considering qualitative methods to better capture preferences and how sustainability-related investment decisions are affected by financial constraints. We also encourage more research on the impact of the war on sustainability-related investor preferences at a later stage when the long-term effects are more inferable.

7 Conclusion

Our evidence indicates that sustainability remains a source of resilience during the war. We find no statistically significant differences in relative fund flows between high sustainability funds and conventional funds in response to the war. Examining specific sustainability strategies, we find that investor preferences for climate action-themed funds have increased, while investor preferences for funds which employ exclusion of military contracting and fossil fuels have decreased after the outbreak of the war. The simultaneously increased preference for climate action-themed funds and acceptance of fossil fuels speaks to the need to secure energy supplies as Europe moves away from Russian oil and gas. Investigating these effects, we find no statistically significant difference in relative fund flows between institutional and retail investors. Furthermore, we find that high sustainability funds and climate action-themed funds perform better relative to their peers during the war, strengthening the claim that sustainability may be beneficial to fund resilience during crises. While we do not find a statistically significant relationship between sustainability and downside risk exposure, we argue that sustainability may provide protection through superior risk- and downside risk-adjusted performance during the war.

Our thesis supports the idea of sustainability as a source of fund resilience, whilst providing interesting evidence on changing investor preferences regarding key sustainability-related themes and exclusion criteria. While investors may have responded to a short-term need by increasingly accepting controversial industries like fossil fuels and military contracting, we see the contours of a turning point in which investors may accelerate the green transition.

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Appendix

A Variable Description

Table A.1: Variable Description

Variable name	Description
Relative Flow	Weekly net flows as a percentage of the ending total net assets of the previous week.
FF5 Alpha	The resulting intercept of regressing each fund's excess return on the five factors of the Fama-French five-factor model.
Sharpe Ratio	Excess return divided by the standard deviation of the excess return.
Sortino Ratio	Excess return divided by downside volatility derived using the €STR as the desired target return.
mVaR	Value at risk estimated using a Cornish-Fisher expansion as proposed by Favre and Galeano (2002) with a 95% confidence level.
hVaR	Value at risk estimated using the empirical quantile method with a 95% confidence level.
mES	Expected shortfall calculated using Boudt et al. (2008)'s modification with a 95% confidence level.
hES	Expected shortfall estimated as the average value of returns given that the value at risk threshold using the empirical quantile method with a 95% confidence level is exceeded.
Post	Indicator variable for the post-treatment period which is defined as all observations including and subsequent to one week prior to the official date of the Russian invasion of Ukraine on 24 February 2022.
Institutional	Indicator variable for institutional funds. A fund is categorised as institutional if either data provider (Morningstar Direct and Refinitiv Eikon) identifies the fund as institutional or the initial investment amount is greater than a $100,000 equivalent.
High Sust.	Indicator variable for high sustainability funds. A fund is categorised as a high sustainability fund if the fund has an SFDR rating of 9 and has had an average Morningstar Sustainability Rating of 4 or 5 during the time period of consideration.
Climate Action	Indicator variable for mutual funds with a thematic investment strategy targeted at climate action.
MC Exclusion	Indicator variable for funds that have reported a military contracting exclusion policy throughout the time period of consideration.
FF Exclusion	Indicator variable for funds that have reported a fossil fuel exclusion policy throughout the time period of consideration and have had an average product involvement in fossil fuels of less than 10%.
1-week lagged return	Percentage return of the fund in the previous week.
TNA	Total net assets at the end of the previous week.
OR ($\star$)	Ordinal variable ranging from 1 to 5 stars indicating Morningstar's overall rating.
Fed Rate	Weekly observations of the Federal Effective Rate.

Continued on next page

Table A.1 Continued from previous page

Variable name	Description
MSCI Return	Weekly return observations of the MSCI World Index (EUR).
VIX	Weekly observations of the CBOE volatility index.
Fund Age	Age of the fund defined as the number of months since the inception date.
Expense Ratio	The total expense ratio of the fund computed as the net asset value-weighted average of the share classes in the fund.
Mkt(β_M)	Coefficient estimate for market risk exposure derived from the Fama-French five-factor model.
SMB(β_s)	Coefficient estimate for the Small Minus Big factor derived from the Fama-French five-factor model.
HML(β_h)	Coefficient estimate for the High Minus Low (value premium) factor derived from the Fama-French five-factor model.
RMW(β_r)	Coefficient estimate for the Robust Minus Weak factor derived from the Fama-French five-factor model.
CMA(β_c)	Coefficient estimate for the Conservative Minus Aggressive factor derived from the Fama-French five-factor model.
FF5 Adj. R^2	Adjusted R^2 from regressing the excess return for each fund on the five factors of Fama-French.
Avg. Return	The fund's average return calculated over each subperiod.

B Balance Assessment

Table B.1: Statistical Hypothesis Tests for Covariate Balance: High Sustainability

This table presents the results of statistical hypothesis tests used to assess the covariate balance when considering high sustainability funds and the control group of conventional funds. For the continuous variables, we use a Welch Two Sample t-test. For the binary variable (Institutional) we use a two-sample test for equality of proportions and for the ordinal variable (OR) we use Wilcoxon rank sum tests. The two last-mentioned tests are conducted using continuity correction and all tests are performed using a two-sided alternative.

Panel A: High Sustainability and Conventional Full Sample

Variable	Conventional	High Sustainability	Statistic	P-value
Mkt(β_M)	0.847	0.934	-5.469***	0.000
SMB(β_s)	0.577	0.328	6.736***	0.000
HML(β_h)	0.001	-0.198	5.493***	0.000
RMW(β_r)	0.013	0.123	-2.720***	0.007
CMA(β_c)	-0.016	-0.124	2.584**	0.011
FF5 Adj. R^2	0.730	0.810	-6.907***	0.000
Avg. Return	0.185	0.051	7.129***	0.000
Log(TNA)	3.937	4.510	-2.978***	0.003
Fund Age	140.008	130.552	1.001	0.319
Expense Ratio	1.489	1.440	0.744	0.458
Institutional	0.335	0.400	1.456	0.228
OR	N/A	N/A	30492.500***	0.001

Panel B: High Sustainability and Conventional Matched Sample

Variable	Conventional	High Sustainability	Statistic	P-value
Mkt(β_M)	0.903	0.934	-1.314	0.190
SMB(β_s)	0.344	0.328	0.237	0.813
HML(β_h)	-0.172	-0.198	0.641	0.522
RMW(β_r)	0.124	0.123	0.025	0.980
CMA(β_c)	-0.081	-0.124	0.769	0.443
FF5 Adj. R^2	0.794	0.810	-0.816	0.416
Avg. Return	0.089	0.051	1.448	0.149
Log(TNA)	4.917	4.510	1.482	0.140
Fund Age	133.705	130.552	0.250	0.803
Expense Ratio	1.380	1.440	-0.660	0.510
Institutional	0.419	0.400	0.020	0.888
OR	N/A	N/A	5785.500	0.519

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.2: Statistical Hypothesis Tests for Covariate Balance: Climate Action

This table presents the results of statistical hypothesis tests used to assess the covariate balance when considering funds that employ a thematic investment strategy targeted at climate action and their control group. For the continuous variables, we use a Welch Two Sample t-test. For the binary variable (Institutional) we use a two-sample test for equality of proportions and for the ordinal variable (OR) we use Wilcoxon rank sum tests. The two last-mentioned tests are conducted using continuity correction and all tests are performed using a two-sided alternative.

Panel A: Climate Action and Control Full Sample

Variable	Control	Climate Action	Statistic	P-value
Mkt(β_M)	0.859	0.985	-6.494***	0.000
SMB(β_s)	0.467	0.423	1.061	0.292
HML(β_h)	-0.029	-0.307	4.652***	0.000
RMW(β_r)	0.074	-0.044	1.667	0.101
CMA(β_c)	-0.053	-0.045	-0.128	0.899
FF5 Adj. R^2	0.754	0.786	-2.209**	0.031
Avg. Return	0.173	-0.017	6.882***	0.000
Log(TNA)	4.145	4.335	-0.728	0.469
Fund Age	130.592	134.772	-0.405	0.687
Expense Ratio	1.418	1.469	-0.709	0.481
Institutional	0.377	0.368	0.000	1.000
OR	N/A	N/A	23049.500***	0.000

Panel B: Climate Action and Control Matched Sample

Variable	Control	Climate Action	Statistic	P-value
Mkt(β_M)	0.995	0.985	0.324	0.747
SMB(β_s)	0.434	0.423	0.098	0.922
HML(β_h)	-0.280	-0.307	0.362	0.718
RMW(β_r)	-0.050	-0.044	-0.061	0.951
CMA(β_c)	-0.164	-0.045	-1.201	0.233
FF5 Adj. R^2	0.788	0.786	0.091	0.928
Avg. Return	-0.012	-0.017	0.097	0.923
Log(TNA)	4.587	4.335	0.683	0.496
Fund Age	110.772	134.772	-1.588	0.115
Expense Ratio	1.360	1.469	-1.035	0.303
Institutional	0.333	0.368	0.039	0.844
OR	N/A	N/A	1710.000	0.597

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.3: Statistical Hypothesis Tests for Covariate Balance: Military Contracting Exclusion

This table presents the results of statistical hypothesis tests used to assess the covariate balance when considering funds that exclude military contracting (MC Exclusion) and their control group. For the continuous variables, we use a Welch Two Sample t-test. For the binary variable (Institutional) we use a two-sample test for equality of proportions and for the ordinal variable (OR) we use Wilcoxon rank sum tests. The two last-mentioned tests are conducted using continuity correction and all tests are performed using a two-sided alternative.

Panel A: Military Contracting Exclusion and Control Full Sample

Variable	Control	MC Exclusion	Statistic	P-value
Mkt(β_M)	0.865	0.908	-2.070**	0.042
SMB(β_s)	0.434	0.442	-0.143	0.887
HML(β_h)	-0.042	-0.101	1.753*	0.084
RMW(β_r)	0.079	0.176	-2.280**	0.025
CMA(β_c)	-0.056	-0.111	1.329	0.188
FF5 Adj. R^2	0.760	0.788	-1.749*	0.084
Avg. Return	0.178	0.159	0.870	0.387
Log(TNA)	4.117	4.842	-2.750***	0.007
Fund Age	131.597	139.371	-0.568	0.572
Expense Ratio	1.399	1.138	3.338***	0.001
Institutional	0.371	0.371	0.000	1.000
OR	N/A	N/A	37123.500***	0.000

Panel B: Military Contracting Exclusion and Control Matched Sample

Variable	Control	MC Exclusion	Statistic	P-value
Mkt(β_M)	0.904	0.908	-0.170	0.865
SMB(β_s)	0.538	0.442	0.910	0.365
HML(β_h)	-0.093	-0.101	0.198	0.843
RMW(β_r)	0.205	0.176	0.488	0.626
CMA(β_c)	-0.138	-0.111	-0.395	0.693
FF5 Adj. R^2	0.768	0.788	-0.658	0.512
Avg. Return	0.136	0.159	-0.747	0.456
Log(TNA)	4.854	4.842	0.036	0.971
Fund Age	155.043	139.371	0.838	0.403
Expense Ratio	1.206	1.138	0.641	0.522
Institutional	0.371	0.371	0.000	1.000
OR	N/A	N/A	2381.000	0.759

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.4: Statistical Hypothesis Tests for Covariate Balance: Fossil Fuel Exclusion

This table presents the results of statistical hypothesis tests used to assess the covariate balance when considering funds that exclude fossil fuel (FF Exclusion) and their control group. For the continuous variables, we use a Welch Two Sample t-test. For the binary variable (Institutional) we use a two-sample test for equality of proportions and for the ordinal variable (OR) we use Wilcoxon rank sum tests. The two last-mentioned tests are conducted using continuity correction and all tests are performed using a two-sided alternative.

Panel A: Fossil Fuel Exclusion and Control Full Sample

Variable	Control	FF Exclusion	Statistic	P-value
Mkt(β_M)	0.857	0.895	-3.468***	0.001
SMB(β_s)	0.455	0.316	5.674***	0.000
HML(β_h)	-0.041	-0.099	3.360***	0.001
RMW(β_r)	0.068	0.181	-5.642***	0.000
CMA(β_c)	-0.047	-0.166	5.389***	0.000
FF5 Adj. R^2	0.754	0.804	-5.873***	0.000
Avg. Return	0.174	0.157	1.476	0.141
Log(TNA)	4.090	4.875	-6.021***	0.000
Fund Age	131.316	141.115	-1.367	0.172
Expense Ratio	1.409	1.189	5.377***	0.000
Institutional	0.372	0.401	0.702	0.402
OR	N/A	N/A	146550.500***	0.000

Panel B: Fossil Fuel Exclusion and Control Matched Sample

Variable	Control	FF Exclusion	Statistic	P-value
Mkt(β_M)	0.884	0.895	-0.785	0.433
SMB(β_s)	0.330	0.316	0.403	0.687
HML(β_h)	-0.104	-0.099	-0.247	0.805
RMW(β_r)	0.185	0.181	0.145	0.885
CMA(β_c)	-0.168	-0.166	-0.079	0.937
FF5 Adj. R^2	0.794	0.804	-0.873	0.383
Avg. Return	0.156	0.157	-0.052	0.958
Log(TNA)	4.824	4.875	-0.311	0.756
Fund Age	133.275	141.115	-0.854	0.393
Expense Ratio	1.153	1.189	-0.688	0.492
Institutional	0.428	0.401	0.276	0.600
OR	N/A	N/A	37161.000	0.567

Note: *p<0.1; **p<0.05; ***p<0.01

Figure B.1: Love Plot: High Sustainability

This figure presents a love plot which displays covariate balance as measured by standardised mean difference (SMD) and variance ratio between high sustainability and conventional funds for the full and matched samples. The fully drawn vertical lines imply perfect balance while the dotted vertical lines illustrate thresholds for adequate balance of [-0.1, 0.1] and [0.5, 2] for SMD and variance ratio respectively.

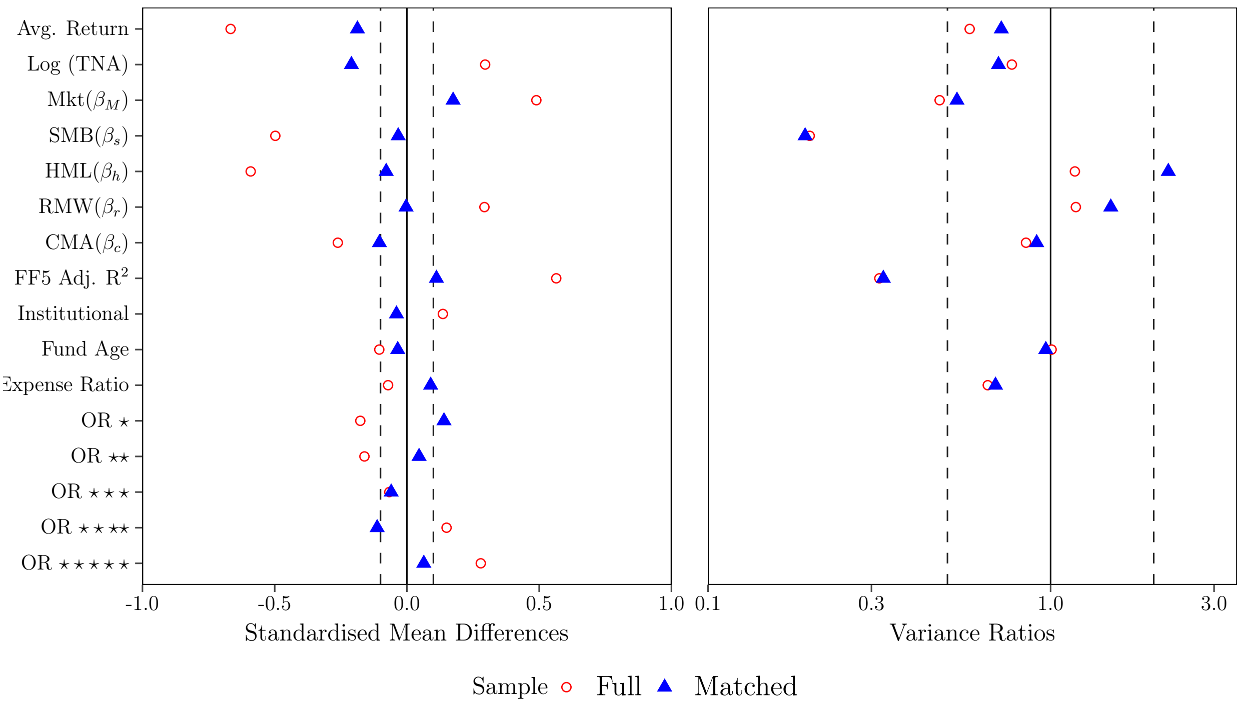


Figure B.2: Love Plot: Climate Action

This figure presents a love plot which displays covariate balance as measured by standardised mean difference (SMD) and variance ratio between funds that employ a thematic investment strategy targeted at climate action and funds that do not employ this strategy for the full and matched samples. The fully drawn vertical lines imply perfect balance while the dotted vertical lines illustrate thresholds for adequate balance of [-0.1, 0.1] and [0.5, 2] for SMD and variance ratio respectively.

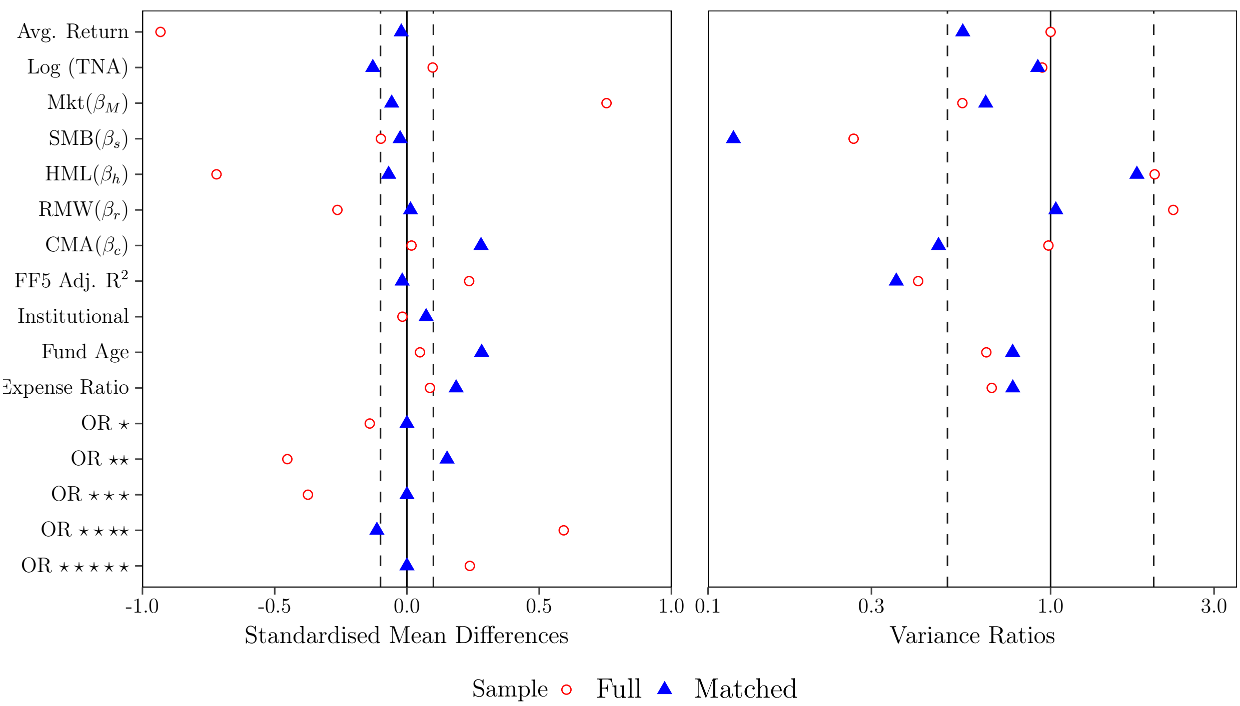


Figure B.3: Love Plot: Military Contracting Exclusion

This figure presents a love plot which displays covariate balance as measured by standardised mean difference (SMD) and variance ratio between funds that exclude military contracting and funds that do not employ this policy for the full and matched samples. The fully drawn vertical lines imply perfect balance while the dotted vertical lines illustrate thresholds for adequate balance of [-0.1, 0.1] and [0.5, 2] for SMD and variance ratio respectively.

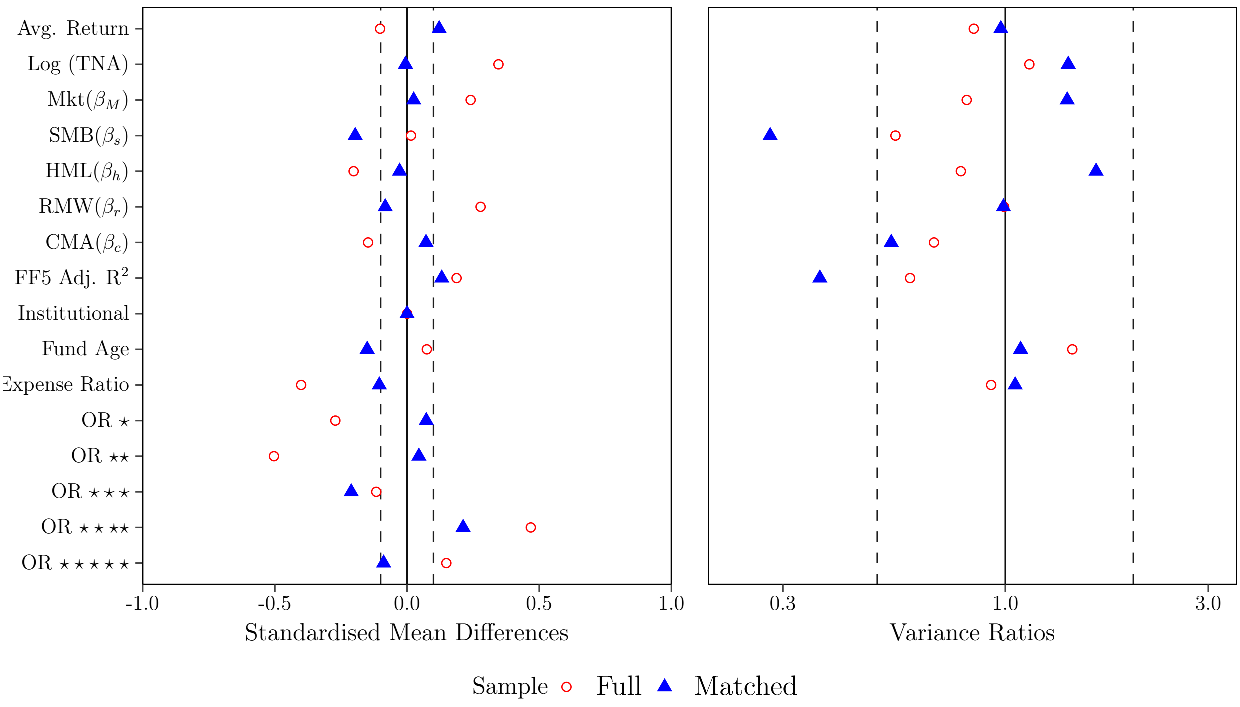
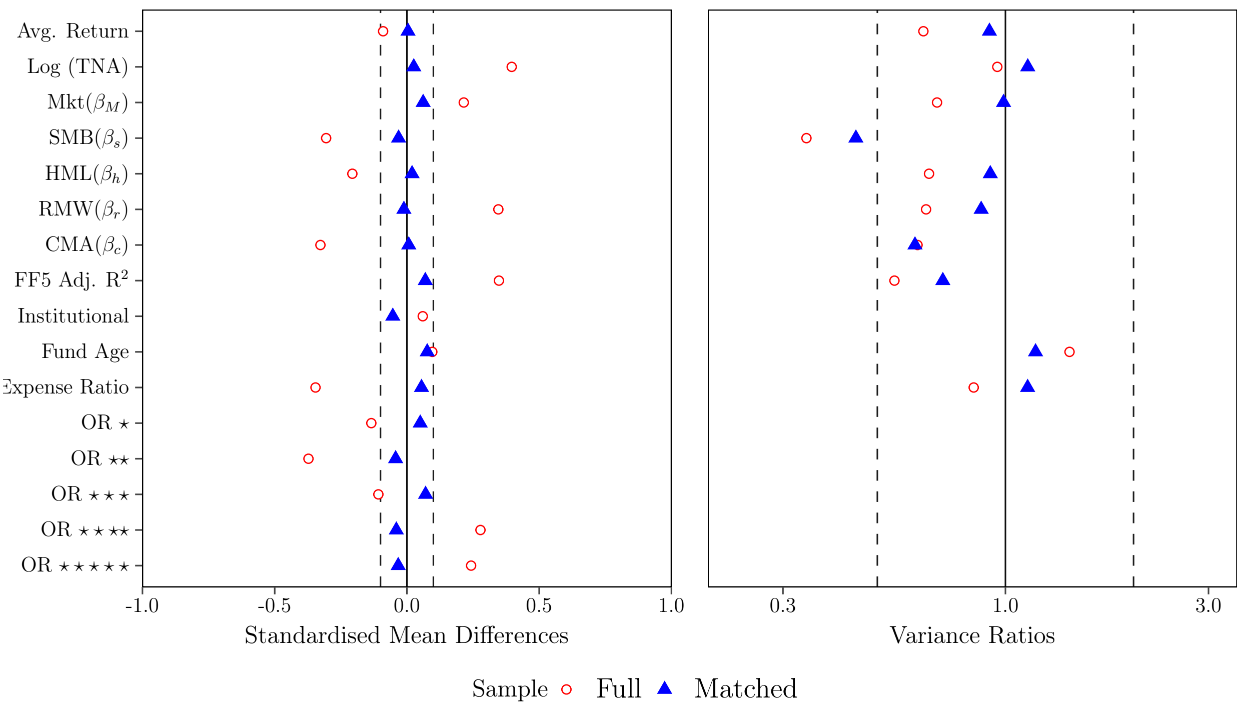


Figure B.4: Love Plot: Fossil Fuel Exclusion

This figure presents a love plot which displays covariate balance as measured by standardised mean difference (SMD) and variance ratio between funds that exclude fossil fuel and funds that do not employ this policy for the full and matched samples. The fully drawn vertical lines imply perfect balance while the dotted vertical lines illustrate thresholds for adequate balance of [-0.1, 0.1] and [0.5, 2] for SMD and variance ratio respectively.



C Parallel Trends

Figure C.1: Trend Development of Relative Flows: High Sustainability

This figure displays the relative flow development for the high sustainability funds and the matched conventional funds. Trends are estimated using loess regression and the grey area represents the confidence level (95%) for the trend line estimation. The fully drawn vertical line marks the division between the pre- and post-period.

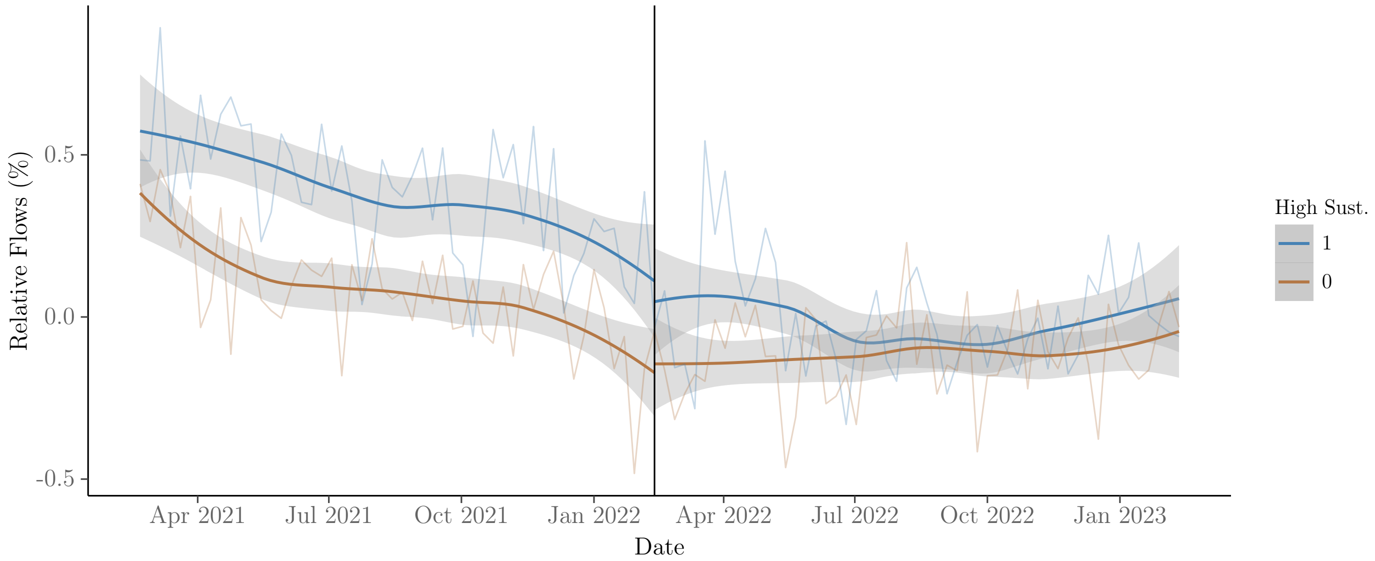


Figure C.2: Trend Development of Relative Flows: Climate Action

This figure displays the relative flow development for funds that employ a thematic investment strategy targeted at climate action and the matched control group. Trends are estimated using loess regression and the grey area represents the confidence level (95%) for the trend line estimation. The fully drawn vertical line marks the division between the pre- and post-period.

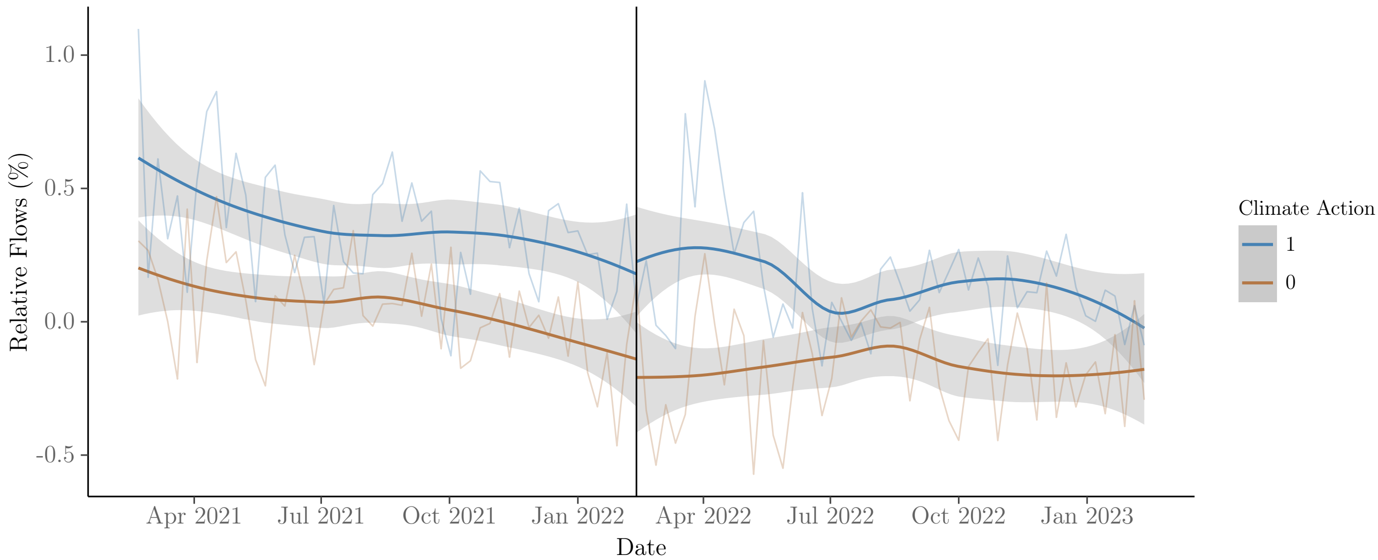


Figure C.3: Trend Development of Relative Flows: Military Contracting Exclusion

This figure displays the relative flow development for funds with a military contracting exclusion policy and the matched control group. Trends are estimated using loess regression and the grey area represents the confidence level (95%) for the trend line estimation. The fully drawn vertical line marks the division between the pre- and post-period.

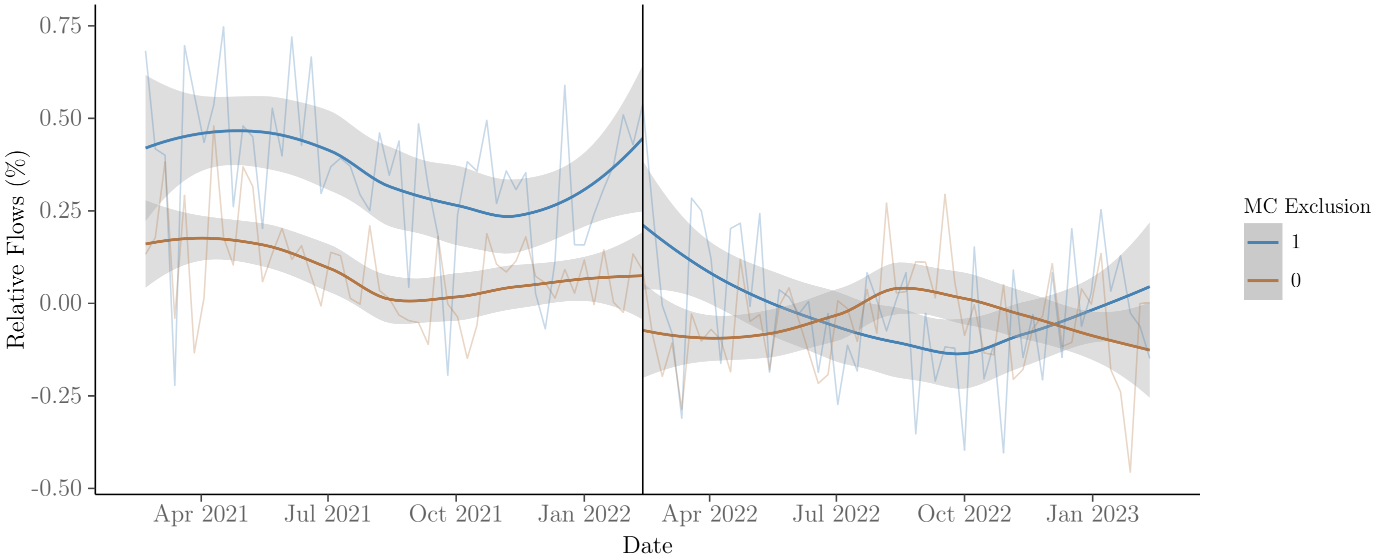
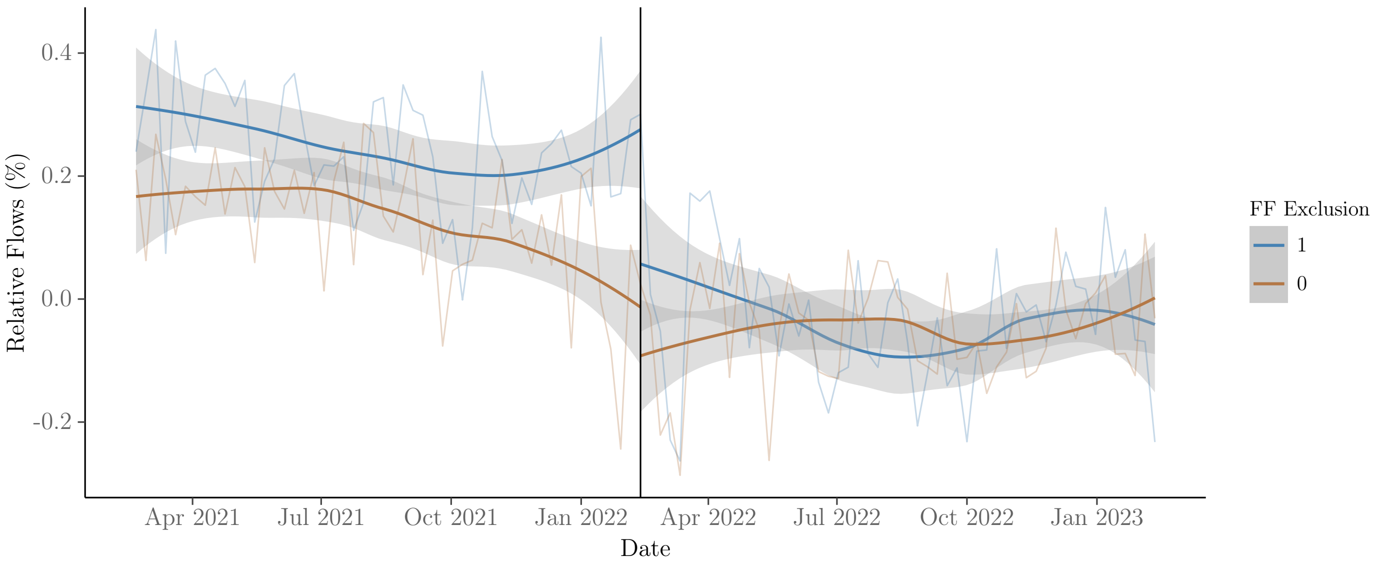


Figure C.4: Trend Development of Relative Flows: Fossil Fuel Exclusion

This figure displays the relative flow development for funds with a fossil fuel exclusion policy and the matched control group. Trends are estimated using loess regression and the grey area represents the confidence level (95%) for the trend line estimation. The fully drawn vertical line marks the division between the pre- and post-period.



D Robustness

Figure D.1: Morningstar Style Box

This figure provides a visual representation of the nine-grid square that makes up the Morningstar Style Box. The vertical axis represents the size category while the horizontal axis represents the investment styles.

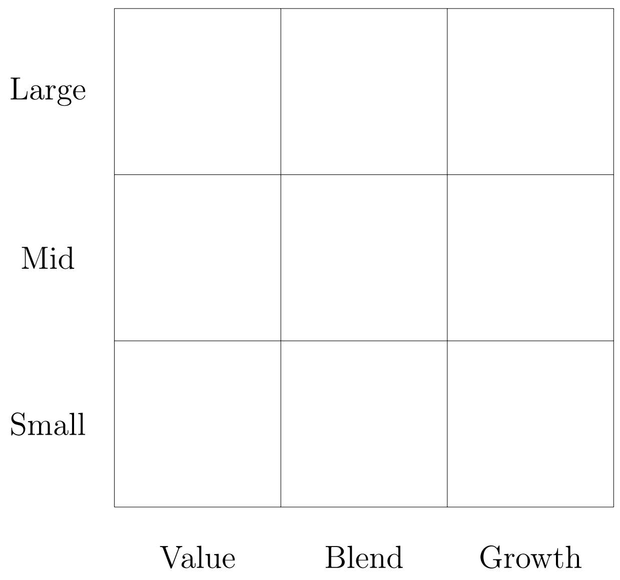


Table D.1: Alternative Style Benchmark: Relative Flows

This table presents the difference-in-differences and triple difference-in-differences estimations in Equation 4.7 and 4.9 using samples matched on Fama-French's five factors (FF5) and the Morningstar Style Box (MSB) while controlling for the other strategies. The panels present the results for each of the three sustainability strategies: climate action, military contracting exclusion and fossil fuel exclusion. All regressions are performed using two-way fixed effects and control variables.

Panel A: Climate Action

	Dependent variable:			
	Relative Flow			
	(1)	(2)	(3)	(4)
Climate Action×Institutional×Post			0.295	0.354*
			[1.474]	[1.707]
Climate Action×Post	0.147*	0.163*	0.044	0.026
	[1.717]	[1.669]	[0.416]	[0.215]
Institutional×Post			−0.239**	−0.303**
			[−2.060]	[−2.517]
Style	FF5	MSB	FF5	MSB
Interaction	Double	Double	Triple	Triple
Observations	11,742	11,742	11,742	11,742
Adjusted R^2	−0.004	−0.005	−0.004	−0.003

Panel B: Military Contracting Exclusion

	Dependent variable:			
	Relative Flow			
	(1)	(2)	(3)	(4)
MC Exclusion×Institutional×Post			0.314**	−0.015
			[2.125]	[−0.097]
MC Exclusion×Post	−0.161**	−0.176**	−0.256***	−0.172*
	[−2.237]	[−2.404]	[−2.965]	[−1.812]
Institutional×Post			−0.288***	0.040
			[−2.879]	[0.407]
Style	FF5	MSB	FF5	MSB
Interaction	Double	Double	Triple	Triple
Observations	14,420	14,420	14,420	14,420
Adjusted R^2	−0.009	−0.006	−0.007	−0.006

Panel C: Fossil Fuel Exclusion

	Dependent variable:			
	Relative Flow			
	(1)	(2)	(3)	(4)
FF Exclusion×Institutional×Post			0.057	0.043
			[0.707]	[0.553]
FF Exclusion×Post	−0.076*	−0.090**	−0.100**	−0.109**
	[−1.925]	[−2.371]	[−2.041]	[−2.266]
Institutional×Post			−0.097	−0.084
			[−1.595]	[−1.497]
Style	FF5	MSB	FF5	MSB
Interaction	Double	Double	Triple	Triple
Observations	55,414	55,414	55,414	55,414
Adjusted R^2	−0.001	0.000	−0.001	0.000

Note: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets

Table D.2: Alternative Style Benchmark: Performance and Downside Risk

This table presents a summary of the difference-in-differences coefficients estimated from Equation 4.8 using samples matched on Fama-French's five factors (FF5) or the Morningstar Style Box (MSB) while controlling for the other strategies. Each panel presents the difference-in-differences coefficients from two independent regressions for each of the performance and downside risk measures as dependent variables. All regressions are performed using control variables.

Panel A: Climate Action

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
Climate Action×Post (MSB)	0.174*** [4.582]	0.047** [2.191]	0.072** [2.331]	0.009 [0.066]	−0.037 [−0.248]	−0.055 [−0.355]	−0.145 [−0.937]
Climate Action×Post (FF5)	0.120*** [3.474]	0.067*** [3.274]	0.102*** [3.422]	0.224* [1.918]	0.062 [0.424]	0.204 [1.616]	−0.126 [−0.952]
Observations	228	228	228	228	228	228	228
Adjusted R^2 (MSB)	0.105	0.110	0.113	0.178	0.100	0.165	0.151
Adjusted R^2 (FF5)	0.170	0.093	0.096	0.164	0.070	0.148	0.107

Panel B: Military Contracting Exclusion

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
MC Exclusion×Post (MSB)	−0.015 [−0.559]	0.003 [0.152]	−0.0001 [−0.004]	0.112 [1.154]	0.127 [1.069]	0.098 [0.815]	0.072 [0.500]
MC Exclusion×Post (FF5)	−0.009 [−0.289]	−0.007 [−0.357]	−0.006 [−0.189]	0.088 [0.842]	0.079 [0.607]	0.119 [0.925]	0.054 [0.365]
Observations	280	280	280	280	280	280	280
Adjusted R^2 (MSB)	0.195	0.416	0.396	0.339	0.272	0.331	0.331
Adjusted R^2 (FF5)	0.186	0.392	0.362	0.347	0.265	0.346	0.339

Panel C: Fossil Fuel Exclusion

	Dependent variable:						
	FF5 Alpha	Sharpe Ratio	Sortino Ratio	mVaR (5%)	hVaR (5%)	mES (5%)	hES (5%)
FF Exclusion×Post (MSB)	−0.009 [−0.558]	−0.005 [−0.491]	0.002 [0.135]	0.086 [1.583]	0.010 [0.154]	0.119* [1.789]	0.079 [1.063]
FF Exclusion×Post (FF5)	0.006 [0.424]	0.014 [1.489]	0.031** [2.005]	0.101* [1.943]	−0.013 [−0.211]	0.140** [2.236]	0.093 [1.296]
Observations	1,076	1,076	1,076	1,076	1,076	1,076	1,076
Adjusted R^2 (MSB)	0.145	0.391	0.374	0.375	0.259	0.363	0.321
Adjusted R^2 (FF5)	0.185	0.428	0.403	0.381	0.254	0.369	0.323

Note: *p<0.1; **p<0.05; ***p<0.01
T-statistics are reported in brackets