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Mutual Funds and Economic Uncertainty

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Mutual Funds and Economic Uncertainty

Abstract

This dissertation entails three essays on mutual funds and economic uncertainty. First, I[1] build on data collected under the EMIR framework to provide new insights into derivatives trading by European equity mutual funds, of which 46% are trading derivatives. Three types of contracts account for 78% of funds' derivatives trades: currency forwards, equity futures, and equity options. I find that the derivatives trading behaviour is related to the fund-family affiliation and the investment strategy. Over time, cash inflows and currency risk seem to have a significant influence. The results suggest that derivatives are used for transaction costs or risk reduction purposes. Second, I analyse how COVID-19-related stringency and economic support measures actually affected the corporate sector using a large international firm-level dataset. I find robust evidence that stringency measures had a statistically and economically significant positive impact on listed firms, that small and employment-intensive companies profited most from economic support measures, and that highly leveraged or even Zombie firms profited more from these support measures than others. Third, I provide new insights into the performance of active mutual funds in times of economic uncertainty. Active funds can increase their performance during crisis periods based on their level of activity. However, this positive performance moderation can only be observed during severe economic turbulence, and the level of fund activity has, in general, a negative impact on fund performance. Nevertheless, the direction changes during crisis periods, where active fund managers can outperform their more passive peers. Finally, the results show that higher cash reserves alone cannot explain the superior performance of active funds during economic turmoil.

[1] While the term "I" is used in the introduction and conclusion of this dissertation, it does not necessarily refer to me directly in these chapters since the first and second essays are the result of collaboration with my co-authors.

Betreuer: Christoph Kaserer Michael Haimann

Offene Investmentfonds und ökonomische Unsicherheit

Kurzfassung

Diese Dissertation umfasst drei Aufsätze über offene Investmentfonds und ökonomische Unsicherheit. Zunächst nutze ich Daten, die im Rahmen der EMIR-Richtlinie erhoben wurden, um neue Erkenntnisse über den Derivatehandel europäischer offener Aktienfonds zu gewinnen, von denen 46% mit Derivaten handeln. Der Derivatehandel der Fonds konzentriert sich zu 78% auf lediglich drei Arten von Finanzinstrumenten. Ich zeige, dass das Derivatehandelsverhalten mit der Zugehörigkeit der Fondsfamilie und der Anlagestrategie zusammenhängt. Im Laufe der Zeit scheinen die Geldflüsse und das Währungsrisiko einen erheblichen Einfluss zu haben. Die Ergebnisse deuten darauf hin, dass Derivate zur Reduzierung von Transaktionskosten oder des Risikos eingesetzt werden. Zweitens analysiere ich anhand eines internationalen Datensatzes, wie sich COVID-19-bezogene Einschränkungen und wirtschaftliche Unterstützungsmaßnahmen tatsächlich auf Unternehmen auswirkten. Ich finde robuste Belege dafür, dass einschränkende Maßnahmen eine signifikante positive Auswirkung auf börsennotierte Unternehmen hatten, dass kleine und beschäftigungsintensive Unternehmen am meisten von wirtschaftlichen Unterstützungsmaßnahmen profitierten und dass Unternehmen mit hohem Fremdkapitalanteil oder sogar Zombie-Unternehmen mehr von Unterstützung profitierten als andere. Drittens liefere ich neue Erkenntnisse über die Rendite aktiver offener Aktienfonds in Zeiten ökonomischer Unsicherheit. Aktive Fonds können ihre Rendite in Krisenzeiten abhängig von ihrem Aktivitätsniveau steigern. Diese positive Moderation kann jedoch nur während schwerer wirtschaftlicher Turbulenzen beobachtet werden, und das Niveau der Fondsaktivität hat im Allgemeinen einen negativen Einfluss auf die Fondsrendite. Allerdings ändert sich die Richtung dieses Effekts in Krisenzeiten. Hier können aktive Fondsmanager ihre passiveren Konkurrenten übertreffen. Schließlich zeigen die Ergebnisse, dass höhere Barreserven allein die überlegene Leistung aktiver Fonds während wirtschaftlicher Turbulenzen nicht erklären können.

Overview

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List of Abbreviations

CBOE	Chicago Board Options Exchange
CD	Contract of difference
CDS	Credit default swap
CFI	Classification of financial instruments
CO	Commodity
COVID-19	Coronavirus Disease 2019
CR	Credit
CU	Currency
DAX	Deutscher Aktienindex
EEA	European Economic Area
EMIR	European Markets Infrastructure Regulation
EQ	Equity
ESMA	European Securities and Markets Authority
ETF	Exchange-traded Fund
EU	European Union
FE	Fixed effect
FR	Forward rate agreement

FU	Future
FW	Forward
G7	Group of Seven
IR	Interest rate
ISIN	International Securities Identification Number
LEI	Legal entity identifier
MOVE	Merrill Lynch Option Volatility Estimate
OECD	Organisation for Economic Co-operation and Development
OP	Option
OT	Others
OTC	Over-the-counter
OVX	Cboe Crude Oil ETF Volatility Index
OxCGRT	Oxford COVID-19 Government Response Tracker
SEC	US Securities and Exchange Commission
SME	Small and medium-sized enterprise
SW	Swap
TR	Trade repository
UCITS	Undertakings for Collective Investments in Transferable Securities
US	United States of America
USD	United States dollar
VIX	CBOE Volatility Index
VSTOXX	EURO STOXX 50® Volatility

Contribution to Essays

Essay 1: Equity Funds and Derivatives: Evidence from Linked Fund-Trade Data

Authors: Daniel Bias, Claudia Guagliano, Martin Haferkorn, Michael Haimann, Christoph Kaserer

Michael Haimann collected all the data, constructed the sample, and conducted all analyses. Daniel Bias, Christoph Kaserer, and Michael Haimann were jointly involved in reviewing the literature, developing the research design, interpreting the results, and preparing and revising the manuscript. Claudia Guagliano and Martin Haferkorn supported in accessing the EMIR data, interpreting the results, and editing the manuscript.

Daniel Bias   Claudia Guagliano   Martin Haferkorn

Michael Haimann   Christoph Kaserer

Essay 2: Cui Bono? Large-scale Evidence on the Impact of COVID-19 Policy Measures on Listed Firms

Authors: Michael Haimann, Christoph Kaserer, Kristian Ljubicic

Michael Haimann and Kristian Ljubicic jointly collected the data. Michael Haimann constructed the sample, developed the research design, and conducted all analyses. Michael Haimann and Christoph Kaserer were both involved in reviewing the literature, discussing the research design, interpreting the empirical analyses, and preparing the manuscript. Michael Haimann, Christoph Kaserer, and Kristian Ljubicic jointly revised the manuscript.

Michael Haimann Christoph Kaserer Kristian Ljubicic

Essay 3: Chaos is a Ladder: Mutual Fund Management in Times of Economic Uncertainty

Authors: Michael Haimann

Michael Haimann reviewed the literature, developed the research design, collected all the data, conducted all analyses, interpreted the results, and prepared and revised the manuscript.

Michael Haimann

I dedicate this dissertation to my family.

Thank you for your unwavering support and love.

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0 Introduction

To this day, mutual funds are time and again controversially discussed not only in academic literature but also by regulators of financial markets. The former is oftentimes puzzled by the sheer existence of the large mutual fund industry due to its arguable underperformance (cf. Pástor and Vorsatz (2020)), while the latter are typically more concerned about the protection of investors, and more specifically, retail investors, to which mutual funds are open. The European Commission has, for instance, just recently released its new retail investment strategy, once again placing mutual funds into focus.[1] Therefore, this dissertation aims to add to the mentioned ongoing debates with new insights. However, it does not solely focus on mutual funds but is also a product of its time. The COVID-19 pandemic, a global crisis with widespread impact across societies and economies, was unprecedented in its extent and gave, amongst others, rise to numerous questions regarding the implications of economic turmoil. Hence, the three essays of this dissertation focus on mutual funds, economic uncertainty, and the combination of both themes.

In the *first essay*, I analyse how mutual funds use derivatives by employing data collected under the European Markets Infrastructure Regulation (EMIR) framework. Of particular interest are the motives of derivatives trading by funds. For instance, if funds use derivatives to hedge their risk in times of uncertainty, that would be less of a concern for regulators aiming to protect retail investors than funds using derivatives for speculative purposes. Picking up on the themes of government policies and economic uncertainty, the *second essay* of this dissertation focuses on COVID-19-related stringency and economic support measures. While restrictive measures undoubtedly harm the economy in the short-term, it is even for those policies an open question whether they, after all, harmed the corporate sector when taking into account long-term consequences. Hence, by assessing

[1] https://finance.ec.europa.eu/publications/retail-investment-strategy_en, last accessed on 9 December 2023.

stock market responses, I gain insights into how governments balanced these short- versus long-term trade-offs. Finally, I address the puzzle in the literature of a large, underperforming mutual fund industry. I do so by picking up the popular argument that active funds perform when it matters most for investors (cf. Kosowski (2011)) and analysing the performance of mutual funds during economic uncertainty based on their level of fund activity.

0.1 Research questions and designs

Each essay employs a specific empirical strategy and dataset to address the research question. I outline these three research designs.

0.1.1 Equity Funds and Derivatives: Evidence from Linked Fund-Trade Data

Following the financial crisis in 2008, derivatives markets and the use of derivatives were put into the spotlight by global regulators. Consequently, various regulatory frameworks, such as EMIR in the European Union (EU), now require derivatives transactions to be reported to the authorities. This increased transparency enables granular analysis of derivatives transactions, leading to a better understanding of the market and making it easier to spot potentially problematic development at an earlier stage. In the EU, the use of derivatives by Undertakings for Collective Investments in Transferable Securities (UCITS) funds is regulated and limited by the UCITS regulatory framework. In addition, derivatives usage by mutual funds was put under supervisory scrutiny also in the US in the aftermath of the financial crisis. With the new rule 18f-4 of the Investment Company Act,[2] the US Securities and Exchange Commission (SEC) put new limitations on derivatives usage by mutual funds. However, this new rule is interestingly based on limited empirical evidence since research on derivatives usage by UCITS funds relies on low-frequency holding or survey data thus far.

[2] https://www.sec.gov/files/rules/final/2020/ic-34084.pdf, last accessed 13 December 2023.

I use a large-scale dataset of derivatives trades that originates from the mandatory reporting of any derivative contract traded in the EU under the EMIR framework, which allows me to sketch the anatomy of derivatives trading by European equity mutual funds, that are, UCITS equity funds.[3] In particular, I assess the types of derivatives traded by European equity funds, their decision to use or refrain from using derivatives, the factors influencing the extent of their derivative activities, and the underlying motives of derivative trading by mutual equity funds.

I link my comprehensive sample of 4,555 European equity UCITS funds with information on derivatives trades in the period from 1 July to 31 December 2016. Doing so, I note that 46% of the European equity funds exercise at least one derivatives trade over this period. Analysing which types of derivatives are traded by European equity funds reveals that three types of contracts account for 78% of the derivatives trades. Forwards on currencies are the most important contract type (51% of trades), followed by futures on equity (17%) and options on equity (10%).

Moving on, I analyse which fund characteristics can explain the decision to trade derivatives and the trading behaviour. I do so by regressing derivatives trading dummies on multiple fund characteristic fixed effects, where the statistic of interest is the R-squared, as it indicates which part of the variation in the funds' decision to trade or in their trading behaviour can be explained by the respective characteristics. Notably, fund family affiliation emerges as the primary determinant for the decision to trade derivatives, while other fund-specific features have limited explanatory power. With regard to the trading behaviour, it turns out that the fund family affiliation and the fund benchmark have strong predictive power for the trading volume and frequency. Hence, I conclude that the trading infrastructure provided by the fund family as well as the predetermined investment strategy, are essential determinants of the trading behaviour.

Concerning the funds' potential motives to trade derivatives, it can be noted that these instruments might be used, among others, to economise on transaction costs, to mitigate risks, or to enhance returns by equity UCITS funds (e.g. Koski and Pontiff, 1999). Hence,

[3] Directive 2009/65/EC of the European Parliament and the European Council defines Undertakings for Collective Investments in Transferable Securities (UCITS), generally speaking, as open-end UCITS funds established in the European Union, cf. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A02009L0065-20140917, last accessed 13 December 2023.

I conduct three tests that exploit the granular information of my dataset to shed light on the underlying motives.

First, aggregating net fund flows on a daily basis and grouping them in 5% quantiles shows a positive (negative) association between the probability of buying (selling) an equity future and the size of the net inflow (outflow). Analogously, I identify a similar pattern for currency forwards. The more inflows funds receive in currencies that are not the base currency, the larger the number of currency forward trades hedging the associated currency risk.

Next, I shift my focus on the role of the time-varying fund and market characteristics for derivatives trading activities by regressing a daily derivatives trading dummy on lagged fund and market characteristics. Consistent with the transaction cost motive, I find the funds' cash flows to be an important and robust trigger for executing a derivative trade. The only market risk variable which appears to have a significant and robust impact on the probability of trading derivatives is the currency risk. Notably, I do not find any significant impact of past performance on the probability of executing a trade.

The final step of my trading motive analyses looks at the interconnection of derivatives usage and the risk-return profile of active derivatives using funds compared to derivatives non-trading funds. Even though the beta of trading funds with respect to the benchmark is slightly higher, these funds have less convexity for high benchmark returns and more convexity for low benchmark returns. Hence, derivatives using funds seem to have less downside risk. Using the kernel density of the risk-adjusted return shows that the risk of derivatives trading funds has a lower probability mass at the tails. These findings align with the risk mitigation motive of trading derivatives. Lastly, I do not find any statistically significant difference in the risk-adjusted returns of derivatives traders and non-traders. This, again, corroborates the presumption that derivatives are used for economising transaction costs.

0.1.2 Cui bono? Large-scale Evidence on the Impact of COVID-19 Policy Measures on Listed Firms

Government policies tackling the COVID-19 crisis are grounded on two major pillars. First, governments implemented contact reductions like stay-at-home policies, school closures, etc. Such measures are often labelled as stringency measures. Second, governments provided economic support either to companies mostly affected by these measures or to citizens directly.

The *second essay* of this dissertation assesses whether, and if so, in which direction these stringency and economic support measures actually affected companies by addressing the following questions. First, did the stringency measures harm the corporate sector? Second, were the massive economic support measures able to offset these potential negative effects? And thirdly, controlling for the exposure of the firms' business model to the pandemic, did companies profit differently from these economic support measures?

While there is no doubt that stringency measures in the short term impose a substantial economic burden, it remains open whether these measures genuinely negatively impact the corporate sector in the long term. Actually, the stock market's response to the COVID-19 outbreak can analytically be split up into a change in dividend expectations, i.e. short- and long-term growth consequences for the corporate sector, as well as in a change in discount rates (cf. e.g. Gormsen and Koijen (2020)). Stricter government policies might hamper economic activity in the short term, but at the same time, they might improve medium- and long-term growth expectations. If the latter outweighs the former, government interventions that might have a high economic cost in the short term could nevertheless be beneficial and, hence, improve the mood on the stock markets. Assessing the trade-off between short-term economic costs and long-term benefits of government policies during the COVID-19 pandemic is an empirical question which this essay addresses by looking at stock market responses.

It is also indisputable that support measures might not have affected the corporate sector in a uniform way. By design, governments focused their interventions on smaller and more employment-intensive firms due to the nature of the crisis. Hence, if measures were effectively chosen, I should observe the strongest effects for those types of companies that entered into financial difficulties due to COVID-19-related business interruptions. However, as support measures were in many cases based on financial ratios realised before or at the very beginning of the crisis for practical reasons, the question arises to what extent firms, which were already in financial difficulties before the crises, i.e. firms with non-viable business models known as Zombie firms, also profited from these government measures.

To address these research questions, I employ a cross-country fixed effect panel regression approach, where the dependent variable is the abnormal daily stock price reaction as measured by the Fama-French 3-factor model or by a Cahart 4-factor model. The sample covers 25 countries, 11,910 companies, and more than four million return observations over the period January 2020 to August 2021. The sample is then linked with the Oxford COVID-19 Government Response Tracker (OxCGRT) (cf. Hale et al. (2021)). To address heterogeneity concerns, this approach is grounded on two pillars . First, by assembling a large cross-country panel dataset, I can analyse the impact of Government measures varying over time. This alleviates potential concerns about the clustering of residuals. Second, as I have a large panel, I can control for a large set of fixed effects and, as a consequence, eliminate effects coming from unobserved variables.

I identify the following answers to the above-mentioned questions. First, I find robust evidence that stringency measures did not only not harm the corporate sector as represented by the universe of listed firms but rather sheltered them from further disruptions. Second, the evidence with respect to economic support measures is less robust. Depending on the set of controls and fixed effects, I find both positive and negative effects on stock prices. Third, smaller, highly levered, and more employment-intensive companies profited most from economic support measures. While these results may be in line with an official policy of sheltering small and medium-sized enterprises (SMEs) and human capital-intensive firms from the Corona shock waves and labour market disruptions, it also seems that Governments unintentionally supported firms in financial difficulties already before the financial crisis. Fourth, the existence of unintended consequences of economic support measures is further corroborated by looking at their impact on Zombie firms, as my results robustly show that these firms benefited more from economic support measures than others.

0.1.3 Chaos is a Ladder: Mutual Fund Management in Times of Economic Uncertainty

To this day, the popularity of active equity mutual funds remains a puzzle (e.g., Pástor and Vorsatz (2020)): On one hand, it is well-established that these funds overall perform worse than passive benchmarks net of fees (cf. among others Jensen (1968), Elton et al. (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), Pástor and Stambaugh (2002), Fama and French (2010)). On the other hand, active equity mutual funds are, despite this underperformance, able to attract vast amounts of assets from investors. This apparent contradiction is usually rationalised with the notion that active fund managers can justify their fees in times of economic uncertainty: Moskowitz (2000) suggested that active mutual funds might be able to provide a partial hedge during recessions. Kosowski (2011) supported this notion by attributing the established inferior performance of US domestic open-end funds only to expansion and not recession periods. Finally, Glode (2011) formulated it into a model according to which fund managers can generate state-dependent active returns.

Interestingly, Pástor and Vorsatz (2020) and Mirza et al. (2020) recently cast doubt on this popular hypothesis. While one would expect superior performance of active funds during the COVID-19 pandemic following the argument of state-dependent active returns, they observe that most active funds failed to deliver. Pástor and Vorsatz (2020) find that active US equity funds, on average, significantly underperformed their benchmarks during this crisis and Mirza et al. (2020) find negative risk-adjusted performance for most types of European mutual funds in the first half of 2020.

This ongoing discussion of mutual fund performance motivates the *third essay* of the dissertation at hand, which aims to reassess whether chaos is genuinely a ladder for active mutual funds or if they fail to justify their cost even in times of economic uncertainty. As opposed to most previous studies, however, I do not define a fund only as active or passive but account for the degree of fund activity. The more granular distinction allows me to assess whether a more substantial deviation from the funds' benchmarks leads to superior performance during economic uncertainty or even vice versa.

The following research questions are addressed. First, do more active equity mutual funds perform better in times of economic uncertainty? Second, is this performance moderation stable over time? Third, do active funds generate higher returns than their more passive counterparts in times of economic uncertainty? Fourth, why do active funds profit from economic turmoil?

The empirical design of this essay follows a fixed effect panel regression approach, with the dependent variable being the monthly fund return, net of fees, and adjusted for benchmark returns. To do so, I build a large international data set of 42,985 active equity mutual funds. The sample period ranges from January 2000 to October 2022, encompassing a comprehensive range of economic states from low volatility periods to major economic crises inducing high levels of economic uncertainty, such as the Global Financial Crisis in 2008 or the COVID-19 pandemic in 2020. In order to assess the performance of active funds during economic turmoil within funds as well as across the fund sample, I conduct moderation analyses interacting the funds' level of activity with the degree of economic uncertainty. The question of whether the performance moderation is stable over time is addressed by splitting the sample into multiple sub-periods and, in another test, classifying each month based on its level of uncertainty. Regarding the question of why active funds profit from economic uncertainty, there are possibly two major mechanisms at work that need to be disentangled. On one hand, a correlation of fund activity with superior performance during economic uncertainty could simply be the result of high and, in crisis periods, beneficial cash holdings, which tend to be also correlated with higher activity measures (cf. Osterhoff and Kaserer (2016)). On the other hand, active fund managers could generate superior returns in economic uncertainty by skillfully adjusting their portfolios, e.g., reducing the share of negatively affected stocks, which would be in line with the model by Glode (2011). I isolate the latter explanation by calculating a cash-adjusted measure of fund activity.

My findings can be summarised as follows. First, more active fund managers can use their skills to generate higher performance during economic uncertainty. Second, this only holds for periods with severe economic turbulence and cannot be observed in more stable phases of the economy. Third, overall fund activity, defined via the tracking error, has a negative impact on performance. However, active managers break even during severe economic uncertainty, where they can generate economically significant superior results. Fourth, the superior performance of active funds during economic crises cannot be explained by higher cash reserves alone.

0.2 Contributions

The three essays of this dissertation expand on various areas of the existing literature. In the following, I briefly summarise their main contributions.

The *first essay* contributes to the literature on derivatives usage by UCITS funds in multiple ways. First, I can complement previous evidence on which types of derivatives equity funds use (e.g., Fong, Gallagher and Ng, 2005; Cao, Ghysels and Hatheway, 2011; Cici and Palacios, 2015; Natter et al., 2016; Benz et al., 2019) by using trade-level data and proving an anatomy of derivatives trading by equity UCITS funds. Second, my results indicate that the propensity and frequency of trading derivatives are, to a large extent, embedded in fund-fixed characteristics. The trading infrastructure provided by the fund family, the predetermined investment strategy, incentive schemes, as well as personal traits of the fund manager may be the underlying economic drivers here. Third, I extend the literature by adding granular evidence on the motives behind derivatives usage. Doing so, my results support the presumption that economising on transaction costs and mitigating risk is a major driver for a fund's decision to trade derivatives.

In the *second essay*, I investigate how COVID-19-related stringency and economic support measures actually affected the corporate sector. Doing so, I expand on the literature in the following ways. First, several studies have documented the severe and unprecedented impact of the Corona outbreak on stock and bond markets (cf. among others Baker et al. (2020), Bannigidadmath et al. (2021), Bretscher et al. (2020), Gormsen and Koijen (2020), Kargar et al. (2021), Ramelli and Wagner (2020)). However, only a small number of studies analysed the impact of Government policy interventions on stock markets or on the corporate sector more generally (e.g., Bannigidadmath et al. (2021), Zaremba et al. (2020)). In this regard, this essay adds further evidence to the interaction of Government crisis responses and stock market reactions. Second, by using a large international firm-level dataset with daily frequency, I am able to identify the relative impact of different levels of government intervention intensities on stock price performance. Third, and even more importantly, I can study the impact of government interventions depending on firm characteristics. To the best of my knowledge, this is the first paper to address the latter question based on such a broad firm-level data set.

The *third essays* contributes to the literature by reassessing the popular yet still controversially discussed hypotheses that the underperformance of active mutual funds is at least to some degree outweighed by their superior performance when it matters most for investors. First, by building a large-scale international data set of active mutual funds entailing multiple significant economic crises as opposed to most studies in this strand of literature only focusing on US domestic funds, I provide new empirical evidence for the relationship between fund activity and performance during economic uncertainty. Second, I employ a granular measure of general economic uncertainty instead of the common simplification of classifying a period only as a recession or expansion period (e.g., Kosowski (2011)). Finally, to the best of my knowledge, I am the first to ask how the degree of a fund's activity influences its performance during economic uncertainty.

0.3 Outline

The remainder of this dissertation is organised as follows. In Chapter 1, I analyse the usage of derivatives by mutual funds by employing data collected under the EMIR framework. Chapter 2 focuses on how COVID-19-related stringency and economic support measures actually affected the corporate sector. By assessing the performance of mutual funds during economic uncertainty based on their level of fund activity in Chapter 3 I address the puzzle in the literature of a large underperforming mutual fund industry. Finally, Chapter 4 summarises the main results and highlights their contributions and implications.

1 Equity Funds and Derivatives: Evidence from Linked Fund-Trade Data

Key words: UCITS Funds, Derivatives Trading, Fund Families, Flows, Risks
JEL Codes: G10, G20, G23

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Note: In this chapter I use the first-person plural narrative.

Abstract

Building on data collected under the EMIR framework, we provide new insight into the types of derivatives that UCITS equity funds trade, why some of them trade derivatives while others do not, what makes some more active traders, and what motives drive derivatives trading. 46% of UCITS equity funds are trading derivatives. Three types of contracts account for 78% of funds' derivatives trades: currency forwards, equity futures, and equity options. We find that the derivatives trading behaviour is related to the fund family affiliation and the investment strategy. Over time, cash inflows, as well as currency risk, seem to have a significant influence. Our results suggest that derivatives are mainly used by UCITS funds for transaction cost or risk mitigation purposes.

1.1 Introduction

After the financial crisis in 2008, global regulators started to shed more light on derivatives markets, including the use of derivatives by market participants. Under various regulatory frameworks (such as EMIR in the EU) derivatives transactions are reported to the authorities, enabling a granular analysis of derivatives transactions, leading to a better understanding of the market and making it easier to spot potentially problematic development at an earlier stage. In the EU, the use of derivatives by UCITS funds is regulated and limited by the UCITS regulatory framework. In the US, in the aftermath of the financial crisis, derivatives usage by mutual funds was put under supervisory scrutiny. With the new rule 18f-4 of the Investment Company Act,[1] the SEC put new limitations on derivatives usage by mutual funds. Notwithstanding the recognised positive effects of these instruments, such as risk mitigation and economising on transaction costs, the SEC was concerned about how these instruments might build up leverage, illiquidity, and counterparty risks. Interestingly, this new rule is grounded on limited empirical evidence since, hitherto, research on derivatives usage by UCITS funds relies on low-frequency holding or survey data.

In this paper, we use a large-scale dataset of derivatives trades that originates from the mandatory reporting of any derivative contract traded in the EU under the European Markets Infrastructure Regulation 648/2012 (EMIR). This allows us to sketch the anatomy of derivatives trading by European equity mutual funds, that are, UCITS equity funds.[2] In detail, we are interested in understanding (i) what types of derivatives are traded by equity funds, (ii) why some of them trade derivatives, while others do not, (iii) what makes some of them more active traders, and (iv) whether derivatives usage is driven by transaction cost, risk management or return enhancing motives. While there is a literature strand that deals with questions (i) and (ii), research on questions (iii) and (iv) is very limited.[3]

[1] https://www.sec.gov/files/rules/final/2020/ic-34084.pdf, last accessed 13 December 2023.
[2] Directive 2009/65/EC of the European Parliament and the European Council defines Undertakings for Collective Investments in Transferable Securities (UCITS), generally speaking, as open-end UCITS funds established in the European Union, cf. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A02009L0065-20140917, last accessed 13 December 2023.
[3] For a detailed review of the relevant literature refer to Section 1.2.

Our comprehensive sample consists of 4,555 European equity UCITS funds. We link these funds with information on derivatives trades in the period from July 1 to December 31, 2016. We find that 46% of the European equity funds exercise at least one derivatives trade over this period. This fraction lies slightly above the finding of Benz et al. (2019) that 40% of US equity funds hold derivatives positions in their portfolio.

We first analyse which types of derivatives are traded by European equity funds. Interestingly, three types of contracts account for 78% of the derivatives trades. Forwards on currencies are the most important contract type (51% of trades) followed by futures on equity (17%) and options on equity (10%). The granular information of our dataset allows us to distinguish long and short trades, which are equally important for currency forwards. However, more than 70% of the future equity trades are long positions, while the equity options are mostly short positions (64% for calls and 57% for puts).

Next, we analyse which fund characteristics can explain the decision to trade derivatives and the trading behaviour. We show that the fund family affiliation is the most important determinant for funds' decision to trade derivatives. Other fund-fixed characteristics, such as the fund family size, the fund's investment area, investment strategy, the base currency, domicile, or size, have only low explanatory power. Among the derivatives trading funds, it turns out that the fund family affiliation and the fund benchmark have strong predictive power for the trading volume and frequency. These results indicate that the trading infrastructure provided by the fund family as well as the predetermined investment strategy are essential determinants for the trading behavior.

Equity UCITS funds can have various motives to trade derivatives, for example, to economise on transaction costs, to mitigate risks, or to enhance returns (e.g., Koski and Pontiff, 1999). To shed light on the underlying motives, we conduct three tests that exploit the granular information of our dataset.

First, aggregating net fund flows on a daily basis and grouping them in 5% quantiles, we find a positive (negative) association between the probability of buying (selling) an equity future and the size of the net inflow (outflow). Taking into account the currency of the net flows and relating them to the fund's base currency, we find a similar pattern for currency forwards. The more inflows funds receive in currencies that are not the base currency, the larger the number of currency forward trades hedging the associated currency risk.

Second, we investigate the role of time-varying fund and market characteristics for derivatives trading activities. Technically, we regress a daily derivatives trading dummy on lagged fund and market characteristics plus fund and day fixed effects. In line with the transaction cost motive, we find the funds' cash flows to be an important and robust trigger for executing a derivative trade. Regarding market risk variables, we only find currency risk to have a significant and robust positive impact on the probability of trading derivatives. The fund's return risk, as well as the tracking error, do not have an impact at all. Also, past performance does not have any impact on the probability of executing a trade. These results also hold in a variety of robustness checks.

Finally, we analyse how derivatives usage is associated with the risk-return profile of active derivatives using funds compared to derivatives non-trading funds. Even though the beta of trading funds with respect to the benchmark is slightly higher, that is, 0.65 as compared to 0.58, these funds have less convexity for high benchmark returns and more convexity for low benchmark returns. Hence, these funds seem to have less downside risk. Using the kernel density of the risk-adjusted return, we indicate that the fund risk has a lower probability mass at the tails. These results are in line with the notion that funds are using derivatives for risk mitigation purposes but not for leverage-increasing or other return-enhancing strategies. Moreover, in terms of risk-adjusted returns, we do not find any statistically significant difference, even though it is higher by 75 basis points per year for derivatives using funds. This, again, is in line with the presumption that derivatives are used for economising on transaction costs.

We contribute to the literature on derivatives usage by UCITS funds in multiple ways. First, by exploiting our daily trade data, we are able to provide an anatomy of derivatives trading by equity UCITS funds. To the best of our knowledge, this is the first paper using trade-level data. Hitherto, the literature had to rely on rather low-frequency reporting data. In this way, we can complement previous evidence on which types of derivatives equity funds use (e.g. Fong, Gallagher and Ng, 2005; Cao, Ghysels and Hatheway, 2011; Cici and Palacios, 2015; Natter et al., 2016; Benz et al., 2019).

Second, our results indicate that the propensity and frequency of trading derivatives are, to a large extent, embedded in fund-fixed characteristics. The trading infrastructure provided by the fund family, that is, the parent investment company, the predetermined investment strategy, incentive schemes, and the personal traits of the fund manager may be the underlying economic drivers here, but not the size, geographic focus, base currency, or domicile of the fund.

Third, we enlarge the literature by adding granular evidence on the motives for derivatives usage. Our results support the presumption that economising on transaction costs and mitigating risk is a major driver for a fund's decision to trade derivatives on any specific day. Due to the lack of granular data, the literature has been scarce on this question so far. In this regard, our results point in the same direction as those presented by Natter et al. (2016) and Benz et al. (2019).

The rest of the paper is organised as follows. In Section 1.2, we provide an overview of the relevant literature. In Section 1.3, we outline our empirical strategy. Section 1.4 describes the linked fund-trade dataset. Section 1.5 presents the results. Finally, Section 1.6 concludes.

1.2 Literature review

As has been already pointed out, there is an existing strand of literature which deals with questions (i) and (ii). However, these papers had to rely on low-frequency reporting data, mainly US data. Evidence at the EU level is much more limited. It is, therefore, interesting to see how the results reported here relate to the results reported in this paper and based on high-frequency trading data.

In general, the likelihood of trading derivatives has been found to be clearly below 20% in most studies focusing on US UCITS funds (cf. Cao, Ghysels and Hatheway, 2011; Cici and Palacios, 2015). This is true even though the vast majority of funds are allowed to use derivatives. For instance, Cao, Ghysels and Hatheway (2011) and Deli and Varma (2002) report that between 65 and 77% of US UCITS funds are allowed to use derivatives. Natter et al. (2016) note that in their sample of US equity UCITS funds, almost 90% are allowed to trade derivatives, but only a tenth of them are actually doing it. Interestingly, Chen (2011) shows that for hedge funds, this likelihood is 71%. In a much broader sample of US UCITS funds, Benz et al. (2019) find that 40% use derivative instruments. While this number is close to our findings, the other numbers reported in the literature are far lower. It could well be that derivatives usage has changed over time, leading to a more substantial fraction of derivatives using funds in more recent studies.

Concerning question (i), that is, what type of derivatives are traded by UCITS funds, it has been shown that they are concentrating their holdings on futures and forwards, mostly in FX underlyings (cf. Cao, Ghysels and Hatheway, 2011; Fong, Gallagher and Ng, 2005). Looking at option usage by equity funds only, Natter et al. (2016) show that there is a strong focus on equity options. Cici and Palacios (2015) report that this comes to a large extent from writing call options. These results are in line with our findings.

Regarding question (ii), that is, the question of what makes a fund to be a derivatives user, our paper is most closely related to Koski and Pontiff (1999). Using survey-based data, they find that about a fifth of equity UCITS funds are using derivatives, and the most important determinants for doing so are affiliation with a large fund family or a high turnover. Turnover is identified as an important determinant also in other studies (cf. Deli and Varma, 2002; Natter et al., 2016) even though Cici and Palacios (2015) do not detect a statistically significant relationship. Whether fund size impacts the likelihood of trading derivatives is less clear. While Johnson and Yu (2004), Cici and Palacios (2015) and Natter et al. (2016) identify fund size as an important determinant, Koski and Pontiff (1999) find no statistically significant relationship and Deli and Varma (2002) even find a negative one.

Assessing the impact of investment styles, Koski and Pontiff (1999) do not find a strong relation, apart from the fact that small-cap and growth funds are below-average derivatives users. Deli and Varma (2002) also confirm the latter result. What seems to be more critical in this regard is whether a fund is focused on specific asset classes, with debt funds being the heaviest derivatives users. Deli and Varma (2002) conclude from this evidence that being a derivatives trading fund is driven by the extent to which derivatives allow for reduction of transaction costs. It fits into this picture that Cao, Ghysels and Hatheway (2011) and Deli and Varma (2002) find funds investing internationally to use more derivatives.

At EU level, Guagliano et al. (2019) analysed the drivers of credit default swaps (CDS) usage by UCITS funds and found that only a limited number of funds use CDS; funds that are part of a large group are more likely to use these instruments; fixed-income funds that invest in less liquid markets, and funds that implement hedge-fund strategies, are particularly likely to rely on CDS; and fund size becomes the main driver of net CDS notional exposures when these exposures are particularly large.

Some papers have investigated the impact of personal characteristics of the fund manager on derivatives usage. For instance, Koski and Pontiff (1999) and Natter et al. (2016) do not find tenure to have an impact, while Cici and Palacios (2015) find a negative one. Inconclusive results have also been reported with respect to age and education levels, while it has also been reported that female fund managers have a lower likelihood to use options (Cici and Palacios, 2015).

Overall, it could be said that our results are in line with the findings in the literature. However, because of our granular daily data, we are able to observe the relative impact of these different variables. This is especially true when it comes to question (iii), that is, why funds are trading a given volume of derivatives on any specific day. This question has not yet been analysed in the literature to the best of our knowledge.

An important question is, of course, to learn more about the motives of why funds are trading derivatives. This is the question (iv) analysed in this paper. In principle, there are three reasons for doing so. First, equity funds might want to economise on transaction costs by using derivatives to build synthetic equity positions. Second, derivatives are helpful for risk management purposes, for instance, concerning currency risk exposure, but also tail risks in equity positions. Third, derivatives could also be used for return-enhancing motives. For instance, equity funds, which typically are not allowed to build up leverage, could be inclined to do so synthetically. Technically speaking, derivatives could be used to increase the delta and gamma risk of a fund. In this way, the fund is building up market risk exposure, it otherwise would not have. This is something regulators are very concerned about.[4] Also, derivatives can be used for betting on specific price movements adding idiosyncratic risk to the fund. Apart from the return risk implications derivatives usage might have, regulators are also concerned about the fact that these contracts could add liquidity or counterparty risk to the funds. The latter should be a minor concern in a European context, as there is a central clearing obligation due to EMIR rules.

[4] A more detailed exposition of regulatory concerns on derivatives usage by UCITS funds can be found in rule 18f-4 under the Investment Company Act; cf. https://www.sec.gov/files/rules/final/2020/ic-34084.pdf, last accessed 13 December 2023.

Since data is not readily available, there have only been a few papers analysing the relationship between a fund's risk profile and its derivatives activities so far. Moreover, it can easily be seen that the analysis of this question suffers from a severe endogeneity problem, as a fund with a higher risk profile might decide right from the beginning to use more derivatives. However, using derivatives will actually reduce its risk profile.

Hence, the literature so far is giving only an indication of the correlation of these two variables, at best. Koski and Pontiff (1999) show that there is no significant difference in the risk levels of derivatives using and non-derivatives using funds. Similar results are also reported by Fong, Gallagher and Ng (2005), Cao, Ghysels and Hatheway (2011), Cici and Palacios (2015), and Natter et al. (2016), while Chen (2011) finds derivatives using hedge funds even to have less risk. Similarly, Natter et al. (2016) show that derivatives using equity UCITS funds have less systematic risk. Moreover, Natter et al. (2016) show that option-using equity funds have higher risk-adjusted returns. They argue that besides transaction costs, this might be caused by hedging strategies implemented using protective puts or covered calls. Guagliano et al. (2019) find that fixed income funds that use credit default swaps tend to be subject to increased tail risk. In a comprehensive analysis of US UCITS funds, Benz et al. (2019) show that exposures coming from derivatives are very small, that is, below one percent of the fund's net asset value. Accordingly, the impact of derivatives on the risk-adjusted fund performance seems to be relatively weak or even statistically not detectable.

1.3 Empirical strategy

1.3.1 Derivatives trading behaviour and fund characteristics

Using trading data from mandatory reporting allows us to observe derivative trading and non-derivative trading equity funds. To provide insights into a fund's general decision to use or not use derivatives, we analyse the role of the fund family and other fund characteristics. According to the results in the literature, we conjecture that the geographic investment focus, as measured by the investment area, the investment strategy, as measured by the benchmark, as well as the fund's size or the size of the fund family, should play an important role. Technically, we regress the derivatives trading fund dummy ($DerivativesFund_i$), that is, a dummy that is set to one if the fund trades derivatives during our sample period on the following fund family and fund-specific fixed effects:

$$\begin{aligned} DerivativesFund_i = \alpha + \lambda_{familysize} + \lambda_{family} + \lambda_{invarea} + \lambda_{currency} + \\ \lambda_{domicile} + \lambda_{benchmark} + \lambda_{size} + \epsilon_i, \end{aligned} \tag{1.1}$$

where i denotes a fund, $\lambda_{familysize}$ denotes fund family-size-decile fixed effects, λ_{family} fund family fixed effects, $\lambda_{invarea}$ investment area fixed effects, $\lambda_{currency}$ base-currency fixed effects, $\lambda_{domicile}$ fund-country fixed effects, $\lambda_{benchmark}$ benchmark fixed effects, and λ_{size} fund-size-decile fixed effects. ϵ_i is the error term. Successively, we add the various fixed effects to the model. The statistic of interest is the adjusted R-squared. It tells us which part of the variation in the funds' decision to use or not use derivatives can be explained by these characteristics.

To analyse the propensity and the extent of a fund's derivative use, we aggregate the trade-level data on the fund-day level and construct two measures for a fund's daily derivative use. The daily derivatives trading dummy ($DTD_{i,t}$) equals one if a fund i makes at least one derivative trade on day t. $notional_{i,t}$ is the natural logarithm of the total notional of a fund's derivatives trades on day t. We use both variables as the dependent variable of the fixed effects approach to identify fund characteristics that can explain the propensity and the extent of funds' daily derivative use. Here, the variation over time allows us also to include fund fixed effects (λ_i). Presumably, the variation of a fund's derivative use over time is also a reaction to time-variant market and fund characteristics. To test which time-varying characteristics matter, we estimate the following linear probability model,

$$DTD_{i,t} = \alpha + \beta x_{i,t-1} + \lambda_t + \lambda_i + \epsilon_{i,t}, \tag{1.2}$$

where the variable of interest is the β on a lagged fund characteristic $x_{i,t-1}$. As fund characteristics x, we follow the literature and test various proxies for fund flows, fund risks, and fund returns. Time-varying fund characteristics are lagged by one day to alleviate simultaneity concerns. All models include day and fund fixed effects. Since our dependent variable is a dummy, we also estimate a logit model as a robustness test.

1.3.2 Derivatives trading behaviour and fund returns

To uncover motives for derivatives trading, we are interested in analysing whether derivatives trading is associated, and if so, in what direction with fund returns. One should bear in mind that this impact can be multifaceted. First, derivatives trading could be used for economising on transaction costs. In this case, risk-adjusted net returns should be positively affected. Second, derivatives could be used to hedge price and currency risk in the underlying portfolio. In this case, the delta risk (volatility) of the fund portfolio should decrease. By using non-linear derivatives, also the gamma risk of the fund, that is, the convexity of the payoff profile, would be reduced. However, derivatives could also be used to increase delta and gamma risk. For instance, by creating synthetic leverage via derivatives positions, the delta risk of the fund would increase. If, again, non-linear derivatives are used, also the gamma risk would increase.

Disentangling these different effects is not an easy task. However, using daily trading data, we are able to propose an approach that allows us to isolate the different impact types of derivatives. For this purpose, we first emphasise that the observed excess return of a fund could be written as follows:

$$r_{i,t} = \alpha_{i,t} r_{mm,t} + \beta_{i,t} r_{b,i,t} + (1 - \alpha_{i,t} - \beta_{i,t})(r_{d,i,t}) + \epsilon_{i,t}. \tag{1.3}$$

The return index i stands for the fund, mm for the money market rate, b for the fund's benchmark, and d for the fund's derivatives position. α and β represent the portfolio weights of the cash and stock position. Subtracting $r_{mm,t}$ from both sides and re-writing gives us

$$r_{i,t} - r_{mm,t} = \beta_{i,t}(r_{b,i,t} - r_{mm,t}) + (1 - \alpha_{i,t} - \beta_{i,t})(r_{d,i,t} - r_{mm,t}) + \epsilon_{i,t}. \tag{1.4}$$

Next, we apply a second-order Taylor approximation to write the return of the derivatives position as follows:

$$r_{d,i,t} - r_{mm,t} \approx \Omega_{i,t}(r_{b,t} - r_{mm,t}) + \Gamma_{i,t}\kappa_{i,t}(r_{b,t} - r_{mm,t})^2 + \nu_{i,t}. \tag{1.5}$$

The Ω and the Γ denote the well-known Greeks of option pricing theory. Ω represents the elasticity of the derivatives' price with respect to the underlying and can be regarded as representing the delta risk. Γ is the second derivative of the derivatives' price and represents the gamma risk of the fund. κ is a scaling factor capturing the non-linearity of the second derivative.

Now, substituting Equation 1.5 into Equation 1.4 and adding a dummy variable d indicating whether on that particular day the fund i had a derivatives position and re-writing, we get:

$$\begin{aligned} r_{i,t} - r_{mm,t} = \beta^0_{i,t} + \beta^1_{i,t} d_{i,t} + (\beta^4_{i,t} + \beta^5_{i,t} d_{i,t})(r_{b,t} - r_{mm,t}) \\ + (\beta^6_{i,t} + \beta^7_{i,t} d_{i,t})(r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t} \end{aligned} \tag{1.6}$$

Moreover, as $\beta^0_{i,t}$ can be considered as the risk-adjusted return, we add the constant $\beta^1_{i,t} d_{i,t}$ in order to infer whether there is any difference in the risk-adjusted return depending on whether the fund trades derivatives or not. Now, Equation 1.6 is estimated in a time-series approach. We use daily observations over one month for each fund and set d equal to one if the fund did at least one derivatives trade over the month. More specifically, the equation then looks as follows:

$$r_{i,t} - r_{mm,t} = \beta^k_i + \beta^m_i (r_{b,t} - r_{mm,t}) + \beta^n_i (r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t} \tag{1.7}$$

We set $k = 0, 1$, $m = 2, 3$, or $n = 4, 5$ depending on whether the fund is a derivatives trader (0, 2, 4) or not (1, 3, 5). This procedure provides us with a monthly estimate of each beta factor for each fund, which makes a total of more than 25,000.[5]. We can then make inferences on the betas and, as a consequence, on the impact of derivatives trading on returns and their distribution.

[5] We estimate the beta factors per month and fund in our sample, i.e. 6 times $4,555$ estimations for each beta factor

Finally, in order to better detect risk management activities going on in the fund, we would allow for a different convexity in the downward and upward case. Therefore, we re-write the preceding equation as follows:

$$\begin{aligned} r_{i,t} - r_{mm,t} = \beta_i^k &+ \beta_i^n (r_{b,t} - r_{mm,t}) \\ &+ \beta_i^p bot_{b,t} (r_{b,t} - r_{mm,t})^2 + \beta_i^q top_{b,t} (r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t} \end{aligned} \tag{1.8}$$

Here, $bot_{b,t}$ is a dummy variable set to one, if the respective benchmark b was among the 25% worst performing benchmarks on day t, and zero otherwise. Similarly, $top_{b,t}$ is a dummy variable set to one, if the respective benchmark b was among the 25% best-performing benchmarks on day t, and zero otherwise.

1.4 Data

1.4.1 Sample construction and fund data

We obtain data on funds from the Morningstar Direct database. The sample construction starts with all open-ended UCITS funds that are classified as equity funds, domiciled in the EU, and have an inception date before or equal to December 31, 2015. Furthermore, we exclude funds with missing information on the ISIN or the primary prospectus benchmark, and funds that have a benchmark inception date after December 31, 2015. Moreover, we obtain the funds' Legal Entity Identifier (LEI) from Bloomberg. We disregard funds with missing LEI since the LEI identifies counterparties in the derivatives trading data. In line with related papers (e.g., Natter et al., 2016), we exclude funds with a net asset value below 5m US dollars to deal with the incubation bias (Evans, 2010). We end up with a comprehensive sample of 4,555 European equity UCITS funds.

1.4.2 Data on derivatives trades

We make use of a proprietary regulatory dataset on derivatives trades that must be reported under Article 9 of the European Market Infrastructure Regulation (EMIR).[6] The EMIR-originated data is provided at different levels of granularity to the authorities. The highest level of granularity is the trade activity data (also referred to as flow data). This data provides various messages to track the life cycle of a derivative transaction. Each message has a particular action type that defines the content and the status of the transaction (e.g. new, modified, canceled/terminated trade).[7]

We obtain the EMIR flow data in the period from July 1 to December 31, 2016. We filter out new transactions, that is, transactions of action type N. The dataset provides a variety of fields to describe the complex universe of derivative transactions. We use information on counterparties, asset class, contract type, counterparty side (buy/sell), and notional amount. For exchange-traded derivatives, the reporting of asset class and contract type is not standardised during our sample period. Therefore, we rely on a methodology developed and tested by the European Securities and Markets Authority (ESMA) to categorise derivatives using a variety of other codes, for example, exchange or Classification of Financial Instruments (CFI) codes. Further, we apply various cleaning steps to filter out unrealistic values.[8]

In the EMIR data, counterparties are identified by the Legal Entity Identifer (LEI). Using information on the LEIs of European equity UCITS funds, we can identify 2,085 of the 4,555 funds in the EMIR data. Hence, 45.8% of the equity funds make at least one derivative trade over our sample period.

1.4.3 Descriptive statistics of sample

Our sample of derivatives trading funds has 271,585 fund-day observations of 2,085 distinct funds in the period from July 1 to December 31, 2016. Each of these funds makes at least

[6] Regulation (EU) No 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories; cf. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32012R0648, last accessed 13 December 2023.

[7] A more detailed description of EMIR data reporting and aggregation can be found in Appendix B.

[8] A detailed description of all EMIR variables can be found in Commission Implementing Regulation (EU) 2017/105 published on October, 19, 2016; cf. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.L_.2017.017.01.0017.01.ENG&toc=OJ:L:2017:017:TOC, last accessed 13 December 2023.

one derivative trade during our sample period. We construct three measures to aggregate a fund's trades on a fund-day level. These are a derivatives trading dummy that indicates whether a fund trades on a certain day, the number of trades per day, and the traded notional per day. A detailed definition of all variables can be found in Appendix A. 1. It should be noted that all variables are winsorised at the 1% and 99% level.

Table 1.1
Summary statistics of funds

This table presents summary statistics of derivatives trading funds in Panel A and non-trading funds in Panel B. Reported are the number of observations (N), mean value (Mean), standard deviation (SD), 25% percentile (p25), median (p50) and 75% percentile (p75). There are 2,085 derivatives trading funds and 2,470 derivatives non-trading funds. A detailed description of all variables can be found in Table A. 1.

	N	Mean	SD	p25	p50	p75
Panel A: Derivatives trading funds						
derivatives trading dummy	271,585	0.3950	0.4889	0.0000	0.0000	1.0000
#trades	271,585	2.3301	10.3928	0.0000	0.0000	2.0000
traded notional	271,585	5.2311	6.7786	0.0000	0.0000	12.3664
fund size	231,274	457.26	776.79	55.23	162.99	478.63
family size	271,585	14.78	14.18	4.00	10.00	22.00
net flow	247,336	0.0084	0.0188	0.0005	0.0022	0.0072
pos. net flow	247,336	0.0048	0.0122	0.0000	0.0006	0.0035
neg. net flow	247,336	0.0051	0.0119	0.0001	0.0012	0.0043
return	271,585	0.0051	0.0356	-0.0171	0.0060	0.0299
return-benchmark	244,406	-0.0076	0.0262	-0.0195	-0.0037	0.0069
return-family	271,585	0.0006	0.0250	-0.0117	0.0000	0.0133
fund risk	270,578	0.0095	0.0056	0.0065	0.0080	0.0104
tracking error	244,406	0.0078	0.0061	0.0041	0.0062	0.0098
currency risk	198,975	0.0019	0.0025	0.0000	0.0004	0.0035
Panel B: Derivatives non-trading funds						
fund size	253,386	243.33	465.60	31.10	88.79	240.72
family size	298,292	11.56	12.61	3.00	8.00	15.00
net flow	273,373	0.0068	0.0167	0.0002	0.0015	0.0053
pos. net flow	273,373	0.0040	0.0107	0.0000	0.0004	0.0025
neg. net flow	273,373	0.0041	0.0105	0.0001	0.0008	0.0031
return	298,292	0.0035	0.0388	-0.0200	0.0050	0.0309
return-benchmark	259,134	-0.0087	0.0281	-0.0218	-0.0049	0.0074
return-family	298,292	-0.0003	0.0260	-0.0125	0.0000	0.0127
fund risk	297,480	0.0099	0.0060	0.0067	0.0082	0.0105
tracking error	259,134	0.0085	0.0063	0.0046	0.0071	0.0106
currency risk	212,699	0.0017	0.0025	0.0000	0.0000	0.0036

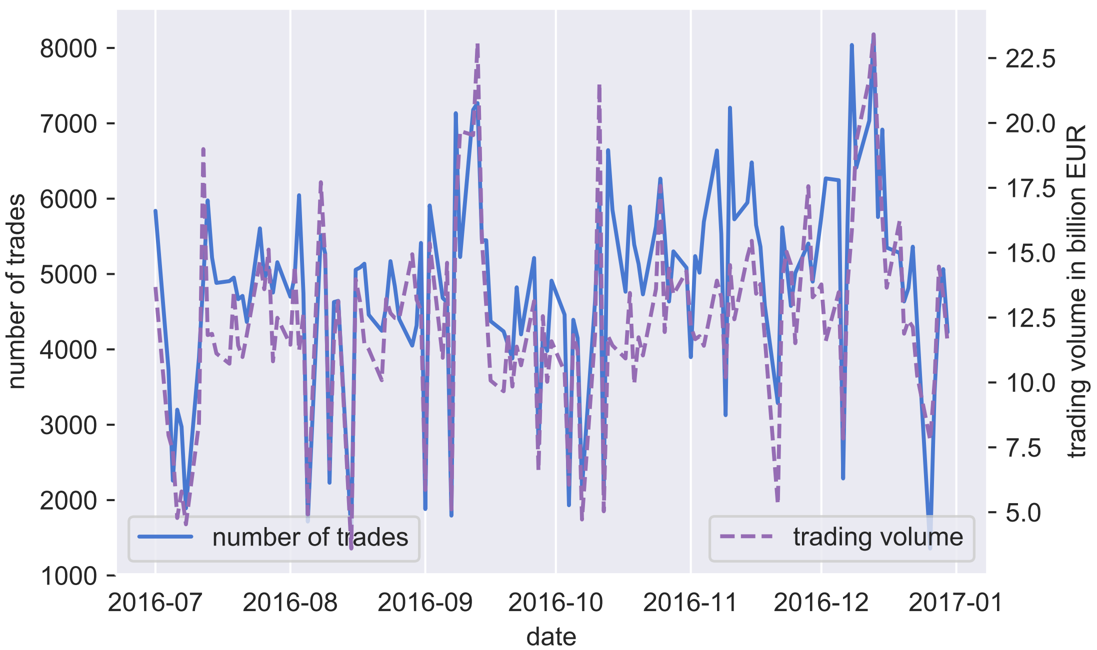
Descriptive statistics of the derivatives trading funds are given in Panel A of Table 1.1. The average fund trades on 40% of the days and makes about 2.3 trades per day. The average (median) derivatives trading fund has a net asset value of approx. USD 457m

(163m) and belongs to a fund family with a total of 15 (10) funds. The characteristics of the 2,470 non-trading funds in our sample can be found in Panel B of Table 1.1. Non-trading funds tend to be smaller, to belong to smaller fund-families, and to have slightly higher return volatility and tracking errors.

1.5 Derivatives trading of equity funds

1.5.1 Which types of derivatives are traded by equity funds?

Figure 1.1
Number of derivatives trades and trading volume per day
This figure illustrates the number of derivatives trades per day and the trading volume per day over our sample period, which ranges from July 1 to December 31, 2016. The notional of a trade is winsorised at the 1% and 99%-level.



The trade-level data allows us to identify possible trading patterns over time and to shed light on underlying asset classes and derivative types used. In the period from July 1 to December 31, 2016, the 2,085 funds executed 627,895 trades. Figure 1.1 illustrates the number of trades and the trading volume per day over our sample period. As expected, the number of trades and the trading volume are highly correlated. We do not observe any time trend or other systematic trading patterns in funds' daily trading activities.

Table 1.2
Which types of derivatives are traded by equity funds?

This table presents the relative distribution of trades across underlying asset classes (rows) and derivative types (columns). CO denotes commodity, CR credit, CU currency, EQ equity, IR interest rate, OT others, and UNDEF undefined asset class. CD denotes contracts for difference, FR forward rate agreement, FU futures, FW forwards, OP options, OT other, and SW swaps. Panel A presents the distribution of trades across underlying asset classes and derivative types and Panel B the distribution of notional across underlying asset classes and derivative types.

Panel A: Relative to total number of all derivative trades								
	CD	FR	FU	FW	OP	OT	SW	Total
CO	0.00%	0.00%	0.01%	0.00%	0.01%	0.00%	0.00%	0.01%
CR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%
CU	0.00%	0.08%	1.91%	50.93%	0.19%	0.18%	0.14%	53.43%
EQ	0.18%	0.00%	16.88%	0.00%	10.41%	0.00%	0.63%	28.09%
IR	0.00%	0.00%	0.15%	0.00%	0.00%	0.00%	0.00%	0.16%
OT	0.00%	0.00%	1.86%	0.00%	0.13%	0.12%	0.00%	2.11%
UNDEF	0.00%	0.00%	12.67%	0.00%	3.52%	0.00%	0.00%	16.19%
Total	0.18%	0.08%	33.48%	50.93%	14.25%	0.30%	0.78%	100.00%
Panel B: Relative to total notional of all derivative trades								
	CD	FR	FU	FW	OP	OT	SW	Total
CO	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.10%	0.10%
CU	0.00%	0.00%	5.99%	23.56%	0.37%	0.02%	0.14%	30.09%
EQ	0.04%	0.00%	28.14%	0.00%	13.37%	0.00%	0.00%	41.55%
IR	0.00%	0.00%	1.20%	0.00%	0.00%	0.00%	0.00%	1.20%
OT	0.00%	0.00%	3.96%	0.00%	0.21%	0.02%	0.00%	4.20%
UNDEF	0.00%	0.00%	14.32%	0.00%	8.54%	0.00%	0.00%	22.86%
Total	0.04%	0.00%	53.62%	23.56%	22.50%	0.04%	0.23%	100.00%

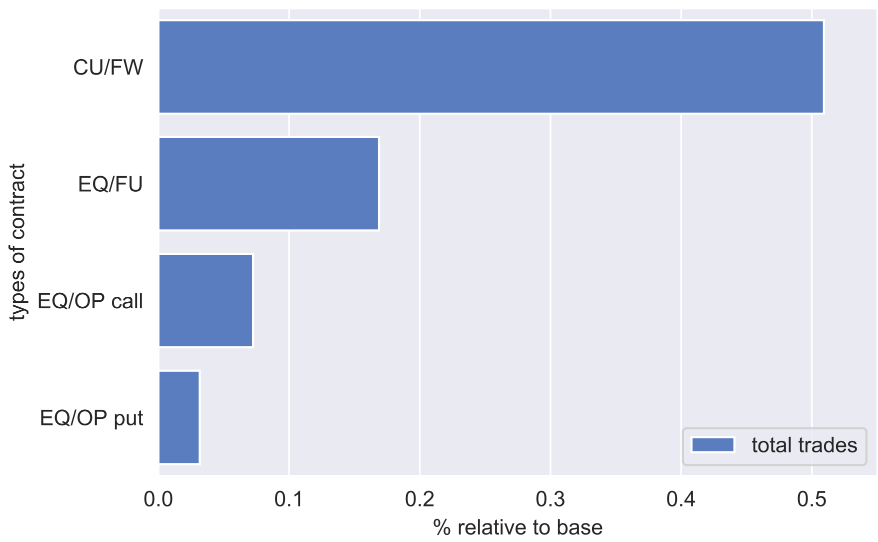
Table 1.2 presents the relative distribution of derivative trading activities across asset classes and derivative types. Panel A is based on the total number of trades. Interestingly, three types of contracts account for approximately 78% of all trades, with forward contracts on currencies being responsible for 51% and future and option contracts on equities for 17% and 10%, respectively. These contracts represent 93% of all classified trades. Hence, other contract types, such as swaps, forward rate agreements, or contracts for differences, as well as other underlyings, such as commodities, credit, or interest rates, play a minor role.

Figure 1.2

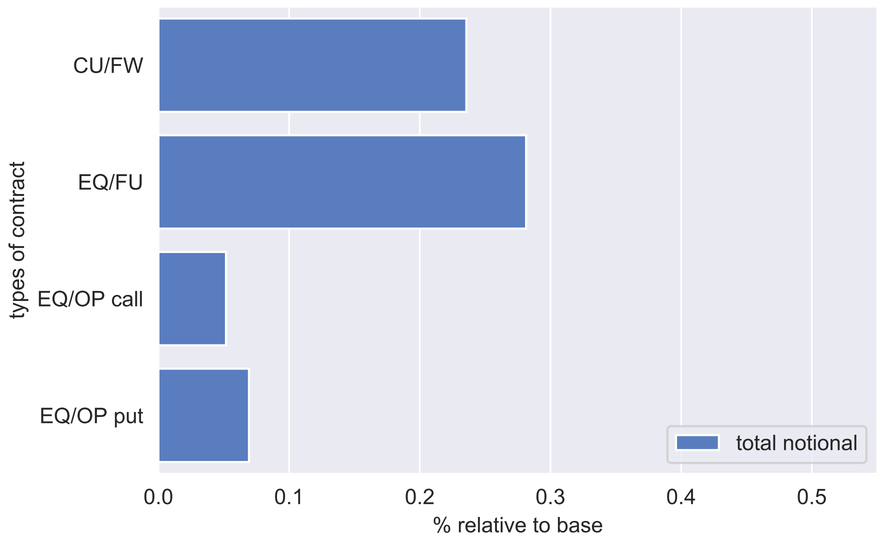
Most important derivative contract types

Subfigure (a) illustrates the share of the most important derivatives contract types that are traded by European mutual equity funds relative to the total number of trades, whereas Subfigure (b)) visualises the respective shares based on the total notional volume of trades. The three most important contract types are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP). For the options on equity, we report trades of call and put options separately. For the relative importance of all traded contract types, please refer to Table 1.2.

(a) Total trades



(b) Total notional



Panel B presents the relative distribution of the notional. Here, currency forwards, equity futures, and equity options account for 65% of the overall trade volume and 84% of the classified trade volume[9]—however, the relative importance of these three contract types is slightly lower compared to the number of trades. The importance of the three major derivatives contract types is summarised in Figure 1.2. In this figure, we also distinguish between call and put options on equities. The former is the dominant type representing about 70% of all traded options on equities. However, based on the notional, the volume of traded puts becomes larger than those of traded calls and represents 57% of the classified equity option trading volume.

Figure 1.3
Most important derivative contract types: long and short trades
This figure illustrates how the total number of trades of the three major derivatives contract types are distributed across long and short trades. The three most important contract types are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP). For the options on equity, we report trades of call and put options separately.

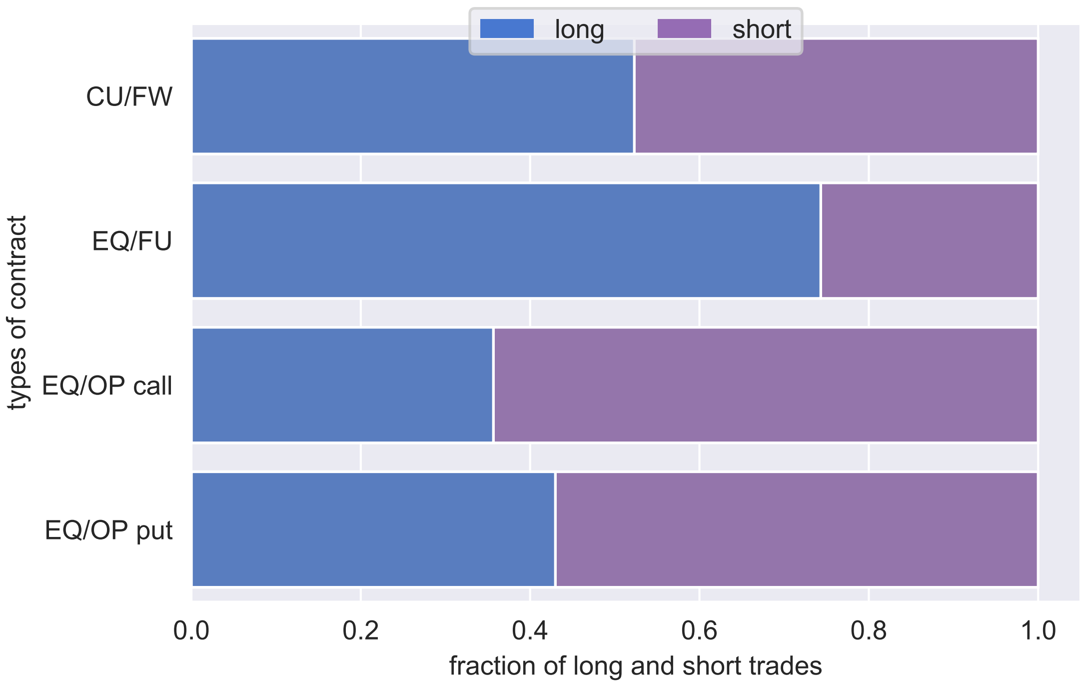


Figure 1.3 illustrates the share of long and short trades for the three major contract types, with options on equities being split into calls and puts. Trades of forwards on

[9] 16% (23%) of the trades (notional) cannot uniquely be assigned to one asset class and are, therefore, classified as undefined.

currencies are almost equally balanced across long and short trades (52% to 48%). For futures on equities, long trades are clearly dominating with more than 74%. By contrast, equity UCITS funds write a call option in 64% and a put option in 57% of the option trades. Hence, short positions on calls are the prevailing contract type when it comes to option trading, representing about 62% of those trades.

1.5.2 Which fund characteristics explain the decision to trade derivatives?

Our data allows us to distinguish between derivatives trading and non-derivatives trading equity funds. During our sample period, 2,085 of 4,555 equity funds (45.8%) make at least one derivative trade. To learn more about a fund's general decision whether to use or not to use derivatives, we regress the derivative trading dummy on various fixed effects. These fixed effects control for fund family size, fund family, investment area, base currency, domicile, benchmark, and deciles of fund size. The adjusted R-squared of the models tells us which part of the overall variation can be explained by these fund characteristics.

Table 1.3 presents the results. First, we include fixed effects for the deciles of fund family size based on the number of funds belonging to a family. They can only explain 1.9% of the overall variation. Next, we add fund family fixed effects to the model. This increases the adjusted R-squared to 34.7%. Hence, a fund's affiliation to a specific fund family can explain a substantial part of the decision to use or not to use derivatives. Successively, we add further fixed effects for the investment area, base currency, domicile, benchmark, and deciles of fund size. Although each of these fixed effects on its own can explain between 3.6% and 7.7% of the overall variation, they can only further increase the adjusted R-squared to 39.8%, on top of the fund family fixed effects. Hence, we conclude that fund family characteristics are the most important driver for making a fund a derivatives trader or not. Interestingly, we have seen that fund family size delivers only a minor explanation here. Hence, there must be other characteristics, such as the trading infrastructure, a general policy on derivatives usage, the existing know-how, the hiring policy, etc., which come into play here.

Table 1.3

Which fund characteristics explain the decision to trade derivatives?

This table presents estimates from linear regressions of the derivatives trading dummy on various fixed effects. This dummy equals one if a fund makes at least one derivative trade during our sample period. The fixed effects control for the size of the fund family, the fund family, the investment area, the base currency, the domicile, the benchmark, and deciles of fund size. They are successively added to the model. The full regression model is stated in Equation 1.1. The sample consists of derivatives trading and non-derivatives trading funds. We report for each fixed effect the individual adjusted R-squared (from a regression model with only this fixed effect) and the adjusted R-squared of the combined model (with this fixed effect and all fixed effects up to here) as well as the number of observations of the combined model (Obs). A detailed description of all variables can be found in Table A. 1.

	Individual	Combined Model	
	Adj. R^2	Adj. R^2	Obs
Family size FE	0.019	0.019	4,555
Family FE	0.347	0.347	4,308
Investment area FE	0.045	0.367	4,301
Currency FE	0.036	0.368	4,298
Domicile FE	0.077	0.370	4,298
Benchmark FE	0.074	0.383	3,879
Fund size FE	0.037	0.398	3,836

A detailed comparison of derivatives trading and non-trading funds in terms of their fixed characteristics can be found in Appendix A. 3, where it can be seen that both groups are similar, however, with some systematic differences. For instance, trading funds tend to belong to larger fund families and also tend to be larger themselves. Moreover, derivatives trading funds prefer to choose Luxembourg or Ireland as their domicile. Overall, these differences are relatively slight, which corroborates the findings of the regressions on the derivative trading dummy that the most important characteristics determining the decision whether a fund is a derivatives trading or non-trading fund are on the fund family level rather than connected to a specific fund.

1.5.3 Which fund characteristics explain the extent of derivatives trading?

In this chapter, we would like to understand better why some funds are active derivatives traders while others only execute trades infrequently. For this, we apply a fixed effects approach again. However, the dependent variable is now the daily observation of a fund's derivatives use. The models include the fixed effects of Equation 1.1 plus fund fixed effects, which we can now use since there is variation in a fund's derivative use over time.

Table 1.4 presents the results. In Panel A, the dependent variable is the natural logarithm of a fund's traded notional per day. Unsurprisingly, a fund's affiliation to a fund family already explains 30.0% of the overall variation in the daily notional. Only a minor part of this, i.e., 2.6%, relates to the size of the fund family. Adding fixed effects for investment area, currency, domicile, benchmark, and fund size lifts the adjusted R-squared to 39.3%. Particularly, a fund's benchmark seems important since it can explain by its own 12.9% of the overall variance. However, including a fund fixed effect adds the largest part of the explained variation. This increases the overall adjusted R-squared to 56.0%. Panel B presents the same analysis for the derivatives trading dummy that equals one if a fund makes at least one trade on a day. The results are very similar. In this case, all fixed effects together can explain 51.5%.

Overall, this evidence can be interpreted as follows. The decision to become active in the derivatives market is embedded in the overall environment the investment company running the whole fund family delivers. This might be related to the trading infrastructure, the specific derivatives know-how available in the company, the existence of a general policy on handling derivatives contracts, and, of course, the particular selection of fund managers hired by this investment company. However, once these preconditions are given, the specific trading activity displayed by a single fund is determined by fund-specific characteristics. One can think of the fund's specific trading strategy, which might be correlated with the chosen benchmark, the personal traits of the fund manager, the incentive scheme in place, etc. Unfortunately, we do not have data on these fund characteristics.

Table 1.4

Which fund characteristics explain the extent of derivatives trading?

This table estimates from linear regressions of two dependent variables on various fixed effects. In Panel A, the dependent variable is the natural logarithm of a fund's traded notional per day. In Panel B, the dependent variable is the daily derivatives trading dummy which equals one if a fund makes at least one derivative trade on a day and zero otherwise. The fixed effects control for the size of the fund family, the fund family, the investment area, the currency, the domicile, the benchmark, deciles of fund size, and the fund. They are successively added to the model. The sample consists of derivatives trading funds. We report for each fixed effect the individual adjusted R-squared (from a regression model with only this fixed effect) and the adjusted R-squared of the combined model (with this fixed effect and all fixed effects up to here) as well as the number of observations of the combined model (Obs). A detailed description of all variables can be found in Table A. 1.

	Individual	Combined Model	
	Adj. R^2	Adj. R^2	Obs
Panel A: Notional per day			
Family size FE	0.026	0.026	271,585
Family FE	0.300	0.300	271,585
Investment area FE	0.028	0.316	271,585
Currency area FE	0.009	0.317	271,585
Domicile FE	0.009	0.323	271,585
Benchmark FE	0.129	0.377	271,585
Fund size FE	0.064	0.393	269,231
Fund FE	0.558	0.560	269,231
Panel B: Daily derivatives trading dummy			
Family size FE	0.032	0.032	271,585
Family FE	0.276	0.276	271,585
Investment area FE	0.028	0.290	271,585
Currency FE	0.014	0.292	271,585
Domicile FE	0.010	0.299	271,585
Benchmark FE	0.126	0.350	271,585
Fund size FE	0.041	0.362	269,231
Fund FE	0.513	0.515	269,231

1.5.4 What are funds' motives to trade derivatives?

As has already been explained, we can think of three fundamental economic rationales for an equity UCITS fund to trade derivatives. First, equity funds might want to economise on transaction costs by using derivatives to build synthetic equity positions. Second, derivatives are helpful for risk management purposes, for instance, with respect to currency risk exposure, but also tail risks in equity positions. Third, derivatives could be used to create synthetic leverage or speculate on specific price movements.

To shed more light on this question, we conduct three different analyses in the following. First, we exploit the granular structure of our data to uncover how daily flows affect derivatives trades. If derivatives trades are motivated by transaction cost savings or risk mitigation purposes, we should observe a specific pattern related to daily fund flows. Second, we analyse whether time-varying fund and market characteristics impact the trading decision of a fund. Each of the three rationales mentioned above leads to different hypotheses concerning the time-varying patterns of underlying fund-specific variables. Third, by using a non-linear regression approach, we aim to detect whether derivatives trading is associated with risk-adjusted returns and the fund's delta and gamma risk.

1.5.4.1 Derivatives trading and aggregate time-varying fund flows

In the first step, we investigate how the trading activity is related to daily fund flows. Based on the transaction cost perspective, we hypothesise that funds should tend to go long in equity futures if there are net inflows, while they should go short if there are net outflows. Of course, we have to take into account that this relationship might interfere with other reasons for trading derivatives. For instance, funds have to replace maturing derivatives positions, or they might spread their trades over more extended periods. Therefore, significant noise in trading behaviour arises. Nevertheless, according to the transaction cost hypothesis, there should be a relationship between a fund's net flows and its equity futures trading behaviour.

To uncover this relationship, we extract daily net fund flows measured relative to the net asset value of the fund. We aggregate the net flows of all funds to a daily net flow of all the funds in our sample. After that, we split these daily observations into the group of days with net outflows and with net inflows. Each group is then divided into 5% quantiles. We also observe whether a fund on any particular day or the following four trading days is a net buyer or seller of equity futures based on the notional volume. Using this information, for each day, we calculate the ratio of funds being net buyers or net sellers relative to all fund observations. Of course, on any day, there are many funds that are not trading at all. The results are visualised in Figure 1.4. As expected, the likelihood for a fund to be a net seller is the higher, the larger the net outflow is. Also, the likelihood of being a net buyer is positively associated with the size of the net inflow.

Figure 1.4

How do fund flows affect the trading of equity futures?

This figure illustrates the relation between daily fund flows and trades of equity futures in the following days. Daily flow observations are split into mainly outflows or inflows using the direction of the relative net flow. Subfigure (a) groups the outflow observations into 5% quantiles. It shows the percentage of fund day observations with more short FU/EQ trades than long ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund outflow in t = 0. Subfigure (b) groups the inflow observations into 5% quantiles. It shows the percentage of fund day observations with more long FU/EQ trades than short ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund inflow in t = 0. The percentages also take into consideration observations with no equity future trade activity. The quantiles are calculated per day. The sample consists of funds, which reported at least one FU/EQ trade in the second half of 2016.

(a) Fund outflow

(b) Fund inflow

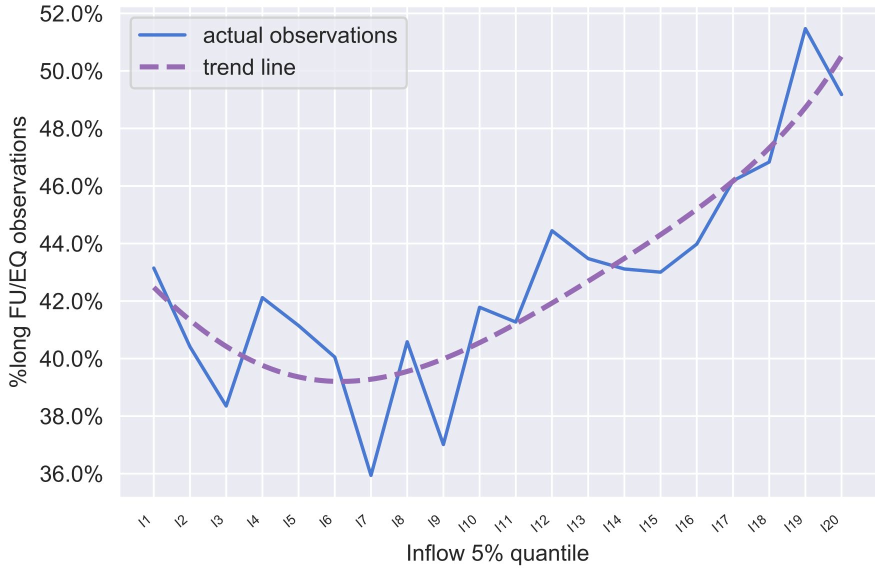
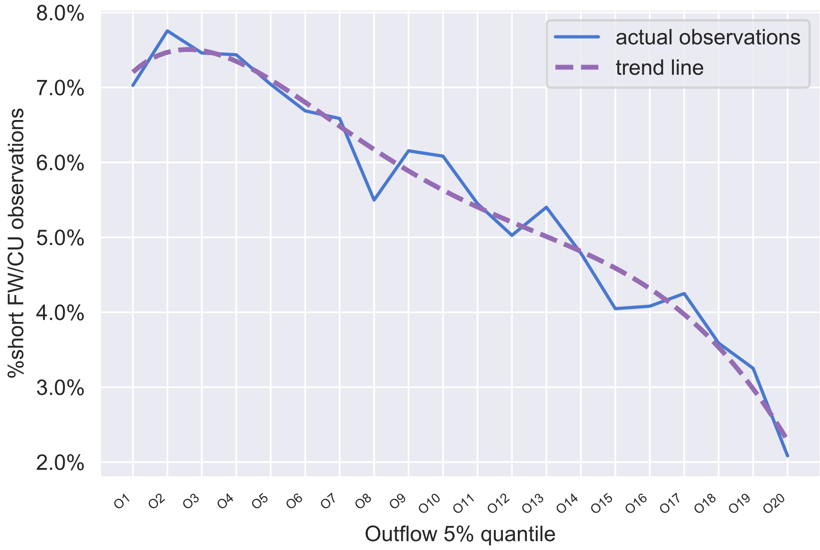


Figure 1.5

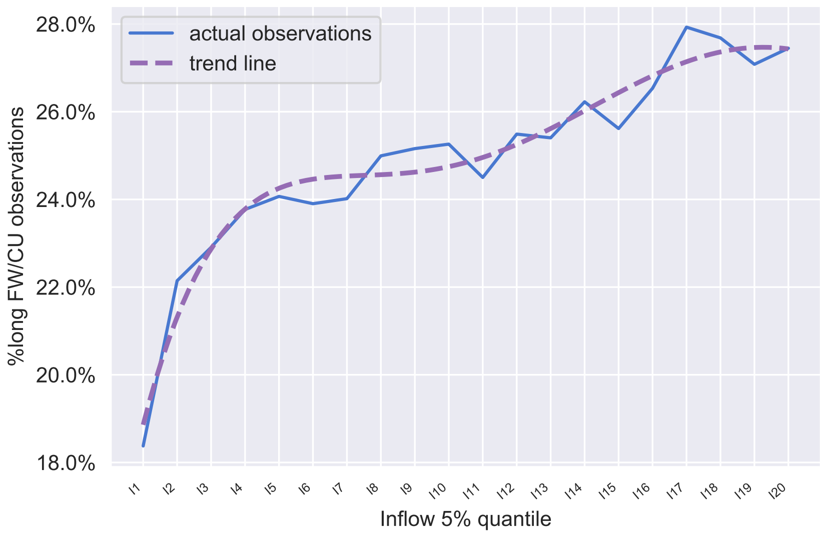
How do fund flows in non-base currencies affect trading of currency forwards?

This figure illustrates the relation between daily fund flows and trades of currency forwards in the following days. Daily flow observations are split into mainly outflows or inflows using the direction of the relative net flow. Subfigure (a) groups the outflow observations into 5% quantiles. It shows the percentage of fund-base currency-day observations with more short FW/CU trades than long ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund-base currency outflow in t = 0. Subfigure (b) groups the inflow observations into the quantiles. It shows the percentage of fund-base currency-day observations with more long FW/CU trades than short ones in terms of the traded notional aggregated over t = 0 to 4 by the quantiles of the relative fund-base currency inflow in t = 0. Multiple share classes of a fund with the same base currency are aggregated to a single fund-base currency observation. The percentages also take into consideration observations with no currency forward trade activity. The quantiles are calculated per day. A long FW/CU trade is defined as buying the fund's base currency or selling its benchmark currency and a short trade vice versa. The sample consists of funds, which reported at least one FW/CU trade in the second half of 2016.

(a) Fund-currency outflow



(b) Fund-currency inflow



Next, we repeat a similar analysis for currency forwards. Again, we calculate the net flows of each fund. However, this time net flows are calculated with respect to each share class being denominated in a different currency with respect to the benchmark currency. Hence, a net inflow implies that the fund is long in the benchmark currency and short in the share class currency, assuming that the net inflow is quickly invested in benchmark-related equities. To reduce this currency risk, the fund should enter into a forward contract where it sells the benchmark currency against the share class currency. We define this to be a long currency forward position. Hence, under the risk management hypothesis, we expect larger net inflows to be associated with buying more currency forwards. In contrast, larger net outflows should be associated with selling more currency forwards.

We analyse this hypothesis in the same manner as before. Again, we calculate daily net flows and group these days in 5% quantiles for the group of net outflows and net inflows. Finally, we investigate whether higher net inflows (outflows) are associated with a higher likelihood for a fund to be a net currency forward buyer (seller). Figure 1.5 visualises the results. As can be seen, our evidence clearly corroborates the risk management hypothesis. Funds are much more likely to buy (sell) a currency forward if they experience a large inflow (outflow).

1.5.4.2 Derivatives trading and time-varying fund characteristics

In this section, we analyse the role of the time-varying fund and market characteristics for derivatives trading activities. Again, we come back to our hypothesis that trading activity should be closely related to the fund's net in- and outflows, if the transaction cost motive is a relevant driver. If derivatives are used for risk mitigation purposes, we should observe more currency trades in those cases where currency risk increases. Concerning other time-varying risk measures, we do not have clear hypotheses. Hence, if we detect the funds to adapt their trading behaviour to other time-varying risk measures, such as return volatility in the benchmark or tracking error, we cannot make any inference on whether this is due to risk mitigation or return enhancing purposes.

Technically, we use a linear prediction model and regress the daily derivatives trading dummy on various proxies for fund flows, fund risk, and fund return, which are lagged by one day. Additionally, we calculate the same model for fund flows only looking at equity future trades. All models include day and fund fixed effects to control for unobserved time-varying characteristics. Table 1.5 presents the results for fund flows, whereas Table 1.6 shows the ones for fund risk and return.

Table 1.5

How do fund flows affect derivatives trading?

This table presents estimates from linear probability models of trading dummies on measures of fund flows lagged by one day following Equation 1.2. In Panel A, the dependent variable is the daily derivatives trading dummy. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. Panels B and C only consider equity future trades. In Panel B, the respective long dummy equals one if a fund buys at least one equity future trade on a day and zero otherwise. In Panel C, the short dummy equals one if a fund sells at least one equity future trade on a day and zero otherwise. The measures of fund flows are the rolling 5-day net flows (Column 1), the rolling 5-day positive net flows (Column 2) and the rolling 5-day negative net flows (Column 3). The sample consists of derivatives trading funds. All models include day and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)
Panel A: All derivatives trades			
	net flow	pos. net flow	neg. net flow
flow	0.386***	0.549***	0.346***
	(6.18)	(5.41)	(3.50)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	247,336	247,336	247,336
Adj. R^2	0.528	0.528	0.528
Panel B: FU/EQ long trades			
	net flow	pos. net flow	neg. net flow
flow	0.016	0.144**	-0.078*
	(0.50)	(2.27)	(-1.73)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	247,336	247,336	247,336
Adj. R^2	0.684	0.684	0.684
Panel C: FU/EQ short trades			
	net flow	pos. net flow	neg. net flow
flow	0.045*	0.019	0.141***
	(1.73)	(0.43)	(2.83)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	247,336	247,336	247,336
Adj. R^2	0.338	0.338	0.338

In Panel A, we regress the daily derivatives trading dummy on three proxies for a fund's flows. The hypothesis, again, is that funds may use derivatives to manage flows in a cost-efficient way. In our standard case, we measure fund flows over the 5 preceding trading days. In Column 1, we use the rolling net flow. The coefficient is 0.386 and statistically significant at the 1%-level. This coefficient can be interpreted in the way that a one standard deviation increase of the net flow increases the probability of a trade by 0.73 percentage points. In Columns 2 and 3, we differentiate between positive and negative net flows. The coefficient on positive net flows is 0.549 and statistically significant at the 1%-level, whereas the coefficient on negative net flows is 0.346 and also significant at the 1%-level. This finding clearly supports the hypothesis that funds use derivatives to manage in- and outflows in a cost-efficient way. This result is robust to the use of alternative measurement periods of funds' flows (cf. Appendix A. 4).

Additional support for this hypothesis is delivered in Panels B and C. There, we use a dummy set to one if the fund buys (sells) an equity future. It can be seen that for futures long trades, the coefficient on positive net flows is positive, while on negative net flows, it is negative. Correspondingly, the coefficient on negative net flows is positive for the dummy representing the funds being short on the equity future. This is exactly in line with the transaction cost hypothesis, as the funds are supposed to buy equity futures in case of net inflows and to sell equity futures in case of net outflows.

In Panel A of Table 1.6 we analyse the role of specific fund risk variables. In Column 1, we use the fund's currency risk. It is measured by the standard deviation of the daily exchange rates of the respective share class's base currency to the base currency of the fund's benchmark. As a measurement period, we use the 20 preceding trading days. Finally, the standard deviation is aggregated to the fund level by using the weighted average calculated on the basis of net assets of the respective share classes. The coefficient is 4.965 and statistically significant at the 1%-level. A one standard deviation increase of the currency risk raises the probability of a trade by 1.24 percentage points. This result is in line with the risk management hypothesis, as funds, in this case, should react to changes in the currency risk. Of course, as at this stage, we do not take into account whether funds are going short or long in the respective currency, we cannot totally rule out that this behavior is also in line with speculative behavior. In Columns 2 and 3 of

Panel A of Table 1.6, we use the rolling one-month standard deviation of the fund return and the rolling one-month tracking error. Both coefficients are statistically insignificant.

Table 1.6
How do fund risks and returns affect derivatives trading?

This table presents estimates from linear probability models of the daily derivatives trading dummy on lagged measures of fund risk in Panel A and fund return in Panel B following Equation 1.2. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. In Panel A, we measure fund risk by the rolling one-month currency risk (Column 1), the one-month standard deviation of returns (Column 2) and the one-month rolling tracking error (Column 3). In Panel B, we measure fund return by three proxies for the fund performance. These are the rolling one-month fund return (Column 1), the rolling one-month relative return to the benchmark (Column 2) and the rolling one-month relative return to the family (Column 3). The sample consists of derivatives trading funds. All models include day and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)
Panel A: Fund risks			
	currency	sd(return)	tracking error
risk	4.965***	-0.234	0.447
	(3.00)	(-0.57)	(1.13)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	198,973	270,578	244,406
Adj. R^2	0.534	0.534	0.532
Panel B: Fund returns			
	return	return-benchmark	return-family
return	-0.023	-0.021	-0.038
	(-0.48)	(-0.41)	(-0.78)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	271,585	244,406	271,585
Adj. R^2	0.533	0.532	0.533

In Panel B, we analyse the relationship between a fund's return and the daily decision to trade a derivative. In Column 1, the variable of interest is the rolling one-month fund return. In Column 2, we use the relative return to the benchmark. In Column 3, the relative return to the family is looked at. The coefficients are not statistically significant. Hence, there does not seem to be a linear relationship between a fund's past performance and the decision to use derivatives.

To show the robustness of our results, we conduct two additional tests. First, we use alternative time periods to measure fund flows in Appendix A. 4 and fund risks and returns in Appendix A. 5. Using alternative measurement periods, we find similar results. Second, instead of the linear probability model, we estimate a conditional logit model. The results in Appendix A. 6 and Appendix A. 7 confirm our finding that fund flows and currency risk are positively related to the propensity to trade.

1.5.4.3 Derivatives trading and a funds' risk-profile

Finally, after having dissected the derivatives trading behaviour of equity UCITS funds, we will analyse whether we see any relation to the risk-/return profile of the funds. Evidently, we cannot say anything about causality here. However, given that our analysis has delivered extensive evidence indicating that funds are using derivatives for transaction cost or risk mitigation purposes, it would be interesting to see whether this picture can be completed by looking at the funds' returns.

Table 1.7

Are returns of actively derivatives trading funds and non-trading funds different?

This table compares predicted returns of actively derivatives trading funds and non-derivatives trading funds. Actively derivatives trading funds only include funds in the top four deciles of the trading funds sample in terms of the number of reported trades. These actively trading funds represent more than 95% of the trades.
The returns are predicted following Equation 1.8, which decomposes in the following parameters: β_i^k estimates the risk-adjusted return, $r_{i,t}$ stands for the return of fund i on day t, $r_{mm,t}$ for the money market rate, and $r_{b,t}$ for the return of the fund's benchmark b on day t. $bot_{b,t}$ and $top_{b,t}$ are dummies indicating, whether the respective benchmark was among the 25 percent worst or best performing ones on day t. The regression is estimated for each fund and month separately. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively.

	Trading	Mean	SD	Skew.	t-stat
β_i^k	No	2.5e^{-5}	0.002	-0.140	-1.055
	Yes	5.5e^{-5}	0.002	0.001	
$r_{b,t} - r_{mm,t}$	No	0.580	0.573	-0.606	-7.676***
	Yes	0.655	0.534	-0.892	
$bot_{b,t}(r_{b,t} - r_{mm,t})^2$	No	27.010	129.259	1.507	-2.116**
	Yes	32.031	137.180	1.804	
$top_{b,t}(r_{b,t} - r_{mm,t})^2$	No	-15.157	102.543	-2.736	3.493***
	Yes	-21.860	109.062	-2.938	
Adj. R^2	No	0.407	0.313	0.116	-7.578***
	Yes	0.448	0.295	0.038	

Figure 1.6
Do actively derivatives trading funds outperform non-trading funds?
This figure illustrates the predicted daily return of active derivatives trading funds (TF) compared to non-trading funds (NTF) depending on the return of the benchmark index minus the risk-free rate. We predict the returns of TF and NTF using the mean of the parameter estimates for Equation 1.8 per group. Trading funds only include funds in the top four deciles in terms of the number of reported trades. These funds represent more than 95% of the total trade sample.

For this purpose, we estimate Regression 1.8 for each fund and month in our sample separately. In this way, we get more than 25,000 beta estimations. These are then used to make the inferences presented in Table 1.7. In this context, we focus on the comparison of the 40 percent most active derivatives trading funds versus derivatives non-trading funds, as these 40 percent represent more than 95 percent of our derivatives trade sample. Three results are very interesting here.

First, derivatives using funds have a larger downward convexity. This implies that in case of very low benchmark return realisations derivatives using funds have superior returns. In other words, they display less correlation with benchmark returns in the downward case. However, the same is also true in the upward case. This implies that for very high benchmark returns, derivatives using funds have lower returns. One could also say that they have a lower upward convexity. The differences in the coefficients are statistically highly significant. Overall, this finding is in line with the notion that derivatives are used for risk mitigation purposes. To better understand the implications of the results displayed in Table 1.7, Figure 1.6 exemplifies the predicted return difference of actively trading vs. non-trading funds for a range of benchmark excess returns. As one can see, derivatives trading funds have higher returns in the downward case but lower returns in the upward case.

Second, the benchmark beta for derivatives using funds is slightly, but significantly higher compared to non-derivatives using funds. Even though this could be interpreted as if there is more delta risk in these funds, it should be said that the difference, which is equal to 0.075, is very small. Moreover, the negative outcome of having slightly more synthetic leverage are confined by the convexity profile described above.

Third, we also find that risk-adjusted returns in derivatives using funds are slightly higher. However, the difference is 0.3 bp, which would sum up to 75 bp/year. Moreover, this difference is statistically not significant. The finding would be in accordance with funds using derivatives for transaction cost motives. Given the relatively small size of the derivatives positions overall, it is not surprising that this effect could not easily be detected in statistical analysis. Figure 1.7 displays the kernel density function of the risk-adjusted return of actively trading vs non-trading funds. The results discussed above are again corroborated here. The probability mass of the derivatives using funds is shifted towards the middle, indicating the risk-adjusted returns being less risky for derivatives trading funds.

Figure 1.7
Are risk-adjusted returns of actively derivatives trading and non-trading funds different?
This figure shows the kernel density of the estimated risk-adjusted returns by the funds' trading activity according to Equation 1.8, i.e. the kernel density of the estimated β_i^k. Trading funds only include funds in the top four deciles in terms of the number of reported trades. These funds represent more than 95% of the total trade sample.

1.6 Conclusion

In this paper, we use a novel dataset that links a comprehensive sample of European equity UCITS funds with information on derivatives trades. The linked fund-trade data allows us to shed light on equity funds' derivatives trading behaviour.

First, we show that 46% of European equity funds trade derivatives. They primarily trade three types of contracts: currency forwards, equity futures, and equity options. These three types together account for about 80% of all trades. Second, we find that the fund family is an important determinant for the funds' decision to use derivatives. Third, we show that fund fixed characteristics explain 56% of the variation in funds' trading frequency and trading volume. Among the fund fixed characteristics that we can observe, the fund family and the investment strategy matter most. Finally, we shed first light on equity funds' motives to trade derivatives. We provide evidence that equity funds trade derivatives to save transaction costs and to mitigate risks; our findings provide no evidence that they use derivatives predominantly for speculative reasons.

Although we observe very granular information on funds' derivatives trades, this study has some limitations. Importantly, we do not observe the overall derivatives positions in funds' portfolios. Another limitation is that we observe information on funds' derivatives trading behaviour only for a six-month period. These limitations make it difficult to infer the motives of funds to trade derivatives causally. We hope that these limitations can be addressed by future research.

2 Cui bono? Large-scale Evidence on the Impact of COVID-19 Policy Measures on Listed Firms

Key words:	Coronavirus, COVID-19, Economic Support Measures, Employment Intensity, Financial Markets, Government Support, Pandemic, SARS-CoV-2, Stringency Measures, Zombie Firms
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Note:	In this chapter I use the first-person plural narrative.

Abstract

By using a large international firm-level dataset, this paper aims to make a contribution in better understanding how COVID-19 related stringency and economic support measures actually affected the corporate sector. Our most important findings can be summarised as follows: First, we find robust evidence that stringency measures had a statistically and economically significant positive impact on listed firms. Second, with respect to the effects of economic support measures, the evidence seems, at best, to be weakly in favour of a positive impact. Third, small and employment intensive companies profited most from economic support measures. Fourth, also highly leveraged or even Zombie firms profited more from these support measures than others. Overall, the results are in line with official policies aimed at sheltering SMEs and human capital intensive firms from the Corona shock waves. However, it also seems that Governments unintentionally supported firms in financial difficulties or with non-viable business models already before the pandemic.

2.1 Introduction

Government policies tackling with the COVID-19 crisis are grounded on two major pillars. First, governments implemented contact reductions like stay-at-home policies, closures of schools, etc. Such measures are often labelled as stringency measures. Second, governments provided economic support either to companies mostly affected by these measures or to citizens directly.

Now, this paper aims to make a contribution in better understanding whether, and if so, in which direction, these stringency and economic support measures actually affected companies. More specifically, three questions will be addressed. First, did the stringency measures harm the corporate sector? Second, were the massive economic support measures able to offset these potential negative effects? And thirdly, controlling for the exposure of the firms' business model to the pandemic, did companies profit differently from these economic support measures?

It is no question that stringency measures in the short-term inflict a significant economic cost. However, when taking into account also long-term consequences it is an open question, whether such measures really harm the corporate sector. Actually, the stock market's response to the COVID-19 outbreak can analytically be split-up into a change in dividend expectations, i.e. short- and long-term growth consequences for the corporate sector, as well as in a change in discount rates (cf. e.g. Gormsen and Koijen (2020)). Now, stricter contact rules might hamper economic activity in the short-term, but at the same time they might improve medium- and long-term growth expectations. The latter would happen, if the market believes that these measures might help to overcome the health crisis more quickly. Therefore, government interventions that might have a high economic cost in the short-term could nevertheless be beneficial and, hence, improve the mood on the stock markets because of their medium- and long-term benefits. Finally, it is an empirical question whether the measures taken by the governments on balance were harmful or beneficial to the corporate sector. Therefore, by looking at stock market responses, something can be learned about how governments balanced these short- versus long-term trade-offs in their market interventions.

Of course, one has to be careful in interpreting these results, as stock prices are also driven by changes in the discount rates. And it cannot be ruled out that the COVID-19 crisis led to a change in discount rates. However, Gormsen and Koijen (2020) show that future dividend prices returned relatively quickly to their pre-crisis levels. This speaks against the presumption that the crisis had a lasting impact on discount rates. Moreover, by using abnormal returns as dependent variables, we control for the impact of priced risk factors. Hence, we are confident that our results, in fact, are informative with respect to the long-term corporate sector consequences of government interventions.

Evidently, support measures might not have affected the corporate sector in a uniform way. In fact, due to the nature of the crisis, governments focused their interventions on smaller and more employment-intensive firms. Hence, if measures were effectively designed, we should observe the strongest effects for those types of companies which entered into financial difficulties due to the COVID-19-related business interruptions. However, for practical reasons, in many cases, support measures were based on financial ratios realised before or at the very beginning of the crisis. Therefore, it was almost unavoidable that also firms being in financial difficulties already before the crisis, i.e. firms with non-viable business models also called Zombie firms, benefited from these measures. Again, it is an empirical question whether, and if so, to what extent, this has happened.

Combining a large international dataset covering 25 countries, 11,910 companies, and more than four million return observations over the period January 2020 to August 2021 with the Oxford COVID-19 Government Response Tracker (OxCGRT) (cf. Hale et al. (2021)), we are able to identify the following answers to the above-mentioned questions. First, we find robust evidence that stringency measures did not only not harm the corporate sector as represented by the universe of listed firms but rather sheltered them from further disruptions. In fact, a one standard deviation increase in the stringency index lead to an approximate 0.15% daily increase in the firms' stock prices. Hereby, we control for a large set of firm, time and country fixed effects.

Second, the evidence with respect to economic support measures is less robust. Depending on the set of controls and fixed effects, we find positive as well as negative effects on stock prices. However, if we restrict the analysis to European countries, we find weak evidence supporting a positive impact of economic support measures on the corporate sector. Overall, however, the results with respect to economic support measures seem to be inconclusive.

Third, smaller, highly levered, and more employment-intensive companies profited most from economic support measures. In fact, a one standard deviation increase in the economic support index lead to a daily increase in the stock prices of the firms in the highest leverage quintile relative to all other firms by about 0.05% and to a daily decrease in the stock prices of firms in the largest size quintile relative to all other firms by about 0.05%. For the quintile of firms with the highest employment intensity, this marginal effect was 0.03%. While these results may be in line with an official policy of sheltering SMEs and human capital-intensive firms from the Corona shock waves and labour market disruptions, it also seems that Governments unintentionally supported firms in financial difficulties already before the financial crisis.

Fourth, the existence of unintended consequences of economic support measures is further corroborated by looking at the impact of these support measures on Zombie firms, i.e. firms with a non-viable business model already before the crisis. We find robust evidence that these firms profited from economic support measures more than others. In fact, a one standard deviation increase in the economic support index caused the stock prices of Zombie firms to increase by 0.10%.

Overall, this paper contributes to the literature in the following ways. First, several studies have documented the severe and unprecedented impact of the Corona outbreak on stock and bond markets (cf. among others Baker et al. (2020), Bannigidadmath et al. (2021), Bretscher et al. (2020), Gormsen and Koijen (2020), Kargar et al. (2021), Ramelli and Wagner (2020)). However, only a small number of studies analysed the impact of Government policy interventions on stock markets or on the corporate sector more generally. For instance, Bannigidadmath et al. (2021) analyse the impact of lockdowns, stimulus packages and travel bans in an event-study design. Based on a sample of 25 countries, they find negative or inconclusive effects of these government interventions on stock prices. A similar result is also presented by Heyden and Heyden (2021). By analysing index returns in the G7 countries, Narayan, Phan and Liu (2021) come to the conclusion that Government stringency measures tend to have a positive impact on stock markets, with lockdowns appearing to have the strongest effect.

Zaremba et al. (2020) study the impact of stringency policies on a broad set of international stock market indexes. They come to the conclusion that such measures significantly increase market volatility. Hence, they conclude, Government stringency interventions add to the already prevailing uncertainty on the market.

In this regard, this paper adds further evidence to the interaction of Government crisis responses and stock market reactions. By using a large international firm-level dataset with daily frequency, we are able to identify the relative impact of different levels of government intervention intensities on stock price performance. Moreover, and even more importantly, we can study the impact of government interventions depending on firm characteristics. To the best of our knowledge, this is the first paper to address this second question based on such a broad firm-level dataset.

2.2 Empirical strategy

2.2.1 Regression approach

Our empirical strategy is based on a cross-country fixed effect panel regression approach. The dependent variable is the abnormal daily stock price reaction as measured by the Fama-French 3-factor model or by a Cahart 4-factor model. The independent variables are the OxCGRT-indexes for government policy interventions (cf. Hale et al. (2021)), a control for the price of oil following Narayan, Devpura and Wang (2020), as well as firm and country characteristics. A detailed description of all variables can be found in Table B. 1 in the Appendix.

Identifying the impact of COVID-19 Government measures is not an easy task because of obvious endogeneity issues. Most importantly, empirical tests aimed at uncovering any causality of such support measures on stock prices are affected by unobserved heterogeneity. Therefore, our empirical strategy is grounded on two central pillars. First, by assembling a large cross-country panel data set, we can analyse the impact of Government measures varying over time. This alleviates potential concerns about the clustering of residuals. Second, as we have a large panel, we can control for a set of fixed effects and, as a consequence, eliminate effects coming from unobserved variables.

More specifically, we add a list of six fixed effects to our analysis. First, we control for weekday fixed effects, as the implementation of Government measures might be clustered around specific weekdays, for instance, Mondays. This might be correlated with other information coming to the market. Second, we control for industry fixed effects. As the pandemic effects, as well as the support measures, might be correlated with industry affiliation, disentangling the impact of Government measures from effects caused by the virus will not be possible without controlling for industry affiliation. Of course, the effect we measure in this way is an average effect independent of industry affiliation.

Third, we control for country fixed effects. In this way, we eliminate time-invariant country-specific effects, which might be due to the quality of the health system, differences in enforcement, etc. Fourth, we also control for firm fixed effects. Similarly to industry fixed effects, there might also be a correlation of the pandemic effects with the specific business models implemented in companies. Both can be disentangled by using firm fixed effects.

Fifth, we control for day FE. Daily stock price variation in our sample will be correlated due to common risk factors. Any news with respect to these risk factors, including news on the COVID-19 crisis, will impact stock prices. As Government measures might be correlated with such news, we make sure that we get rid of these effects. And finally, as a sixth fixed effect, we interact industry with day fixed effects. This takes account of the fact that the mentioned news might have a different impact on different industries. In this way, we make sure that the Government support effect we see in one country is not driven by news affecting a heavy-weighted industry in this specific country.

To sum up, we think that this approach allows us to measure the average daily impact of Government support measures on companies independently of their country and industry affiliation and unrelated daily information arriving at the markets. In our understanding, this can be regarded as a conservative approach, as the fixed effects might also reap some of the effects caused by Government interventions.

2.2.2 Data

The final sample contains 11,925 firms in the following 25 countries: Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the US. We start by using Refinitiv to extract market data from Datastream and accounting data from Worldscope in USD. We follow Ince and Porter (2006), Griffin, Kelly and Nardari (2010), Schmidt et al. (2019), and Hanauer and Windmüller (2023) to apply static as well as dynamic screens recommended in the literature on the survivorship bias-free data. The final dataset contains 4,617,851 firm-day observations between January 2020 and August 2021.

We calculate abnormal daily stock returns measured by the Fama-French 3-factor model and by a Cahart 4-factor model using factors from Kenneth French's website[1], where factor betas are estimated over a period of two years prior to the observation period from January 2018 to December 2019.

We group all firms into quintiles based on size as measured by revenue, book leverage, and employment intensity. Each firm is assigned a size dummy (*size*) being one if the firm belongs to the 20 percent largest firms, a leverage dummy (*bl*) being one if the firm belongs to the 20 percent highest leveraged firms, and an employment intensity dummy (*ei*), if the firm belongs to the 20 percent with the lowest revenue per employee.

Based on Worldscope data, we follow Favara, Minoiu and Perez-Orive (2021) to identify Zombie firms: A firm is classified as a Zombie firm (*zombie*) if it had above median leverage and an interest coverage ratio less than one in the preceding year and negative sales growth in the preceding three years.

As a measure of government policies, we utilise two major components of the Oxford COVID-19 Government Response Tracker (cf. Hale et al. (2021)): the stringency index (*si*) and the economic support index (*esi*). The former exclusively contains restrictive measures, like closures of schools, stay-at-home policies and cancellations of public events. The latter, in contrast, includes only economic relief policies such as income support and fiscal measures. Data on COVID-19 cases is collected from the Our World in Data Project (cf. Ritchie et al. (2020)). Country-specific control variables are taken from OECD (2021). The West Texas Intermediate price of oil is retrieved from the US Energy Information Administration.[2]

[1] Cf. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, last accessed 13 January 2023.

[2] Cf. https://www.eia.gov/dnav/pet/hist/RWTCD.htm, last accessed 13 January 2023.

2.3 Results

2.3.1 Descriptive statistics

Summary statistics can be found in Table 2.1. For most of our variables, we have between 4 and 5m observations. When it comes to firm characteristics, e.g. employment intensity or Zombie classification, there is a significant drop in observations as the required accounting data is not always reported in the databases we are using. The average (median) firm in our sample has a size measured in terms of revenues of USD 3,108m (174.92m), revenues per employee of USD 862.74 (292.47), and a book leverage ratio of 0.46 (0.23). We identify 114 of 7,912 (1.44%) firms in our sample with sufficient data as Zombies in 2020.

Table 2.1
Summary statistics

This table presents summary statistics of the main variables. Reported are the number of observations (N), mean value (Mean), standard deviation (SD), 25% percentile (p25), median (p50) and 75% percentile (p75). The sample consists of 11,925 firms in 25 countries with 4,617,851 firm-day-observations. A detailed description of all variables can be found in Table B. 1.

	N	Mean	SD	p25	p50	p75
ff3	4,617,851	0.0485	5.6178	-1.5076	-0.0975	1.1690
c4	4,617,851	0.0518	5.6150	-1.5057	-0.0967	1.1863
si	4,617,851	59.50	19.25	53.70	65.28	71.76
esi	4,617,851	56.39	25.91	37.50	62.50	62.50
case growth	4,538,270	0.0283	0.0891	0.0022	0.0064	0.0148
ei	3,132,935	862.74	5830.63	168.26	292.47	561.27
bl	3,672,394	0.4641	6.4118	0.0878	0.2347	0.4014
size	3,864,443	3,108,008	14,910,930	24,084	174,915	1,154,179
zombie	3,229,352	0.0146	0.1199	0.0000	0.0000	0.0000
oil	4,463,287	48.63	15.83	39.67	47.17	62.61
ur	4,507,352	7.3453	3.1698	4.9000	6.7000	9.0000
inflation	4,617,851	0.2663	0.4362	0.0000	0.2666	0.5065
bci	4,581,438	99.60	2.35	98.10	100.00	101.56
cci	3,971,317	99.28	1.47	98.40	99.06	99.99
fdi_in	4,153,698	23468.00	28571.01	2415.31	10274.11	40673.00
fdi_out	4,153,698	35238.56	49806.31	1447.69	15019.02	59376.00
labor	4,486,425	101.54	5.76	96.98	102.97	105.63

2.3.2 Government policies

As a first analysis we run a regression of daily abnormal returns (*ret*) on the OxCGRT stringency index (*si*), the OxCGRT economic support index (*esi*), the growth of daily reported infection cases (*case growth*), and the price of oil (*oil*). We do this regression stepwise by first integrating only a weekday fixed effects ($\lambda_{weekday}$). In every additional step we integrate one more fixed effect, where $\lambda_{industry}$ denotes industry fixed effects, $\lambda_{country}$ country fixed effects, $\lambda_{company}$ company fixed effects, λ_{day} day fixed effects, and $\lambda_{industry \times day}$ industry times day fixed effects. Finally, also several country controls taken from OECD (2021) are added. These include the previous month's inflation rate, unemployment rate, business confidence index, consumer confidence index, and previous quarter's foreign direct investment in- and outflows, and the relative unit labor cost:

$$\begin{aligned} ret_{i,t} = {} & \alpha + \beta_1 si_{c,t-1} + \beta_2 esi_{c,t-1} + \beta_3 case\, growth_{t-1} + \beta_4 oil_{t-1} \\ & + \beta country\, controls + \lambda_{weekday} + \lambda_{industry} + \lambda_{country} + \lambda_{company} \\ & + \lambda_{day} + \lambda_{industry \times day} \end{aligned} \tag{2.1}$$

where i denotes company, t day, and c country.

Results are reported in Table 2.2. We see that the impact of the stringency index is positive throughout all regression steps at extremely high significance levels, even though the magnitude of the effect becomes considerably smaller the more fixed effects and controls are included. Nevertheless, as this result will remain stable over all further analyses we do, it can safely be coined as a robust result. Hence, we see that an increase in stringency measures, such as lockdowns, school closures, stay-at-home policies, had a clearly positive impact on stock prices and, therefore, presumably on the corporate sector. In terms of the economic significance of this effect, it should be noted that a one standard deviation increase in the stringency index lead to an approximate 0.15% daily increase in the firms' stock prices.

With respect to the economic support index results are less clear. In specifications (1) through (5) in Table 2.2 it seems that economic support measures have a positive impact on stock prices. It should be noted in this context that introducing day fixed effects makes the adjusted R^2 jump by a factor of three. Hence, there is a considerable co-movement in international stock prices, most likely due to commonality in pandemic news. Therefore, the estimated impact of policy measures might be biased as long as the impact of these exogenous news is not controlled for. Similarly, also for the stringency measures we can see that their impact is cut to a fourth once the day fixed effects are accounted for.

Moreover, once we also introduce country controls, the impact of the economic support measures even becomes negative. This is a striking result with no obvious explantion. However, we will see in further specifications that this effect is not robust. Therefore, we conclude that we do not find clear evidence in favour of economic support measures having had a positive impact on the corporate sector.

Table 2.2

How did COVID-19 policy measures affect the corporate sector in general?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.1. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0149***	0.0133***	0.0133***	0.00369***	0.00427***	0.00813***
	(83.96)	(70.72)	(70.25)	(12.61)	(14.41)	(18.19)
esi	0.00275***	0.00633***	0.00634***	0.000480**	0.000475**	-0.00194***
	(23.89)	(38.52)	(38.47)	(2.20)	(2.16)	(-6.64)
case growth	-2.580***	-2.294***	-2.293***	-0.252***	-0.278***	-0.501***
	(-74.22)	(-62.84)	(-62.77)	(-5.58)	(-6.12)	(-9.31)
oil	-0.00120***	-0.00093***	-0.00112***			
	(-7.63)	(-5.85)	(-7.00)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	4,367,941	4,367,941	4,367,933	4,367,933	4,367,933	3,182,579
Adj. R^2	0.007	0.008	0.008	0.024	0.031	0.036

Continued on next page

Table 2.2 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0145***	0.0129***	0.0128***	0.00381***	0.00437***	0.00761***
	(82.69)	(69.04)	(68.45)	(13.00)	(14.75)	(17.04)
esi	0.00275***	0.00637***	0.00639***	0.000538**	0.000512**	-0.00176***
	(23.99)	(38.72)	(38.69)	(2.47)	(2.33)	(-6.05)
case growth	-2.601***	-2.314***	-2.314***	-0.280***	-0.308***	-0.545***
	(-74.85)	(-63.41)	(-63.36)	(-6.19)	(-6.78)	(-10.13)
oil	-0.00140***	-0.00114***	-0.00132***			
	(-8.91)	(-7.15)	(-8.28)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	4,367,941	4,367,941	4,367,933	4,367,933	4,367,933	3,182,579
Adj. R^2	0.007	0.007	0.008	0.023	0.030	0.033

And finally, it should be pointed out that the growth of reported infection cases had a statistically and economically strong negative impact on the corporate sector. In fact, a one standard deviation increase in the number of cases lead to an approximate 0.05% daily decrease in the firms' stock prices.

2.3.3 Firm characteristics

In the next step we add firm controls and interaction terms to the panel regression. These firm controls are employment intensity (ei), book leverage (bl), and firm size ($size$) as measured by revenues. In all three cases we use dummy variables indicating that a firm belongs to the largest size quintile, the highest leverage quintile, or the highest employment intensity quintile. All these variables are measured by the end of the year and held constant throughout the year.

Moreover, we create interaction terms of these three firm variables with the economic support index. By doing so, we can analyse whether these firm characteristics caused a different exposure to the COVID-19 crisis. And, more importantly, we can analyse whether the economic support measures did affect firms differently depending on these characteristics:

$$
\begin{aligned}
ret_{i,t} = {} & \alpha + \beta_1 si_{c,t-1} + \beta_2 esi_{c,t-1} + \beta_3 case\ growth_{t-1} + \beta_4 oil_{t-1} + \beta_5 ei_{i,y-1} \\
& + \beta_6 bl_{i,y-1} + \beta_7 size_{i,y-1} + \beta_8 ei_{i,y-1} \times esi_{c,t-1} + \beta_9 bl_{i,y-1} \times esi_{c,t-1} \\
& + \beta_{10} size_{i,y-1} \times esi_{c,t-1} + \beta country\ controls \\
& + \lambda_{weekday} + \lambda_{industry} + \lambda_{country} + \lambda_{company} + \lambda_{day} + \lambda_{industry \times day}
\end{aligned} \tag{2.2}
$$

where i denotes company, t day, c country, and y year.

Now, three interesting results emerge as can be seen from Table 2.3. First, the exposure to the crisis itself did not differ depending on employment intensity, leverage or size. As we use an industry fixed effect this is, of course, only correct to the extent that these characteristics do not perfectly co-vary with the industry affiliation. Therefore, in some sense we are measuring the firm-specific impact beyond a general industry-specific impact.

Second, highly levered firms profited most from economic support measures. The same is true for small firms, i.e. firms not belonging to the 20 percent largest firms. For both interaction terms we find a statistically highly significant effect. In economic terms we can say that a one standard deviation increase in the economic support index lead to a daily increase in the stock prices for the firms in the highest leverage quintile relative to all other firms by about 0.041%. Large firms experienced a daily decrease in stock prices by about 0.043% relative to all other firms for a one standard deviation increase in the economic support index.

This result is in line with policy goals of sheltering SMEs from the shockwaves generated by the pandemic. However, as also highly levered firms profited from these measures, it could be questioned whether these measures were sufficiently targeted. An obvious reason could have been that it might have been hard for the governments to distinguish between firms that were in financial distress because of the pandemic or because of more general reasons. We will come back to this below.

Table 2.3

Did COVID-19 policy measures affect parts of the corporate sector differently?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*casegrowth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0150***	0.0133***	0.0133***	0.00533***	0.00558***	0.00894***
	(77.23)	(66.09)	(65.68)	(17.44)	(18.25)	(18.92)
esi	0.00277***	0.00695***	0.00694***	0.000886***	0.000985***	-0.000837**
	(18.24)	(35.98)	(32.46)	(3.31)	(3.70)	(-2.48)
ei	0.000468	0.0121	0.0390	-0.0117	-0.0206	-0.0386
	(0.02)	(0.59)	(1.05)	(-0.32)	(-0.58)	(-0.92)
bl	-0.0644***	-0.0540***	-0.0333	-0.0274	-0.0172	-0.0287
	(-3.25)	(-2.76)	(-1.05)	(-0.88)	(-0.55)	(-0.76)
size	-0.00513	-0.0123	-0.0291	-0.00317	0.0194	0.00862
	(-0.40)	(-0.99)	(-0.95)	(-0.11)	(0.66)	(0.23)
ei × esi	0.000129	0.000161	0.000196	0.000867**	0.00100**	0.00118***
	(0.42)	(0.52)	(0.47)	(2.11)	(2.52)	(2.58)
bl × esi	0.00134***	0.00110***	0.00174***	0.00171***	0.00151***	0.00166***
	(4.13)	(3.52)	(4.32)	(4.30)	(3.82)	(3.61)
size × esi	-0.000591***	-0.000634***	-0.000948***	-0.00127***	-0.00165***	-0.00137***
	(-2.68)	(-3.08)	(-3.34)	(-4.55)	(-6.04)	(-4.53)
case growth	-2.660***	-2.309***	-2.306***	-0.112**	-0.143***	-0.332***
	(-73.34)	(-60.22)	(-60.07)	(-2.40)	(-3.04)	(-6.06)
oil	-0.00013	0.00030*	0.00029*			
	(-0.86)	(1.92)	(1.83)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	2,746,576	2,746,576	2,746,575	2,746,575	2,746,575	2,124,902
Adj. R^2	0.012	0.013	0.012	0.049	0.063	0.072

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Table 2.3 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0143***	0.0125***	0.0126***	0.00541***	0.00566***	0.00831***
	(74.89)	(63.09)	(62.69)	(17.62)	(18.41)	(17.57)
esi	0.00284***	0.00708***	0.00709***	0.000971***	0.00106***	-0.000626*
	(18.86)	(36.68)	(33.24)	(3.64)	(3.99)	(-1.86)
ei	-0.00234	0.00960	0.0353	-0.0145	-0.0254	-0.0435
	(-0.11)	(0.47)	(0.96)	(-0.40)	(-0.72)	(-1.04)
bl	-0.0610***	-0.0513***	-0.0287	-0.0235	-0.0127	-0.0249
	(-3.11)	(-2.65)	(-0.91)	(-0.76)	(-0.41)	(-0.66)
size	0.00850	-0.000159	-0.0133	0.0141	0.0372	0.0295
	(0.68)	(-0.01)	(-0.44)	(0.48)	(1.28)	(0.79)
ei × esi	0.000160	0.000194	0.000237	0.000897**	0.00107***	0.00127***
	(0.52)	(0.63)	(0.57)	(2.20)	(2.69)	(2.79)
bl × esi	0.00130***	0.00107***	0.00169***	0.00165***	0.00144***	0.00159***
	(4.05)	(3.44)	(4.23)	(4.19)	(3.69)	(3.50)
size × esi	-0.000779***	-0.000812***	-0.00121***	-0.00154***	-0.00193***	-0.00166***
	(-3.60)	(-3.99)	(-4.32)	(-5.57)	(-7.12)	(-5.51)
case growth	-2.680***	-2.329***	-2.327***	-0.134***	-0.165***	-0.360***
	(-73.91)	(-60.73)	(-60.60)	(-2.86)	(-3.52)	(-6.59)
oil	-0.00042***	0.00000	-0.00001			
	(-2.66)	(0.04)	(-0.06)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	2,746,576	2,746,576	2,746,575	2,746,575	2,746,575	2,124,902
Adj. R^2	0.012	0.013	0.012	0.045	0.059	0.066

Third, we find some evidence that employment intensive firms profited from economic support measures more than others. Based on model (6) in Table 2.3 a one standard deviation increase in the economic support index caused an increase in stock prices of the highest employment intensive firm quintile by 0.032%. This could be an indication that economic support measures to some extent were targeted towards labor intensive firms.

As a side remark it should be pointed out that in the regression results presented here the overall negative impact of the economic support index becomes rather weak in specification (6). In many other specifications, however, the impact is positive and statistically significant. This adds to the qualification made above that results with respect to economic support measures suffer from a lack of robustness.

2.3.4 Zombie firms

Hitherto, we have presented robust evidence that highly leveraged firms clearly profited from economic support measures. It is not totally clear, however, whether this is due to the fact that economic support measures were designed to help firms that financially were most heavily affected by the pandemic, or whether also firms being in financial disorder already before the pandemic also profited from these measures.

While we will show in the robustness Section 2.3.5 that, in fact, firms being highly leveraged already before the crisis profited more from these support measures than others, the more general question we will address here is the following. In principle, the Government economic support measures aimed to target economically viable firms, which were just financially hit by the pandemic. Hence, if support measures were purposefully designed, firms with a weak or even non-viable business models should not have profited.

We test this hypothesis by using the Zombie firm definition as laid down in Favara, Minoiu and Perez-Orive (2021). Such firms are characterised by high leverage, low interest coverage ratios and negative sales growth over the last three fiscal years. It can be argued that firms with such fundamentals might not have a viable business model.

Now, by assigning a dummy variable to all those firms fulfilling these criteria we can test whether they have profited from economic support measures relative to all other non-Zombie firms. We do so by substituting book leverage with this new dummy variable (*zombie*) in Equation 2.2 to get:

$$\begin{aligned}
ret_{i,t} = {} & \alpha + \beta_1 si_{c,t-1} + \beta_2 esi_{c,t-1} + \beta_3 case\,growth_{t-1} + \beta_4 oil_{t-1} \\
& + \beta_5 ei_{i,y-1} + \beta_6 zombie_{i,y-1} + \beta_7 size_{i,y-1} + \beta_8 ei_{i,y-1} \times esi_{c,t-1} \\
& + \beta_9 zombie_{i,y-1} \times esi_{c,t-1} + \beta_{10} size_{i,y-1} \times esi_{c,t-1} \\
& + \beta country\,controls + \lambda_{weekday} + \lambda_{industry} + \lambda_{country} + \lambda_{company} \\
& + \lambda_{day} + \lambda_{industry \times day}
\end{aligned} \tag{2.3}$$

where i denotes company, t day, c country, and y year.

Table 2.4

Did COVID-19 policy measures affect Zombie firms differently?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*casegrowth*), and the oil price (*oil*) following Equation 2.3. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Furthermore, a Zombie firm dummy (*zombie*), which equals one if a firm has above median leverage, and interest coverage ratio of less than one and negative sales growth in the preceding three years, is included and interacted with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0148***	0.0132***	0.0132***	0.00541***	0.00563***	0.00882***
	(75.63)	(64.39)	(64.01)	(17.61)	(18.32)	(18.52)
esi	0.00293***	0.00708***	0.00717***	0.00109***	0.00115***	-0.000628*
	(19.40)	(36.45)	(33.71)	(4.03)	(4.29)	(-1.84)
ei	0.00184	0.0124	0.0507	-0.00654	-0.0113	-0.0279
	(0.09)	(0.58)	(1.31)	(-0.17)	(-0.31)	(-0.64)
zombie	-0.103	-0.113	-0.132	-0.145	-0.135	-0.156
	(-1.17)	(-1.29)	(-1.20)	(-1.33)	(-1.25)	(-1.24)
size	-0.00670	-0.0134	-0.00654	0.0169	0.0385	0.0365
	(-0.52)	(-1.07)	(-0.24)	(0.62)	(1.43)	(1.11)
ei × esi	0.0000432	0.0000744	0.0000735	0.000832*	0.000924**	0.00122**
	(0.14)	(0.23)	(0.17)	(1.96)	(2.24)	(2.56)
zombie × esi	0.00287**	0.00291**	0.00349**	0.00364**	0.00341**	0.00337*
	(2.13)	(2.24)	(2.22)	(2.34)	(2.20)	(1.90)
size × esi	-0.000527**	-0.000570***	-0.000867***	-0.00120***	-0.00157***	-0.00132***
	(-2.36)	(-2.73)	(-3.02)	(-4.24)	(-5.69)	(-4.28)
case growth	-2.693***	-2.341***	-2.340***	-0.113**	-0.147***	-0.330***
	(-73.19)	(-60.14)	(-60.05)	(-2.37)	(-3.07)	(-5.91)
oil	-0.00005	0.00039**	0.00040**			
	(-0.34)	(2.45)	(2.47)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	2,600,164	2,600,164	2,600,164	2,600,164	2,600,164	2,019,470
Adj. R^2	0.013	0.014	0.013	0.052	0.068	0.077

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Table 2.4 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0142***	0.0124***	0.0124***	0.00550***	0.00571***	0.00821***
	(73.36)	(61.47)	(61.10)	(17.81)	(18.52)	(17.23)
esi	0.00299***	0.00720***	0.00731***	0.00117***	0.00122***	-0.000422
	(20.00)	(37.13)	(34.47)	(4.36)	(4.56)	(-1.24)
ei	-0.00121	0.00999	0.0475	-0.00916	-0.0158	-0.0319
	(-0.06)	(0.47)	(1.24)	(-0.24)	(-0.43)	(-0.73)
zombie	-0.0895	-0.101	-0.121	-0.136	-0.127	-0.150
	(-1.02)	(-1.17)	(-1.10)	(-1.24)	(-1.17)	(-1.19)
size	0.00690	-0.00133	0.00929	0.0343	0.0563**	0.0573*
	(0.54)	(-0.11)	(0.34)	(1.27)	(2.11)	(1.75)
ei × esi	0.0000798	0.000109	0.000122	0.000872**	0.000996**	0.00131***
	(0.25)	(0.34)	(0.29)	(2.06)	(2.42)	(2.76)
zombie × esi	0.00271**	0.00276**	0.00333**	0.00350**	0.00329**	0.00326*
	(2.02)	(2.13)	(2.10)	(2.23)	(2.10)	(1.82)
size × esi	-0.000715***	-0.000749***	-0.00113***	-0.00147***	-0.00185***	-0.00160***
	(-3.25)	(-3.63)	(-3.98)	(-5.24)	(-6.75)	(-5.25)
case growth	-2.713***	-2.361***	-2.360***	-0.135***	-0.170***	-0.358***
	(-73.78)	(-60.67)	(-60.59)	(-2.83)	(-3.54)	(-6.44)
oil	-0.00034**	0.00009	0.00009			
	(-2.14)	(0.58)	(0.58)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	2,600,164	2,600,164	2,600,164	2,600,164	2,600,164	2,019,470
Adj. R^2	0.012	0.013	0.013	0.048	0.063	0.070

Results are summarised in Table 2.4. We find clear evidence for ill-targeted economic support measures, i.e. Zombie firms profited from these support measures more than others. The effect is not only statistically but also economically significant, as for a one standard deviation increase in the economic support index Zombie firms gained 0.08% in their stock prices per day.

While our international dataset does not include information about the extent of government support received by Zombie firms, this finding is in line with Hoshi, Kawaguchi and Ueda (2023), who show that firms with poor performance before the pandemic were more likely to receive government support in Japan.

2.3.5 Robustness tests

A first important robustness test is related to the measurement of firm characteristics. Most importantly, it could be argued that the findings with respect to firm leverage might, at least to some extent, be driven by reverse causality. In fact, firms being hit most hard by the crisis might be in the focus of any economic support measures implemented by the government. However, for the observations related to the year 2021, these might also be the firms with the strongest increase in leverage.

To get rid of this reverse causality, we re-calculate the results in Table 2.3 using observations for the year 2020 only. Hence, all firm characteristics are derived from financial statements ending in the year 2019, which reasonably is not yet affected by the pandemic. It can be seen in Table 2.5 that the results are unchanged.

Table 2.5

Did COVID-19 policy measures affect parts of the corporate sector differently in 2020?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The observation period is restricted from January 2020 to December 2020. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0183***	0.0171***	0.0171***	0.0104***	0.0109***	0.0129***
	(62.24)	(52.84)	(52.54)	(22.32)	(23.49)	(20.65)
esi	0.00233***	0.00532***	0.00526***	-0.00229***	-0.00232***	-0.00122***
	(10.69)	(19.47)	(18.22)	(-6.31)	(-6.47)	(-2.99)
ei	0.0308	0.0188				
	(1.16)	(0.72)				
bl	-0.0854***	-0.0649***				
	(-3.46)	(-2.65)				
size	-0.0208	-0.0140				
	(-1.34)	(-0.92)				
ei × esi	0.000220	0.000432	0.000551	0.00131***	0.00150***	0.00138***
	(0.56)	(1.09)	(1.16)	(2.77)	(3.27)	(2.78)
bl × esi	0.00166***	0.00124***	0.00171***	0.00164***	0.00142***	0.00169***
	(4.12)	(3.07)	(3.59)	(3.50)	(3.06)	(3.37)
size × esi	-0.000659**	-0.000733***	-0.000808***	-0.00108***	-0.00147***	-0.00154***
	(-2.53)	(-2.89)	(-2.58)	(-3.51)	(-4.92)	(-4.81)
case growth	-2.483***	-2.241***	-2.241***	-0.175***	-0.207***	-0.330***
	(-66.76)	(-56.92)	(-56.93)	(-3.73)	(-4.39)	(-6.00)
oil	0.00213***	0.00299***	0.00300***			
	(5.44)	(7.52)	(7.50)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,591,240	1,591,240	1,591,239	1,591,239	1,591,239	1,382,210
Adj. R^2	0.017	0.018	0.016	0.061	0.076	0.083

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Table 2.5 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0173***	0.0158***	0.0157***	0.0105***	0.0110***	0.0121***
	(58.87)	(48.55)	(48.29)	(22.61)	(23.82)	(19.46)
esi	0.00259***	0.00581***	0.00577***	-0.00201***	-0.00205***	-0.00110***
	(11.92)	(21.25)	(19.97)	(-5.54)	(-5.71)	(-2.68)
ei	0.0270	0.0165				
	(1.02)	(0.64)				
bl	-0.0820***	-0.0633***				
	(-3.36)	(-2.61)				
size	-0.00391	-0.000198				
	(-0.25)	(-0.01)				
ei × esi	0.000255	0.000466	0.000586	0.00134***	0.00158***	0.00149***
	(0.65)	(1.19)	(1.23)	(2.86)	(3.44)	(3.00)
bl × esi	0.00163***	0.00122***	0.00169***	0.00159***	0.00136***	0.00162***
	(4.09)	(3.05)	(3.57)	(3.42)	(2.95)	(3.26)
size × esi	-0.000875***	-0.000928***	-0.00107***	-0.00136***	-0.00177***	-0.00183***
	(-3.39)	(-3.68)	(-3.43)	(-4.48)	(-5.94)	(-5.74)
case growth	-2.496***	-2.247***	-2.248***	-0.195***	-0.228***	-0.360***
	(-67.23)	(-57.20)	(-57.21)	(-4.16)	(-4.84)	(-6.56)
oil	0.00104***	0.00174***	0.00175***			
	(2.63)	(4.32)	(4.32)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,591,240	1,591,240	1,591,239	1,591,239	1,591,239	1,382,210
Adj. R^2	0.016	0.017	0.016	0.055	0.070	0.075

Second, results might be driven by the performance of specific sectors. Hence, we include sector times day (country × industry × day) in Table 2.6. While the stringency and economic support index are absorbed by this additional fixed effect, the remaining results discussed in Section 2.3.3 are still valid.

Table 2.6

Did COVID-19 policy measures affect parts of the corporate sector differently when accounting for sector times day fixed effects?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday, industry and country fixed effects (Column 1), company, day, and industry × day fixed effects are included stepwise. Column 5 additionally includes country controls. Column 6 also accounts for sector × day (industry × country × day) fixed effects. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0133***	0.0133***	0.00533***	0.00558***	0.00894***	
	(66.09)	(65.68)	(17.44)	(18.25)	(18.92)	
esi	0.00695***	0.00694***	0.000886***	0.000985***	-0.000837**	
	(35.98)	(32.46)	(3.31)	(3.70)	(-2.48)	
ei	0.0121	0.0390	-0.0117	-0.0206	-0.0386	-0.0468
	(0.59)	(1.05)	(-0.32)	(-0.58)	(-0.92)	(-1.12)
bl	-0.0540***	-0.0333	-0.0274	-0.0172	-0.0287	-0.0257
	(-2.76)	(-1.05)	(-0.88)	(-0.55)	(-0.76)	(-0.66)
size	-0.0123	-0.0291	-0.00317	0.0194	0.00862	0.0522
	(-0.99)	(-0.95)	(-0.11)	(0.66)	(0.23)	(1.35)
ei × esi	0.000161	0.000196	0.000867**	0.00100**	0.00118***	0.00127***
	(0.52)	(0.47)	(2.11)	(2.52)	(2.58)	(2.69)
bl × esi	0.00110***	0.00174***	0.00171***	0.00151***	0.00166***	0.00166***
	(3.52)	(4.32)	(4.30)	(3.82)	(3.61)	(3.49)
size × esi	-0.000634***	-0.000948***	-0.00127***	-0.00165***	-0.00137***	-0.00176***
	(-3.08)	(-3.34)	(-4.55)	(-6.04)	(-4.53)	(-5.56)
case growth	-2.309***	-2.306***	-0.112**	-0.143***	-0.332***	
	(-60.22)	(-60.07)	(-2.40)	(-3.04)	(-6.06)	
oil	0.00030*	0.00029*				
	(1.92)	(1.83)				
Country Controls	No	No	No	No	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	Yes
Industry × Day FE	No	No	No	Yes	Yes	Yes
Sector × Day FE	No	No	No	No	No	Yes
N	2,746,576	2,746,575	2,746,575	2,746,575	2,124,902	2,114,443
Adj. R^2	0.013	0.012	0.049	0.063	0.072	0.112

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Table 2.6 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0125***	0.0126***	0.00541***	0.00566***	0.00831***	
	(63.09)	(62.69)	(17.62)	(18.41)	(17.57)	
esi	0.00708***	0.00709***	0.000971***	0.00106***	-0.000626*	
	(36.68)	(33.24)	(3.64)	(3.99)	(-1.86)	
ei	0.00960	0.0353	-0.0145	-0.0254	-0.0435	-0.0449
	(0.47)	(0.96)	(-0.40)	(-0.72)	(-1.04)	(-1.08)
bl	-0.0513***	-0.0287	-0.0235	-0.0127	-0.0249	-0.0251
	(-2.65)	(-0.91)	(-0.76)	(-0.41)	(-0.66)	(-0.65)
size	-0.000159	-0.0133	0.0141	0.0372	0.0295	0.0652*
	(-0.01)	(-0.44)	(0.48)	(1.28)	(0.79)	(1.68)
ei × esi	0.000194	0.000237	0.000897**	0.00107***	0.00127***	0.00126***
	(0.63)	(0.57)	(2.20)	(2.69)	(2.79)	(2.66)
bl × esi	0.00107***	0.00169***	0.00165***	0.00144***	0.00159***	0.00165***
	(3.44)	(4.23)	(4.19)	(3.69)	(3.50)	(3.50)
size × esi	-0.000812***	-0.00121***	-0.00154***	-0.00193***	-0.00166***	-0.00192***
	(-3.99)	(-4.32)	(-5.57)	(-7.12)	(-5.51)	(-6.08)
case growth	-2.329***	-2.327***	-0.134***	-0.165***	-0.360***	
	(-60.73)	(-60.60)	(-2.86)	(-3.52)	(-6.59)	
oil	0.00001	-0.00001				
	(0.04)	(-0.06)				
Country Controls	No	No	No	No	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Company FE	No	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	Yes
Industry × Day FE	No	No	No	Yes	Yes	Yes
Sector × Day FE	No	No	No	No	No	Yes
N	2,746,576	2,746,575	2,746,575	2,746,575	2,124,902	2,114,443
Adj. R^2	0.013	0.012	0.045	0.059	0.066	0.104

A third set of robustness tests is related to the question to what extent the results might be driven by the US, as this market represents, of course, a significant part of our data set. Therefore, we repeat the analyses in Tables 2.2 to 2.4 for European countries only. Results are summarised in Tables 2.7 to 2.9.

Table 2.7

How did COVID-19 policy measures affect the corporate sector in Europe?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price following Equation 2.1. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The sample is restricted to European firms. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0110***	0.0106***	0.0106***	0.00658***	0.00686***	0.00773***
	(50.09)	(46.89)	(46.74)	(16.86)	(17.64)	(15.85)
esi	0.00202***	0.00559***	0.00560***	-0.000555**	-0.000791***	-0.00115***
	(16.01)	(26.89)	(26.77)	(-2.05)	(-2.92)	(-3.72)
case growth	-2.418***	-2.115***	-2.112***	-0.235***	-0.274***	-0.282***
	(-57.37)	(-47.24)	(-47.19)	(-4.41)	(-5.13)	(-4.79)
oil	0.00090***	0.00103***	0.00099***			
	(4.57)	(5.08)	(4.88)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,994,686	1,994,686	1,994,686	1,994,686	1,994,682	1,645,596
Adj. R^2	0.007	0.008	0.008	0.019	0.021	0.022

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Table 2.7 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0109***	0.0106***	0.0105***	0.00650***	0.00679***	0.00766***
	(49.82)	(46.50)	(46.32)	(16.55)	(17.39)	(15.66)
esi	0.00204***	0.00561***	0.00562***	-0.000502*	-0.000733***	-0.00105***
	(16.14)	(26.94)	(26.83)	(-1.85)	(-2.71)	(-3.38)
case growth	-2.424***	-2.121***	-2.119***	-0.253***	-0.291***	-0.296***
	(-57.64)	(-47.48)	(-47.43)	(-4.75)	(-5.45)	(-5.02)
oil	0.00087***	0.00100***	0.00096***			
	(4.42)	(4.93)	(4.72)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,994,686	1,994,686	1,994,686	1,994,686	1,994,682	1,645,596
Adj. R^2	0.007	0.008	0.008	0.018	0.021	0.022

In most cases results are qualitatively, but also in terms of economic relevance, unchanged. A slight difference worth to be mentioned is the following: the potential negative impact of economic support measures becomes more evident in European data. In fact, once integrating day fixed effect (cf. specification 4), the sign of the coefficient turns negative in Table 2.7. However, in Table 2.8, the sign stays positive throughout all models. This further corroborates the statement that results with respect to economic support measures suffer from robustness.

Moreover, it can be seen in Table 2.9 that the Zombie-effect discussed above is the same for European companies. A one standard deviation increase in the economic support index also leads the stock price of a European Zombie firm to increase by 0.08%.

Table 2.8

Did COVID-19 policy measures affect parts of the corporate sector differently in Europe?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The sample is restricted to European firms. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0105***	0.00963***	0.00965***	0.00679***	0.00702***	0.00862***
	(47.08)	(42.20)	(41.89)	(16.66)	(17.43)	(16.83)
esi	0.00258***	0.00711***	0.00725***	0.00106***	0.000836***	0.000629*
	(16.02)	(30.81)	(27.26)	(3.23)	(2.59)	(1.70)
ei	-0.0712***	-0.0461*	-0.00452	-0.0558	-0.0593	-0.0567
	(-2.67)	(-1.82)	(-0.09)	(-1.17)	(-1.29)	(-1.14)
bl	-0.0785***	-0.0700***	-0.0636	-0.0390	-0.0448	-0.0220
	(-2.92)	(-2.77)	(-1.44)	(-0.90)	(-1.03)	(-0.45)
size	-0.00501	0.0140	0.105**	0.105***	0.112***	0.123***
	(-0.28)	(0.85)	(2.56)	(2.75)	(2.90)	(2.95)
ei × esi	0.00131***	0.000972***	0.00124**	0.00176***	0.00187***	0.00201***
	(3.68)	(2.75)	(2.44)	(3.55)	(3.88)	(3.99)
bl × esi	0.000779**	0.000853**	0.00153***	0.00130**	0.00129**	0.00122**
	(2.05)	(2.30)	(2.69)	(2.30)	(2.28)	(2.02)
size × esi	-0.000841***	-0.000906***	-0.00181***	-0.00201***	-0.00194***	-0.00205***
	(-3.32)	(-3.69)	(-4.55)	(-5.10)	(-5.09)	(-5.13)
case growth	-2.397***	-2.019***	-2.015***	-0.285***	-0.326***	-0.339***
	(-57.50)	(-45.21)	(-45.08)	(-5.51)	(-6.28)	(-5.84)
oil	0.00208***	0.00245***	0.00258***			
	(11.03)	(12.45)	(12.81)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,367,486	1,367,486	1,367,486	1,367,486	1,367,111	1,114,665
Adj. R^2	0.012	0.014	0.013	0.031	0.037	0.039

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Table 2.8 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0103***	0.00942***	0.00943***	0.00664***	0.00687***	0.00842***
	(46.11)	(41.03)	(40.72)	(16.13)	(16.94)	(16.35)
esi	0.00264***	0.00720***	0.00736***	0.00120***	0.000982***	0.000822**
	(16.43)	(31.15)	(27.67)	(3.65)	(3.04)	(2.22)
ei	-0.0707***	-0.0456*	-0.00181	-0.0528	-0.0570	-0.0523
	(-2.65)	(-1.80)	(-0.04)	(-1.11)	(-1.25)	(-1.05)
bl	-0.0831***	-0.0747***	-0.0700	-0.0460	-0.0492	-0.0287
	(-3.11)	(-2.98)	(-1.60)	(-1.07)	(-1.14)	(-0.59)
size	0.00825	0.0274*	0.122***	0.124***	0.132***	0.149***
	(0.46)	(1.67)	(2.99)	(3.24)	(3.41)	(3.54)
ei × esi	0.00130***	0.000965***	0.00121**	0.00173***	0.00185***	0.00199***
	(3.66)	(2.73)	(2.39)	(3.49)	(3.84)	(3.94)
bl × esi	0.000845**	0.000924**	0.00162***	0.00139**	0.00135**	0.00130**
	(2.24)	(2.50)	(2.88)	(2.49)	(2.40)	(2.16)
size × esi	-0.000994***	-0.00106***	-0.00207***	-0.00227***	-0.00222***	-0.00235***
	(-3.93)	(-4.31)	(-5.19)	(-5.76)	(-5.81)	(-5.87)
case growth	-2.401***	-2.022***	-2.018***	-0.298***	-0.338***	-0.347***
	(-57.71)	(-45.37)	(-45.23)	(-5.79)	(-6.55)	(-5.98)
oil	0.00202***	0.00238***	0.00251***			
	(10.74)	(12.16)	(12.51)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,367,486	1,367,486	1,367,486	1,367,486	1,367,111	1,114,665
Adj. R^2	0.012	0.014	0.013	0.030	0.036	0.037

Table 2.9

Did COVID-19 policy measures affect Zombie firms differently in Europe?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.3. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Furthermore, a Zombie firm dummy (*zombie*), which equals one if a firm has above median leverage, and interest coverage ratio of less than one and negative sales growth in the preceding three years, is included and interacted with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The sample is restricted to European firms. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0104***	0.00959***	0.00961***	0.00671***	0.00693***	0.00856***
	(46.20)	(41.33)	(41.03)	(16.22)	(16.93)	(16.38)
esi	0.00264***	0.00716***	0.00737***	0.00120***	0.000982***	0.000830**
	(16.84)	(30.82)	(28.03)	(3.61)	(3.00)	(2.22)
ei	-0.0686**	-0.0461*	0.00984	-0.0435	-0.0466	-0.0409
	(-2.50)	(-1.77)	(0.19)	(-0.88)	(-0.98)	(-0.79)
zombie	-0.0960	-0.0829	-0.279*	-0.245	-0.254*	-0.207
	(-0.83)	(-0.77)	(-1.74)	(-1.56)	(-1.70)	(-1.14)
size	-0.00544	0.0118	0.104**	0.0981**	0.105***	0.116***
	(-0.30)	(0.71)	(2.52)	(2.51)	(2.67)	(2.72)
ei × esi	0.00126***	0.000923**	0.00121**	0.00175***	0.00185***	0.00199***
	(3.46)	(2.54)	(2.32)	(3.42)	(3.72)	(3.82)
zombie × esi	0.00213	0.00232*	0.00369*	0.00340*	0.00329*	0.00309
	(1.47)	(1.71)	(1.87)	(1.75)	(1.73)	(1.47)
size × esi	-0.000816***	-0.000842***	-0.00172***	-0.00193***	-0.00190***	-0.00200***
	(-3.18)	(-3.38)	(-4.26)	(-4.84)	(-4.91)	(-4.96)
case growth	-2.408***	-2.031***	-2.027***	-0.301***	-0.343***	-0.356***
	(-56.28)	(-44.21)	(-44.12)	(-5.70)	(-6.46)	(-6.02)
oil	0.00218***	0.00256***	0.00268***			
	(11.43)	(12.88)	(13.18)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,306,437	1,306,437	1,306,437	1,306,437	1,306,062	1,068,130
Adj. R^2	0.012	0.014	0.013	0.032	0.038	0.040

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Table 2.9 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0102***	0.00937***	0.00938***	0.00657***	0.00679***	0.00838***
	(45.23)	(40.17)	(39.89)	(15.74)	(16.49)	(15.95)
esi	0.00271***	0.00726***	0.00750***	0.00135***	0.00114***	0.00103***
	(17.31)	(31.19)	(28.47)	(4.06)	(3.48)	(2.77)
ei	-0.0684**	-0.0459*	0.0124	-0.0408	-0.0446	-0.0368
	(-2.50)	(-1.77)	(0.24)	(-0.83)	(-0.94)	(-0.71)
zombie	-0.0990	-0.0863	-0.282*	-0.248	-0.258*	-0.212
	(-0.88)	(-0.83)	(-1.77)	(-1.60)	(-1.73)	(-1.18)
size	0.00775	0.0252	0.121***	0.116***	0.125***	0.142***
	(0.42)	(1.51)	(2.93)	(2.97)	(3.16)	(3.30)
ei × esi	0.00126***	0.000919**	0.00119**	0.00172***	0.00183***	0.00197***
	(3.46)	(2.53)	(2.28)	(3.38)	(3.70)	(3.78)
zombie × esi	0.00217	0.00236*	0.00372*	0.00344*	0.00332*	0.00316
	(1.52)	(1.78)	(1.89)	(1.77)	(1.75)	(1.52)
size × esi	-0.000967***	-0.000994***	-0.00197***	-0.00218***	-0.00217***	-0.00230***
	(-3.77)	(-3.99)	(-4.89)	(-5.47)	(-5.61)	(-5.67)
case growth	-2.411***	-2.033***	-2.030***	-0.314***	-0.355***	-0.363***
	(-56.47)	(-44.35)	(-44.26)	(-5.98)	(-6.71)	(-6.15)
oil	0.00212***	0.00249***	0.00261***			
	(11.13)	(12.58)	(12.87)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	1,306,437	1,306,437	1,306,437	1,306,437	1,306,062	1,068,130
Adj. R^2	0.012	0.014	0.013	0.031	0.037	0.038

Fourth, the question arises whether the impact of COVID-19 Government measures on stock returns varies across different phases of the pandemic. Hence, we estimate Equation 2.2 on sub-samples of our overall dataset for the first wave, i.e. January 2020 to August 2020, and the second wave, i.e. September 2020 to March 2021, of the pandemic. The results are presented in Tables 2.10 and 2.11.

Table 2.10

Did COVID-19 policy measures affect parts of the corporate sector differently in the first wave of the pandemic?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The observation period is restricted to the first wave of the COVID-19 pandemic, i.e., from January 2020 to August 2020. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.0187***	0.0157***	0.0157***	0.0120***	0.0126***	0.0144***
	(31.13)	(24.68)	(24.76)	(15.55)	(16.68)	(16.53)
esi	0.00238***	0.00796***	0.00792***	0.00288***	0.00246***	0.00385***
	(7.20)	(20.88)	(19.73)	(5.06)	(4.30)	(5.56)
ei	-0.0489	-0.0786**				
	(-1.27)	(-2.26)				
bl	-0.166***	-0.122***				
	(-4.22)	(-3.35)				
size	-0.0137	0.0500**				
	(-0.50)	(1.98)				
ei × esi	0.00186***	0.00219***	0.00294***	0.00334***	0.00349***	0.00331***
	(3.49)	(4.20)	(4.71)	(5.31)	(5.66)	(5.31)
bl × esi	0.00173***	0.00129**	0.00133*	0.00126*	0.00126*	0.00136*
	(2.76)	(2.08)	(1.81)	(1.70)	(1.68)	(1.79)
size × esi	-0.00176***	-0.00228***	-0.00284***	-0.00294***	-0.00296***	-0.00284***
	(-4.58)	(-6.04)	(-6.13)	(-6.37)	(-6.50)	(-6.16)
case growth	-2.007***	-1.698***	-1.699***	-0.296***	-0.334***	-0.367***
	(-46.06)	(-38.15)	(-38.16)	(-5.65)	(-6.35)	(-6.22)
oil	0.0123***	0.0143***	0.0143***			
	(17.09)	(19.24)	(19.28)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	498,322	498,322	498,322	498,322	498,198	457,197
Adj. R^2	0.022	0.025	0.023	0.046	0.052	0.052

Continued on next page

Table 2.10 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.0184***	0.0153***	0.0153***	0.0117***	0.0123***	0.0141***
	(30.33)	(23.80)	(23.88)	(15.03)	(16.18)	(16.06)
esi	0.00250***	0.00807***	0.00807***	0.00293***	0.00250***	0.00393***
	(7.58)	(21.06)	(19.99)	(5.13)	(4.37)	(5.66)
ei	-0.0484	-0.0785**				
	(-1.27)	(-2.27)				
bl	-0.175***	-0.130***				
	(-4.52)	(-3.59)				
size	0.0193	0.0841***				
	(0.70)	(3.31)				
ei × esi	0.00187***	0.00220***	0.00294***	0.00333***	0.00348***	0.00329***
	(3.53)	(4.25)	(4.72)	(5.31)	(5.67)	(5.30)
bl × esi	0.00183***	0.00139**	0.00135*	0.00128*	0.00126*	0.00137*
	(2.92)	(2.24)	(1.84)	(1.74)	(1.69)	(1.82)
size × esi	-0.00193***	-0.00246***	-0.00307***	-0.00317***	-0.00319***	-0.00307***
	(-5.03)	(-6.52)	(-6.63)	(-6.85)	(-6.99)	(-6.64)
case growth	-2.015***	-1.707***	-1.707***	-0.311***	-0.348***	-0.378***
	(-46.34)	(-38.38)	(-38.39)	(-5.95)	(-6.63)	(-6.42)
oil	0.0119***	0.0139***	0.0139***			
	(16.53)	(18.63)	(18.67)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	498,322	498,322	498,322	498,322	498,198	457,197
Adj. R^2	0.022	0.025	0.023	0.045	0.051	0.051

Table 2.11

Did COVID-19 policy measures affect parts of the corporate sector differently in the second wave of the pandemic?

This table reports estimates from linear regressions of daily abnormal returns on the stringency index (*si*), the economic support index (*esi*), the growth of confirmed COVID-19 cases (*case growth*), and the oil price (*oil*) following Equation 2.2. The models also include dummy variables which equal one for the quintile of firms with the highest employee intensity (*ei*), the highest book leverage ratio (*bl*), the largest revenues (*size*), and their respective interaction terms with the economic support index. Starting with weekday fixed effects (Column 1), industry, country, company, day, and industry × day fixed effects are included stepwise. Column 6 additionally includes country controls. The observation period is restricted to the second wave of the COVID-19 pandemic, i.e., from September 2020 to March 2021. T-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table B. 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fama-French 3-factor daily abnormal returns						
	FF3	FF3	FF3	FF3	FF3	FF3
si	0.00426***	0.00746***	0.00748***	0.00453***	0.00457***	0.00537***
	(10.13)	(13.23)	(13.26)	(6.16)	(6.19)	(6.60)
esi	-0.000106	-0.000898	0.000284	0.000356	0.000557	0.000150
	(-0.44)	(-1.56)	(0.39)	(0.49)	(0.76)	(0.19)
ei	-0.0145	-0.0279	0.0782	0.0533	0.0586	0.0468
	(-0.42)	(-0.82)	(0.90)	(0.61)	(0.67)	(0.49)
bl	0.0529	0.0538	0.148*	0.145*	0.164*	0.203**
	(1.19)	(1.21)	(1.72)	(1.70)	(1.91)	(2.12)
size	0.00332	-0.00502	0.202**	0.238***	0.243***	0.273***
	(0.14)	(-0.23)	(2.21)	(2.63)	(2.66)	(2.64)
ei × esi	0.000694	0.000736	-0.00110	-0.000807	-0.000823	-0.000573
	(1.47)	(1.58)	(-0.98)	(-0.72)	(-0.74)	(-0.48)
bl × esi	-0.000563	-0.000440	-0.00205*	-0.00213*	-0.00244**	-0.00294**
	(-0.95)	(-0.75)	(-1.88)	(-1.95)	(-2.23)	(-2.49)
size × esi	-0.000131	-0.0000428	-0.00219**	-0.00256***	-0.00261***	-0.00279***
	(-0.39)	(-0.13)	(-2.24)	(-2.63)	(-2.68)	(-2.58)
case growth	-1.123***	-1.171***	-1.130***	-1.328***	-1.440***	-1.733***
	(-3.26)	(-3.31)	(-3.19)	(-3.06)	(-3.34)	(-3.38)
oil	-0.00122**	-0.00374***	-0.00360***			
	(-2.12)	(-5.77)	(-5.56)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	504,122	504,122	504,122	504,122	503,977	458,191
Adj. R^2	0.001	0.001	-0.000	0.009	0.016	0.016

Continued on next page

Table 2.11 continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Carhart 4-factor daily abnormal returns						
	C4	C4	C4	C4	C4	C4
si	0.00392***	0.00681***	0.00684***	0.00431***	0.00437***	0.00507***
	(9.35)	(12.03)	(12.09)	(5.85)	(5.93)	(6.22)
esi	-0.0000257	-0.000715	0.000416	0.000421	0.000651	0.0000974
	(-0.11)	(-1.24)	(0.57)	(0.57)	(0.89)	(0.12)
ei	-0.0139	-0.0260	0.0715	0.0484	0.0511	0.0397
	(-0.40)	(-0.76)	(0.81)	(0.55)	(0.58)	(0.41)
bl	0.0569	0.0563	0.133	0.131	0.152*	0.190**
	(1.27)	(1.26)	(1.55)	(1.53)	(1.78)	(1.99)
size	-0.0232	-0.0307	0.185**	0.219**	0.229**	0.258**
	(-1.01)	(-1.39)	(2.04)	(2.44)	(2.52)	(2.50)
ei × esi	0.000670	0.000696	-0.00106	-0.000785	-0.000758	-0.000523
	(1.43)	(1.50)	(-0.94)	(-0.70)	(-0.68)	(-0.44)
bl × esi	-0.000575	-0.000463	-0.00182*	-0.00190*	-0.00226**	-0.00275**
	(-0.97)	(-0.78)	(-1.66)	(-1.75)	(-2.07)	(-2.32)
size × esi	-0.0000400	0.0000387	-0.00211**	-0.00246**	-0.00258***	-0.00275**
	(-0.12)	(0.12)	(-2.16)	(-2.53)	(-2.66)	(-2.55)
case growth	-1.123***	-1.170***	-1.131***	-1.085**	-1.183***	-1.345***
	(-3.22)	(-3.27)	(-3.16)	(-2.48)	(-2.73)	(-2.62)
oil	-0.000736	-0.00300***	-0.00286***			
	(-1.27)	(-4.61)	(-4.40)			
Country Controls	No	No	No	No	No	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes
Company FE	No	No	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes	Yes
Industry × Day FE	No	No	No	No	Yes	Yes
N	504,122	504,122	504,122	504,122	503,977	458,191
Adj. R^2	0.001	0.001	-0.000	0.008	0.014	0.014

Table 2.10 shows, that almost all findings discussed in Section 2.3.3 are even more pronounced when restricting the observation period to the first wave of the pandemic. In addition to the increased impact of the stringency index on abnormal daily stock returns, the coefficients for the interaction of the economic support index and employment intensity resp. size about double in magnitude compared to the full dataset. With regard to the second wave of the pandemic Table 2.11 shows overall weaker effects compared to the full observation period. Moreover, highly levered firms appear to have profited less from economic support measure during this period of time.

2.4 Conclusion

In this paper we have studied the impact of Government interventions during the COVID-19 pandemic on the corporate sector as represented by listed firms. By using a broad international firm-level data set and combining it with the Oxford COVID-19 Government Response Tracker (OxCGRT) (cf. Hale et al. (2021)), we found robust evidence for Government stringency measures to effectively shelter firms from further disruptions. With respect to the economic support measures the evidence is, however, less clear. If ever, we get a weak indication that in European countries these measures had a positive impact on the corporate sector.

When it comes to the question who was profiting from the economic support measures, we found evidence in line with the underlying policy goals. However, we also uncovered some unintended effects.

More precisely, smaller, highly levered and more employment intensive companies profited most from economic support measures. While this is in line with an official policy of sheltering SMEs and human capital intensive companies from the Corona shock waves, it also seems that Government unintentionally supported firms in financial difficulties already before the financial crisis. This presumption is further corroborated by evidence showing that Zombie firms profited from economic support measures more than others.

3 Chaos is a Ladder: Mutual Fund Management in Times of Economic Uncertainty

Key words:	Mutual Funds, Volatility Timing, Performance Evaluation
JEL Codes:	G10, G15, G20, G23

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Abstract

By using a large international set of active equity mutual funds, this paper provides new insights into the performance of active mutual funds in times of economic uncertainty. First, I find robust evidence that active funds can increase their performance during crisis periods based on their level of activity. Second, this positive performance moderation can only be observed during severe economic turbulence. Third, the level of fund activity has, in general, a negative impact on fund performance. However, the direction changes during crisis periods, where active fund managers can outperform their more passive peers. Fourth, higher cash reserves alone cannot explain the superior performance of active funds during economic turmoil.

3.1 Introduction

To this day, the popularity of active equity mutual funds remains a puzzle (e.g. Pástor and Vorsatz (2020)): On one hand, it is well-established that these funds overall perform worse than passive benchmarks net of fees (cf. among others Jensen (1968), Elton et al. (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), Pástor and Stambaugh (2002), Fama and French (2010)). On the other hand, active equity mutual funds are, despite this underperformance, able to attract vast amounts of assets from investors. This seeming contradiction is usually rationalised with the notion that active fund managers can justify their fees in times of economic uncertainty: Moskowitz (2000) suggested that active mutual funds might be able to provide a partial hedge during recessions. Kosowski (2011) supported this notion by attributing the established inferior performance of US domestic open-end funds only to expansion and not recession periods. Finally, Glode (2011) formulated it into a model according to which fund managers can generate state-dependent active returns. Here, mutual fund managers will optimally focus on realising superior performance in bad states of the economy, which is why they might wrongly appear to underperform passive investment strategies.

However, Pástor and Vorsatz (2020) and Mirza et al. (2020) recently cast doubt on this popular hypothesis by showing that most active funds could not generate superior performance during the COVID-19 pandemic. On the contrary, Pástor and Vorsatz (2020) find that active US equity funds, on average, significantly underperformed their benchmarks during this crisis. Similarly, Mirza et al. (2020) find negative risk-adjusted performance for most types of European mutual funds in the first half of 2020.

Prompted by their findings and using large-scale evidence, this paper aims to reassess whether chaos is genuinely a ladder for active mutual funds or whether they fail to justify their cost even in times of economic uncertainty. In contrast to most previous studies, however, I do not define a fund only as active or passive but account for the degree of fund activity. Doing so allows me to ask whether a more substantial deviation from the funds' benchmarks leads to superior performance during economic uncertainty or even vice versa. The former could be attributed to the managers' skills, while the latter could result from overconfidence. In detail, four questions will be addressed:

First, do more active equity mutual funds perform better in times of economic uncertainty? Second, is this performance moderation stable over time? Third, do active funds generate higher returns than their more passive counterparts in times of economic uncertainty? Fourth, why do active funds profit from economic turmoil?

I follow the well-established practice of measuring the level of fund activity using their tracking error (cf. among others Wermers (2003), Cremers and Petajisto (2009), Huij and Derwall (2011), Ekholm (2012)). However, focusing on the tracking error as a proxy for fund activity highlights the question of why more active funds potentially exhibit superior performance in crisis periods. Osterhoff and Kaserer (2016) have shown that the tracking error of ETFs in the German DAX universe is dependent on cash holdings and flows. Therefore, a correlation of fund activity with superior performance during economic uncertainty could simply be the result of high and, in crisis periods, beneficial cash holdings, especially if activity is measured via the tracking error. On the other hand, active fund managers could generate superior returns in economic uncertainty by skillfully adjusting their portfolios, e.g., reducing the share of negatively affected stocks, which would be in line with the model by Glode (2011). These two potential explanations for superior performance of active funds during crises need to be disentangled to shed light on the mechanisms at work. I do so by calculating a cash-adjusted tracking error.

While there are other measures for fund activity than the tracking error, specifically Active Share introduced by Cremers and Petajisto (2009), calculating these measures would require detailed, highly granular data such as the funds' portfolio histories, significantly restricting the sample. Hence, focusing on the tracking error as the traditional proxy for fund activity enables us to build a large international data set of 42,985 active equity mutual funds.

The sample period ranges from January 2000 to October 2022, encompassing a comprehensive range of economic states from low volatility periods to major economic crises inducing high levels of economic uncertainty, such as the Global Financial Crisis in 2008 or the COVID-19 pandemic in 2020.

I identify the following answers to the abovementioned questions: First, more active fund managers can use their skills to generate higher performance during economic uncertainty. Second, this only holds for periods with severe economic turbulence and cannot be observed in more stable phases of the economy. Third, overall fund activity, defined via the tracking error, has a negative impact on performance. However, active managers break even during severe economic uncertainty, where they can generate economically significant superior results. Fourth, the superior performance of active funds during economic crises cannot be explained by higher cash reserves alone.

By reassessing the while popular also still controversially discussed hypotheses that the underperformance of active mutual funds is at least to some degree outweighed by their superior performance when it matters most for investors, I contribute to the literature in several ways: First, most studies in this strand of literature only include US equity funds. By building a large-scale international data set of active mutual funds entailing multiple significant economic crises, I provide new empirical evidence for the relationship between fund activity and performance during economic uncertainty. Second, instead of classifying a period only as a recession or expansion period (e.g. Kosowski (2011)), I employ the CBOE Volatility Index (VIX) as a comparable, widely accepted, and more granular measure of general economic uncertainty (cf. among others Chatziantoniou et al. (2021), Pham and Nguyen (2022)). Third, to the best of my knowledge, I am the first to ask how the degree of a fund's activity influences its performance during economic uncertainty, as previous studies addressing the hypothesis mentioned above only classified funds as active or passive and did not differentiate by the level of fund activity.

3.2 Empirical strategy

3.2.1 Regression approach

I employ a fixed effect panel regression approach. The dependent variable is the monthly fund return, net of fees, and adjusted for benchmark returns (*net return*). The independent variables are the funds' rolling one-year tracking error (te) as a proxy for fund activity, their flow relative to its assets under management ($flow$), their unadjusted, net of fees, past return ($return$), and the VIX (vix) as a measure of economic uncertainty. All independent variables are lagged by one month to alleviate simultaneity concerns. Additionally, $return$, $flow$, and vix are measured over various period lengths, i.e. 1, 3, 6, and

12 months. In doing so, the mean of *vix* is calculated over the respective period.

To assess whether more active funds perform better in times of economic uncertainty, I conduct moderation analyses on my sample of active equity mutual funds by interacting *te* and *vix*:

$$\begin{aligned} net\ return_{i,t} = \alpha + \beta_1 te_{i,t-1} + \beta_2 flow_{i,t-1} + \beta_3 return_{i,t-1} \\ + \beta_4 te_{i,t-1} \times vix_{t-1} + \lambda_t + \lambda_i + \epsilon_{i,t} \end{aligned} \tag{3.1}$$

where i denotes fund, t denotes month, λ_t denotes month fixed effects, and λ_i denotes fund fixed effects. $\epsilon_{i,t}$ is the error term.

The main coefficient of interest is β_4, which captures how the performance of active funds is moderated by economic uncertainty. Month and fund fixed effects are included to control for effects coming from unobserved variables. More specifically, month fixed effects capture any news, events, or, generally speaking, time variation, which is not fund-specific. This includes the overall economic uncertainty, which is why the non-interacted, standalone *vix* drops out of Equation 3.1. On the other hand, fund fixed effects control for all static fund characteristics. This is particularly important in my international, and hence, diverse sample to capture, among others, any static impact of domicile, investment area, or benchmark on the funds' performance. Such fund characteristics, indeed, might also have a time-varying effect on performance, for which I account in Section 3.3.6.

Next, I analyse whether the impact of fund activity on return is moderated by economic uncertainty differently over time. I start assessing this question by splitting my sample into subsets of 5-year periods (2001 - 2005, 2006 - 2010, 2011 - 2015, 2016 - 2020) and estimating Equation 3.1 separately. In doing so, I additionally alleviate concerns that results on the overall sample might be solely driven by singular extreme uncertainty events such as the Global Financial Crisis in 2008 or the COVID-19 pandemic in 2020. Moreover, I classify the months in the observation period in terms of their risk level (*risk level*): A month is categorised as *calm* if its average VIX is smaller or equal to the overall average VIX in the observation period plus one standard deviation. It is *uncertain* if its VIX exceeds the previous threshold and is smaller or equal to the average VIX in the observation period plus two standard deviations. Finally, a month is classified as *crisis* if its VIX exceeds the average VIX in the observation period plus two standard deviations. According to this categorisation, 231 months are *calm*, 21 are *uncertain*, and 10 can be identified as *crisis*. The latter are October 2002, November 2008, December 2008, January to May 2009, April 2020, and May 2020. Following Kosowski (2011), I can then analyse whether active funds perform when it matters most by running the following regression:

$$\begin{aligned} net\ return_{i,t} = \alpha &+ \beta_1 te_{i,t-1} + \beta_2 flow_{i,t-1} + \beta_3 return_{i,t-1} \\ &+ \beta_4 te_{i,t-1} \times risk\ level_{t-1} + \lambda_t + \lambda_i + \epsilon_{i,t} \end{aligned} \tag{3.2}$$

where *risk level* is a categorical variable, and respective coefficients are to be interpreted relative to *calm* months.

Further, I compare the performance between funds based on their level of activity in times of uncertainty by estimating the following model:

$$\begin{aligned} net\ return_{i,t} = \alpha &+ \beta_1 te_{i,t-1} + \beta_2 flow_{i,t-1} + \beta_3 return_{i,t-1} \\ &+ \beta_4 te_{i,t-1} \times vix_{t-1} + \lambda_t + \lambda_d + \lambda_{ia} + \lambda_s + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

where λ_d additionally denotes domicile fixed effects, λ_{ia} denotes investment area fixed effects, and λ_s denotes strategy fixed effects. Fund fixed effects are explicitly not included to enable the comparison across funds. Therefore, Equation 3.3 incorporates more specific fixed effects to diminish concerns regarding omitted variable bias.

Finally, I address the question of why active funds profit from economic turmoil. As previously mentioned, tracking error as a measure of fund activity is correlated with cash holdings and flows (cf. Osterhoff and Kaserer (2016)). Hence, any impact of fund activity on performance could, in truth, be partially explained by the funds' low-risk cash reserves, which could especially be advantageous in times of economic turmoil. To disentangle my fund activity measure from this mechanism, I calculate a cash-adjusted tracking error. To do so, I first assess the degree to which previous fund flows can explain tracking error:

$$te_{i,t} = \alpha + \sum_{j=1}^{24} (\beta flow_{i,t-j} + \beta normalflow_{i,t-j}) + \epsilon_{i,t} \tag{3.4}$$

where I regress the funds' rolling one-year tracking error (te) on the preceding two years of 24 monthly $flow$ relative to its assets under management as well as $normal\ flow$ not adjusted for assets under management.

I then calculate the cash-adjusted tracking (cte) as the portion of the tracking error that cannot be explained by the fund's cash flows using the coefficients estimated in Equation 3.4 ($\hat{\beta}$):

$$cte_{i,t} = te_{i,t} - \sum_{j=1}^{24}(\hat{\beta} flow_{i,t-j} + \hat{\beta} normalflow_{i,t-j}) \tag{3.5}$$

Substituting tracking error with this new cash-adjusted activity measure in Equation 3.1 leads to the following model:

$$\begin{aligned} net\ return_{i,t} = \alpha + \beta_1 cte_{i,t-1} + \beta_2 flow_{i,t-1} + \beta_3 return_{i,t-1} \\ + \beta_4 cte_{i,t-1} \times vix_{t-1} + \lambda_t + \lambda_i + \epsilon_{i,t} \end{aligned} \tag{3.6}$$

As I do not have data on the cash holdings of funds but only on the respective flows, the cash-adjusted tracking error can only approximate the non-cash-induced effect of fund activity on performance. Nevertheless, it is still an indication of the skill-based impact of fund activity on performance, e.g. via portfolio adjustments.

3.2.2 Data

I obtain data on funds from the Morningstar Direct database. The sample construction starts with all open-end, non-index funds classified as equity funds. The monthly data ranges from January 2000 to October 2022 and is survivorship bias-free. I require funds to have data on at least one nonmissing net return and net assets in the mentioned period. Additionally, in line with, e.g. Fama and French (2010) and Natter et al. (2016), I exclude funds before they first reach a net asset value of 5m US dollars to deal with the incubation bias (cf. Evans (2010)). By doing so, I end up with 42,985 active equity funds. The subsample of US domestic equity funds consists of 6,858 US funds.

Following Pástor, Stambaugh and Taylor (2015) and Pástor and Vorsatz (2020), I aggregate the funds' share classes using the respective Morningstar FundID variable to one observation per fund and month. All analyses use monthly returns net of management fees, administrative fees, and other costs taken out of fund assets. To calculate benchmark-adjusted returns, I subtract the respective benchmark returns, which are also extracted from Morningstar Direct. Using the approach of Pástor and Vorsatz (2020), I replace missing returns with the average return across all funds with the same FTSE/Russell benchmark in the same month. However, this is only implemented if at least one non-missing return for the fund afterward exists. Analogously to the benchmark-adjusted net return, the rolling one-year tracking error is calculated as the standard deviation of the respective benchmark-adjusted net returns over the preceding 12 months. All variables extracted from Morningstar Direct are winsorised at the 1% and 99% levels.

VIX data is obtained from the Chicago Board Options Exchange (CBOE).[1] As additional measures for economic uncertainty, I use the OVX, which is also obtained from the CBOE,[2] the VSTOXX and MOVE indices. The latter two are retrieved from Refinitiv. It should be noted that data on the OVX is only available from September 2009 onward.

3.3 Results

3.3.1 Descriptive statistics

Summary statistics of my sample are presented in Table 3.1. The type of benchmark chosen to calculate the benchmark-adjusted net return and tracking error, indicated in brackets, significantly influences the number of observations remaining in the sample: If those measures are, e.g. calculated using the FTSE/Russell Benchmark, there are about 4m valid fund-month observations, while this number decreases to only 1.6m observations when using the S&P Dow Jones Benchmark due to limitations in the data availability. The average (median) active mutual fund has a monthly return of 0.46% (0.82%), monthly relative flows of -0.09% (-0.21%), prospectus-benchmark-adjusted monthly returns of -0.06% (-0.06%), and an annual prospectus-tracking error of 5.76% (4.69%).

[1] Cf. https://www.cboe.com/tradable_products/vix/vix_historical_data/, last accessed 14 October 2023.
[2] Cf. https://www.cboe.com/us/indices/dashboard/ovx/, last accessed 14 October 2023.

Adjusting the tracking error for cash flows according to Equation 3.5 leads to an average (median) cash-adjusted annual prospectus-tracking error of 5.60% (4.57%). The average (median) VIX is 19.61 (17.47). Its most noteworthy spikes were 82.69 in March 2020 during the COVID-19 pandemic and 80.86 in November 2008 amidst the Global Financial Crisis.

Table 3.1
Summary statistics

This table presents summary statistics of the main variables for all active equity funds. Reported are the number of observations (N), mean value (Mean), standard deviation (SD), 25% percentile (p25), median (p50) and 75% percentile (p75). Benchmark-sensitive variables state whether they are calculated with respect to the FTSE/Russel Benchmark (*ftse*), the Prospectus Benchmark (*prospectus*), or the S&P Dow Jones Benchmark (*s&p*). A detailed description of all variables can be found in Table C. 1.

	N	Mean	SD	p25	p50	p75
net return (ftse)	3,959,493	-0.1264	2.1107	-1.1101	-0.1100	0.8800
net return (prospectus)	2,767,974	-0.0631	1.8610	-0.9300	-0.0600	0.8144
net return (s&p)	1,568,975	-0.1894	2.0914	-1.1306	-0.1517	0.7800
te (ftse)	3,925,375	6.5206	4.3641	3.4940	5.3700	8.2606
te (prospectus)	2,750,466	5.7565	3.9842	3.0543	4.6945	7.2304
te (s&p)	1,555,282	6.3636	4.4490	3.3395	5.1818	7.9766
cte (ftse)	2,343,456	6.3825	4.2783	3.4288	5.2819	8.0982
cte (prospectus)	1,625,323	5.5981	3.9107	2.9663	4.5743	7.0411
cte (s&p)	890,499	6.1662	4.2798	3.2740	5.0621	7.7399
flow	3,694,724	-0.0009	0.0724	-0.0163	-0.0021	0.0098
return	4,460,266	0.4560	5.7163	-2.6100	0.8200	3.8300
vix	6,413,263	19.6077	8.2594	13.9745	17.4727	23.1405

3.3.2 Do more active equity mutual funds perform better in times of economic uncertainty?

I start my analyses by running Equation 3.1 on my sample of actively managed equity mutual funds. Table 3.2 shows the results based on prospectus-benchmark-adjusted returns. I proceed by first only including month and fund fixed effects and including funds' past flows and returns stepwise. The impact of the interaction term tracking error $\times$ VIX on net return is positive and highly statistically significant in all specifications, i.e. if economic uncertainty increases, more active funds can exploit this opportunity better than less active ones to increase their returns. This observation will remain robust, with only very few exceptions throughout all analyses. In economic terms, a one standard deviation increase in the VIX leads to a monthly return increase of about 0.06% for funds with a median tracking error. Given that the median net return equals -0.06%, this effect is sizeable and in support of the model by Glode (2011). It corroborates his argument of active fund managers using their skills to generate superior returns when it matters most.

Past flow and return both have a positive impact on current net returns. However, their inclusion as controls barely impacts the relation of interest. The negative coefficient of the one-year tracking error while accounting for fund fixed effects indicates that funds that increase their tracking error experience a decline in their net return. This could be explained by fund managers becoming overconfident and, hence, unsuccessfully choosing to be more active than their established fund strategy.

As Table 3.2 only presents within-estimators, the comparison of returns between funds based on their degree of activity will be discussed in Section 3.3.4.

Table 3.2

Do more active equity mutual funds perform better in times of economic uncertainty?

This table reports estimates from linear regressions of monthly net returns on tracking error (te) and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. In Column 2 relative fund flow ($flow$) is added as a control variable, while Column 3 adds total fund return, net of fees, ($return$). In Column 4 both fund flow and return are included. Benchmark-sensitive variables are based on the Prospectus Benchmark. $flow$, $return$, and vix are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
	net return	net return	net return	net return
te	-0.0435***	-0.0444***	-0.0431***	-0.0439***
	(-21.68)	(-20.36)	(-21.85)	(-20.46)
flow		0.0398***		0.0208**
		(4.47)		(2.37)
return			0.00965***	0.00916***
			(31.88)	(27.90)
te × vix	0.00159***	0.00164***	0.00159***	0.00163***
	(21.41)	(20.46)	(21.62)	(20.57)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	2,730,275	2,226,007	2,719,210	2,225,923
Adj. R^2	0.0346	0.0354	0.0356	0.0362

3.3.3 Is the performance moderation stable over time?

The results above indicate that funds, on average, can profit more from economic uncertainty the more active they are. However, during the observation period ranging from 2000 to 2022, there is, without a doubt, a wide range of economic states. Hence, I estimate Equation 3.1 separately on the 5-year periods 2001 - 2005, 2006 - 2010, 2011 - 2015, and 2016 - 2020.

Table 3.3

Is the performance moderation stable over time?

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. The regressions are estimated separately on 5-year subsets of the overall observation period: Column 1 reports the results for 2001-2005, Column 2 for 2006-2010, Column 3 for 2011-2015, and Column 4 for 2016-2020. Benchmark-sensitive variables are based on the Prospectus Benchmark. *flow*, *return*, and *vix* are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1) 2001 - 2005	(2) 2006 - 2010	(3) 2011 - 2015	(4) 2016 - 2020
te	0.0131*	-0.0582***	-0.00697	-0.0950***
	(1.66)	(-16.08)	(-1.59)	(-20.71)
flow	-0.113***	-0.111***	-0.0194	-0.0492***
	(-4.13)	(-5.78)	(-1.27)	(-2.79)
return	0.00508***	0.00534***	0.00621***	0.00266***
	(5.58)	(7.84)	(11.24)	(4.54)
te × vix	-0.000228	0.00123***	-0.000289	0.00409***
	(-0.87)	(12.47)	(-1.45)	(20.98)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	280,349	550,951	611,567	583,527
Adj. R^2	0.0398	0.0411	0.0466	0.0463

Results are presented in Table 3.3. I can only observe more active funds profiting from economic uncertainty in 2006 - 2010 and 2016 - 2020, with the latter exhibiting a substantially higher coefficient estimate for the interaction term in question. In these periods, the interaction of interest is positive and statistically highly significant. They also encompass the two events with the most outstanding market reactions in the observation period, significantly outshining any other spike in the VIX: the Global Financial Crisis in

2008 and the outbreak of the COVID-19 pandemic in 2020. While there have been other sources of economic turbulence, e.g. the burst of the dot-com bubble in the early 2000s or the European Debt Crisis at the beginning of the 2010s, I do not find consistent empirical evidence that more active fund managers can utilise less extreme crises to generate superior returns. As depicted in Table 3.3, the coefficient of the interaction term is negative for the periods 2001 - 2005 and 2011 - 2015 but not statistically significant. Analysing not only prospectus-benchmark-adjusted returns, Appendix C. 2 shows that a high fund activity is consistently negatively moderated by economic uncertainty during 2011 - 2015 across all benchmark measures. For the subsample of 2001 - 2005, the direction of the interaction term's coefficient changes based on the choice of the benchmark.

Table 3.4

Do active equity funds perform when it matters most?

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and a month's risk level ($te \times risk\ level$) following Equation 3.2. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Column 1, the Prospectus Benchmark in Column 2, and the S&P Dow Jones Benchmark in Column 3. *flow* and *return* are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)
	net return ftse/russell	net return prospectus	net return s&p
te	-0.00598***	-0.00985***	-0.0149***
	(-6.81)	(-9.25)	(-8.88)
flow	0.0322***	0.0203**	0.0418***
	(4.00)	(2.31)	(3.30)
return	0.00931***	0.00918***	0.00387***
	(32.05)	(27.86)	(5.98)
te × risk level:			
te × uncertain	-0.00686***	0.00550**	0.00862**
	(-3.55)	(2.32)	(2.47)
te × crisis	0.0150***	0.0403***	0.0490***
	(6.67)	(13.95)	(13.38)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	3,239,262	2,225,923	1,274,790
Adj. R^2	0.0396	0.0358	0.0451

Prompted by this finding, I estimate Equation 3.3 to more precisely assess whether active funds perform when it matters most. Results of the periods' classification by risk level are presented in Table 3.4.

In line with my previously discussed results and established literature (cf. Kosowski (2011)), the effect of fund activity on performance is positively and highly significantly moderated by the economy's risk level, i.e., in severe crisis periods, funds with a median tracking error exhibit a performance increase of about 0.19% in *crisis* periods compared to comparatively *calm*, low volatility periods (cf. Table 3.4, Column 2). Results for medium volatility, *uncertain* periods are inconclusive as they vary in direction based on the benchmark choice. However, the sizeable performance enhancement of active funds during the highest volatility periods is a strong corroboration that active fund managers can capitalise on economic chaos to generate superior returns.

Overall, the findings in this section suggest that the ability of more active fund managers to generate superior performance during economic turmoil is not constant. While the performance enhancement can only be proven for periods encompassing exceptional crises and varies substantially between them (cf. Table 3.3), the popular hypothesis of active mutual funds being able to justify their fees when it matters most holds when comparing the performance of active funds during severe crisis periods versus low volatility periods. Less severe economic turmoil, on the other hand, appears insufficient to set the stage for active managers to generate superior returns through their skills.

3.3.4 Do active funds generate higher returns than their more passive peers in times of economic uncertainty?

In order to compare the performance across funds based on their level of activity, I drop fund fixed effects and estimate Equation 3.3. As shown in Table 3.5, tracking error is, in general, negatively correlated with benchmark-adjusted returns in all specifications of the model, i.e. more active fund managers are, on average, unable to turn their deviation from the benchmark into superior returns, net of fees. This underperformance of active mutual funds is in line with the existing literature (cf. among others Jensen (1968), Elton et al. (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), Pástor and Stambaugh (2002), Fama and French (2010), Pástor and Vorsatz (2020)). Adding the interaction term tracking error × VIX in specification (2) corroborates the result of Section 3.3.2, that funds can generate returns through active management in times of uncertainty as argued by Moskowitz (2000), Kosowski (2011), and Glode (2011). Adding past flow and return in specification (3) and domicile, investment-area, and strategy fixed effects in specification (4) does not undermine this statistically highly significant result.

Table 3.5

Do active funds generate higher returns than their more passive peers in times of economic uncertainty?

This table reports estimates from linear regressions of monthly net returns on tracking error (te) following Equation 3.3. The interaction term of tracking error and mean of VIX ($te \times vix$) is added in Column 2. Column 3 additionally includes relative fund flow ($flow$) and total fund return, net of fees, ($return$). Benchmark-sensitive variables are based on the Prospectus Benchmark. $flow$, $return$, and vix are calculated over the preceding three months. All models include month fixed effects. Domicile, investment-area, and strategy fixed effects are added in Column 4. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1) net return	(2) net return	(3) net return	(4) net return
te	-0.00188***	-0.0310***	-0.0304***	-0.0350***
	(-3.16)	(-18.06)	(-16.93)	(-19.47)
flow			0.0838***	0.0969***
			(9.93)	(11.47)
return			0.0134***	0.0131***
			(39.79)	(38.85)
te × vix		0.00135***	0.00136***	0.00147***
		(18.80)	(18.04)	(19.59)
Month FE	Yes	Yes	Yes	Yes
Domicile FE	No	No	No	Yes
Investment-area FE	No	No	No	Yes
Strategy FE	No	No	No	Yes
Fund FE	No	No	No	No
N	2,730,275	2,730,275	2,225,969	2,225,969
Adj. R^2	0.0263	0.0269	0.0285	0.0302

Aggregating the overall effect of fund activity on performance shows that the total effect of the tracking error on net returns becomes positive when the VIX reaches 23.81, which is slightly above its 75%-percentile of 23.14. Moreover, when the VIX reaches its maximum of 82.69 in March 2022, funds with a median tracking error of 4.69 generate a total monthly surplus of 0.41% through their active management according to specification (4) in Table 3.5. These effects are statistically highly significant, in extreme states of the economy noteworthy in magnitude, and qualitative independent of the chosen benchmark (cf. Appendix C. 3). Additionally, they align with previous literature and provide further evidence that active mutual funds overall underperform while generating superior returns when it matters most. Specifically, the results presented corroborate the model by Glode (2011) that investing in generally underperforming actively managed funds can be rational if these funds tend to perform abnormally well in bad states of the economy.

3.3.5 Why do active funds profit from economic turmoil?

Finally, I assess why active equity funds profit from economic uncertainty. In estimating Equation 3.6 with a cash-adjusted activity measure, I aim to disentangle the arguably during crises beneficial impact of cash holdings from other mechanisms through which a high fund activity measure affects returns, e.g. actively adjusting the portfolio to navigate market uncertainty. Results are presented in Table 3.6.

Coefficient estimates for the interaction term of cash-adjusted tracking error and VIX are positive and highly statistically significant. Moreover, their magnitude is very close to estimates of the same models, only differing in using normal, non-cash-adjusted tracking error (cf. Table 3.7, Panel B). I fully acknowledge that the tracking error adjustment described in Section 3.2 can only be an approximation of the non-cash-induced level of fund activity based on the limited data availability. Nevertheless, the fact that my main results stay virtually unchanged when including a cash adjustment in the fund activity measure is a strong indication that larger cash positions can not solely explain more active funds performing better in times of economic uncertainty and that other more complex mechanisms are arguably at work. While a more detailed analysis of the underlying process, how active funds generate superior returns in times of crises, is needed, it is outside the scope of this paper.

Table 3.6

Why do more active equity mutual funds perform better in times of economic uncertainty?

This table reports estimates from linear regressions of monthly net returns on cash-adjusted tracking error (*cte*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of cash-adjusted tracking error and mean of VIX ($cte \times vix$) following Equation 3.6. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Column 1, the Prospectus Benchmark in Column 2, and the S&P Dow Jones Benchmark in Column 3. *flow* and *return* are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)
	net return ftse/russell	net return prospectus	net return s&p
cte	-0.0232***	-0.0450***	-0.0477***
	(-11.83)	(-17.83)	(-13.23)
flow	0.0298**	0.0268**	0.0658***
	(2.56)	(2.27)	(3.64)
return	0.00745***	0.00786***	0.00138*
	(22.39)	(20.95)	(1.82)
cte × vix	0.000870***	0.00175***	0.00168***
	(11.53)	(17.88)	(13.22)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	2,341,765	1,624,683	890,239
Adj. R^2	0.0353	0.0340	0.0429

3.3.6 Robustness

I employ a wide array of robustness tests to corroborate my results: Following Pástor, Stambaugh and Taylor (2015), I focus my analyses on benchmark-adjusted fund returns as they are deemed more appropriate for the cross-section of mutual fund returns than, e.g. returns adjusted using Fama-French factors. However, the question of the right benchmark choice remains. Therefore, I run my analyses not only on returns adjusted using the funds' self-reported Prospectus Benchmark but also on returns adjusted using the S&P Dow Jones Benchmark and FTSE/Russell Benchmark. The latter two are category benchmarks by provider selected by Morningstar to most closely represent the quintessential strategy. Hence, the S&P Dow Jones Benchmark and FTSE/Russell Benchmark do not induce the cherry-picking bias noted by Sensoy (2009) as already stated by Pástor, Stambaugh and Taylor (2015). For instance, Appendix C. 2 and Appendix C. 3 show that my main results are independent of the chosen benchmark and, hence, qualitatively unaffected by such variations in the calculation of the benchmark-adjusted returns and the tracking error.

Next, *return*, *flow*, and *vix* are aggregated over 1, 3, 6, and 12 months to assess how sensitive their impact on the funds' return with respect to the measurement period is. Results of estimating Equation 3.1 using all measurement periods and all discussed types of benchmarks are presented in Table 3.7. The coefficient estimate for the interaction term tracking error × VIX is positive and highly statistically significant in every specification. Hence, the finding that more active mutual funds can generate higher returns during economic uncertainty is not only independent of the choice of the benchmark but also of the specific definition of the explanatory variables.

Table 3.7

Do more active equity mutual funds perform better in times of economic uncertainty? Robustness test using multiple benchmarks and measurement periods.

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX (*te × vix*) following Equation 3.1. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Column 1, the Prospectus Benchmark in Column 2, and the S&P Dow Jones Benchmark in Column 3. *flow*, *return*, and *vix* are calculated over the preceding month in Panel A, the preceding three months in Panel B, the preceding 6 months in Panel C, and the preceding 12 months in Panel D. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)
Panel A: Measurement window of 1 month			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0119***	-0.0326***	-0.0374***
	(-7.31)	(-15.67)	(-12.13)
flow	0.169***	0.144***	0.173***
	(8.46)	(6.60)	(5.42)
return	0.00665***	0.0136***	-0.00896***
	(12.57)	(22.94)	(-8.16)
te × vix	0.000260***	0.00112***	0.00113***
	(4.49)	(14.96)	(11.22)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	3,223,130	2,214,721	1,267,775
Adj. R^2	0.0390	0.0356	0.0451

Continued on next page

Table 3.7 continued

	(1)	(2)	(3)
Panel B: Measurement window of 3 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0223***	-0.0439***	-0.0501***
	(-13.38)	(-20.46)	(-16.21)
flow	0.0323***	0.0208**	0.0409***
	(4.01)	(2.37)	(3.23)
return	0.00936***	0.00916***	0.00394***
	(32.37)	(27.90)	(6.18)
te × vix	0.000731***	0.00163***	0.00171***
	(11.99)	(20.57)	(16.48)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	3,239,262	2,225,923	1,274,790
Adj. R^2	0.0397	0.0362	0.0453
Panel C: Measurement window of 6 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0220***	-0.0405***	-0.0481***
	(-11.87)	(-17.76)	(-14.29)
flow	0.00435	-0.00326	0.00797
	(0.87)	(-0.60)	(1.00)
return	0.00546***	0.00583***	0.00366***
	(27.84)	(26.51)	(8.92)
te × vix	0.000714***	0.00149***	0.00166***
	(9.95)	(17.02)	(13.75)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	3,216,265	2,211,339	1,265,062
Adj. R^2	0.0394	0.0357	0.0450
Panel D: Measurement window of 12 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0230***	-0.0399***	-0.0433***
	(-11.64)	(-16.66)	(-12.23)
flow	-0.0132***	-0.0184***	-0.0103*
	(-4.26)	(-5.52)	(-1.96)
return	0.00286***	0.00304***	0.000896***
	(23.56)	(22.62)	(3.62)
te × vix	0.000783***	0.00152***	0.00150***
	(9.79)	(15.65)	(11.04)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	3,195,067	2,198,255	1,255,920
Adj. R^2	0.0391	0.0354	0.0445

To further tackle endogeneity concerns induced via a potential omitted variable bias, I run Equation 3.1 additionally including benchmark × month, domicile × month, and investment area × month fixed effects. By doing so, I control for any potential time-varying return patterns induced via any of those fund characteristics. This test particularly alleviates potential biases induced via local events affecting only a subset of the multinational fund sample, such as elections, changes in local policies, or natural disasters. As Table 3.8 shows, the additional fixed effects do not weaken my previous findings. If anything, they show that stronger isolation of the performance moderation leads to higher coefficient estimates, specifically when using FTSE/Russell Benchmarks (cf. Panel A, Appendix C. 4).

Table 3.8

Do more active equity mutual funds perform better in times of economic uncertainty? Robustness test using additional fixed effects.

This table reports estimates from linear regressions of monthly net returns on tracking error (te), relative fund flow ($flow$), total fund return, net of fees, ($return$), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. Benchmark-sensitive variables are based on the Prospectus Benchmark. $flow$, $return$, and vix are calculated over the preceding three months. Starting with month and fund fixed, benchmark × month, domicile × month, and investment-area × month fixed effects are included stepwise. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
	net return	net return	net return	net return
te	-0.0439***	-0.0475***	-0.0466***	-0.0471***
	(-20.46)	(-20.30)	(-19.70)	(-20.00)
flow	0.0208**	0.00299	-0.000529	-0.00320
	(2.37)	(0.34)	(-0.06)	(-0.37)
return	0.00916***	0.0129***	0.0146***	0.0146***
	(27.90)	(18.28)	(20.77)	(21.04)
te × vix	0.00163***	0.00182***	0.00181***	0.00183***
	(20.57)	(21.33)	(20.88)	(21.14)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Benchmark × Month FE	No	Yes	Yes	Yes
Domicile × Month FE	No	No	Yes	Yes
Inv. Area × Month FE	No	No	No	Yes
N	2,225,923	2,087,868	2,086,783	2,085,116
Adj. R^2	0.0362	0.232	0.250	0.257

Moreover, one needs to account for my sample of funds being international and, hence, diverse. Due to the vast majority of previous studies in this strand of literature focusing only on US domestic equity mutual funds (cf. among others Fama and French (2010), Kosowski (2011), Pástor and Vorsatz (2020)), I therefore reproduce Table 3.7 using only a subsample of US funds. Doing so also alleviates potential biases introduced via exchange rates, as all variables are denoted in USD. Results for US domestic funds are shown in Table 3.9.

Table 3.9

Do more active equity mutual funds perform better in times of economic uncertainty? Robustness test using multiple benchmarks and measurement periods and restricting the sample to US domestic funds.

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Column 1, the Prospectus Benchmark in Column 2, and the S&P Dow Jones Benchmark in Column 3. *flow*, *return*, and *vix* are calculated over the preceding month in Panel A, the preceding three months in Panel B, the preceding 6 months in Panel C, and the preceding 12 months in Panel D. The sample is restricted to US domestic funds. All models include day and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)
Panel A: Measurement window of 1 month			
	net return ftse/russell	net return prospectus	net return s&p
te	0.00637	-0.0220***	-0.00318
	(1.32)	(-4.75)	(-0.45)
flow	0.0839*	0.0168	0.111*
	(1.69)	(0.35)	(1.68)
return	0.0263***	0.0245***	0.0232***
	(16.58)	(18.16)	(10.98)
te × vix	-0.000126	0.000752***	0.000393*
	(-0.73)	(4.85)	(1.66)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	604,364	666,495	294,347
Adj. R^2	0.0451	0.0439	0.0459

Continued on next page

Table 3.9 continued

	(1)	(2)	(3)
Panel B: Measurement window of 3 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0238***	-0.0408***	-0.0247***
	(-4.81)	(-9.04)	(-3.45)
flow	-0.0426**	-0.0552***	0.0111
	(-2.13)	(-2.94)	(0.41)
return	0.0199***	0.0168***	0.0133***
	(24.24)	(21.12)	(11.52)
te × vix	0.00115***	0.00157***	0.00127***
	(6.34)	(10.10)	(5.26)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	605,807	667,736	295,041
Adj. R^2	0.0464	0.0451	0.0464
Panel C: Measurement window of 6 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0359***	-0.0386***	-0.0137
	(-6.50)	(-8.72)	(-1.64)
flow	-0.0692***	-0.0703***	-0.0199
	(-5.84)	(-6.46)	(-1.18)
return	0.0144***	0.0132***	0.00997***
	(27.10)	(27.77)	(13.70)
te × vix	0.00169***	0.00152***	0.000863***
	(8.01)	(9.52)	(2.88)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	603,557	665,206	293,719
Adj. R^2	0.0471	0.0457	0.0465
Panel D: Measurement window of 12 months			
	net return ftse/russell	net return prospectus	net return s&p
te	-0.0372***	-0.0382***	-0.00228
	(-6.34)	(-8.43)	(-0.26)
flow	-0.0678***	-0.0636***	-0.0425***
	(-8.93)	(-8.98)	(-3.72)
return	0.00705***	0.00677***	0.00495***
	(20.65)	(22.26)	(10.49)
te × vix	0.00176***	0.00152***	0.000410
	(7.61)	(8.76)	(1.24)
Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	601,195	662,540	292,384
Adj. R^2	0.0460	0.0448	0.0459

I again find robust evidence that the effect of fund activity on performance is positively moderated by economic uncertainty. Only when using measurement periods of 1 and 12 months for $return$, $flow$, and vix is the interaction coefficient not statistically significant and positive for one of the benchmarks each. As I assess the performance of funds within a sample of active mutual funds based on their level of activity instead of assessing the overall performance of active US domestic funds, my results are not in contradiction to Pástor and Vorsatz (2020), who document an, on average, underperformance of active US equity funds during the COVID-19 pandemic.

Finally, the VIX measures the implied volatility based on S&P 500 index options and is, first and foremost, a measure of uncertainty in US equity markets. To validate my results for my international sample of equity funds, I also use the VSTOXX, measuring implied volatility in European equities; the MOVE index, measuring the implied volatility of US treasury options; and the OVX index, capturing economic uncertainty via the implied volatility of the price of crude oil. Table 3.10 shows that all economic uncertainty measures lead to the same result for all three benchmark categories qualitatively.

Summing up, this battery of robustness checks shows that the previously presented results hold when using different benchmark measures, alternating the measurement period of the independent variables, adding additional highly granular fixed effects, reducing the sample to US domestic funds, and employing alternative measures of economic uncertainty.

Table 3.10

Do more active equity mutual funds perform better in times of economic uncertainty? Robustness test using multiple benchmarks and economic uncertainty measures.

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Panel A, the Prospectus Benchmark in Panel B, and the S&P Dow Jones Benchmark in Panel C. Column 2 replaces VIX with VSTOXX as the economic uncertainty measure. In Column 3 the MOVE index is used. Column 4 measures economic uncertainty via OVX. *flow*, *return*, and *vix* are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
Panel A: FTSE/Russell				
	net return	net return	net return	net return
te	-0.0223***	-0.0238***	-0.0117***	-0.0332***
	(-13.38)	(-12.78)	(-7.16)	(-17.50)
flow	0.0323***	0.0327***	0.0316***	0.0286***
	(4.01)	(4.05)	(3.92)	(3.12)
return	0.00936***	0.00936***	0.00936***	0.00637***
	(32.37)	(32.39)	(32.32)	(19.68)
te × vix	0.000731***			
	(11.99)			
te × vstoxx		0.000699***		
		(11.46)		
te × move			0.0000659***	
			(4.53)	
te × ovx				0.000599***
				(15.11)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	3,239,262	3,239,262	3,239,262	2,361,411
Adj. R^2	0.0397	0.0397	0.0395	0.0378

Continued on next page

Table 3.10 continued

	(1)	(2)	(3)	(4)
Panel B: Prospectus				
	net return	net return	net return	net return
te	-0.0439***	-0.0450***	-0.0241***	-0.0507***
	(-20.46)	(-19.48)	(-11.38)	(-19.66)
flow	0.0208**	0.0214**	0.0188**	0.0280***
	(2.37)	(2.44)	(2.15)	(2.72)
return	0.00916***	0.00916***	0.00916***	0.00763***
	(27.90)	(27.90)	(27.82)	(20.61)
te × vix	0.00163***			
	(20.57)			
te × vstoxx		0.00148***		
		(19.56)		
te × move			0.000190***	
			(9.95)	
te × ovx				0.00103***
				(19.06)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	2,225,923	2,225,923	2,225,923	1,544,864
Adj. R^2	0.0362	0.0361	0.0355	0.0354
Panel C: S&P Dow Jones				
	net return	net return	net return	net return
te	-0.0501***	-0.0541***	-0.0269***	-0.0434***
	(-16.21)	(-15.75)	(-9.75)	(-12.07)
flow	0.0409***	0.0421***	0.0398***	0.0387***
	(3.23)	(3.32)	(3.14)	(2.70)
return	0.00394***	0.00405***	0.00399***	-0.00245***
	(6.18)	(6.35)	(6.24)	(-3.31)
te × vix	0.00171***			
	(16.48)			
te × vstoxx		0.00167***		
		(15.99)		
te × move			0.000178***	
			(7.76)	
te × ovx				0.000716***
				(9.98)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	1,274,790	1,274,790	1,274,790	920,004
Adj. R^2	0.0453	0.0453	0.0447	0.0456

3.4 Conclusion

Using a large international dataset, this paper analyses whether more active equity mutual funds can use chaos as a ladder to achieve superior returns during economic uncertainty. I do so by measuring fund activity using the tracking error to the respective benchmarks, while I mainly measure economic uncertainty using the VIX.

First, I find that economic uncertainty positively moderates the effect of fund activity on performance. This result is statistically and economically significant and robust to a large variety of robustness tests.

Second, I analyse whether this performance moderation is stable over time. It shows that only in times of most severe economic uncertainty the effect of fund activity on performance is positively and statistically significantly moderated by the level of uncertainty.

Third, when comparing the performance across mutual funds with varying degrees of activity, I find that, on average, the level of activity has a negative impact on fund performance. Nevertheless, it still holds that more active fund managers can utilise economic uncertainty as the aggregated effect of fund activity on performance turns positive during high levels of economic turmoil.

Fourth, while cash flows and holdings are a determinant of tracking error and, hence, fund activity, they cannot solely explain active funds profiting from economic uncertainty.

4 Conclusion

The three essays of this dissertation address research questions on mutual funds and economic uncertainty. The *first essay* provides new insight into the type of derivatives UCITS equity funds trade, why some trade derivatives while others do not, what makes some more active traders, and what motives drive derivatives trading. I achieve this by leveraging extensive high-granular trade-level data collected under the EMIR framework. In the *second essay*, I use a large international firm-level dataset aiming to contribute to a better understanding of how COVID-19-related stringency and economic support measures actually affected the corporate sector. Finally, the *third essay* picks up on the topic of mutual funds from Chapter 1 and combines it with the theme of economic uncertainty from Chapter 2. Here, I use a large international set of active equity mutual funds to provide new insights into their performance in times of economic turmoil. In the following, I summarise the main findings and contributions.

The *first essay* utilises a novel, extensive dataset linking a comprehensive sample of European equity UCITS funds with information on derivatives trades, which enables me to assess equity funds' derivatives trading behaviour.

46% of European equity funds trade derivatives, and about 80% of their trades are focused on only three types of contracts, which are currency forwards, equity futures, and equity options. Next, I demonstrate that the funds' decision to use derivatives is largely influenced by their fund family and that fund-fixed characteristics explain 56% of the variation in funds' trading frequency and trading volume. Here, the investment strategy and, again, fund family matter most. Lastly, I assess equity funds' motives to trade derivatives. I show that equity funds trade derivatives to save transaction costs and mitigate risks; my findings provide no evidence that they use derivatives predominantly for speculative reasons.

The first contribution of this essay lies in the anatomy of derivatives trading by equity UCITS fund, which I can provide using the high-granular daily trade data. Doing so, I meaningfully complement previous evidence on which types of derivatives equity funds use (e.g., Fong, Gallagher and Ng, 2005; Cao, Ghysels and Hatheway, 2011; Cici and Palacios, 2015; Natter et al., 2016; Benz et al., 2019). Second, I identify main drivers of the funds' propensity and frequency of trading derivatives lying in their fixed characteristics. Finally, the essay exploits the granular trading data to add detailed evidence on the motives for the usage of derivatives. While my results support the rationals to use derivatives to economise on transaction costs and mitigate risk, I do not find evidence of speculative usage of those instruments by funds. These results align with the, due to limited data availability, scarce results in the existing literature (cf. Natter et al. (2016) and Benz et al. (2019)).

The *second essay* leans on the theme of economic uncertainty and assesses the impact of Government interventions during the COVID-19 pandemic on the corporate sector as represented by listed firms. To do so, I employ a broad international firm-level data set and link it with the Oxford COVID-19 Government Response Tracker (cf. Hale et al. (2021)). I show with robust evidence that Governments effectively sheltered firms from further disruptions with their stringency measures, whereas the results for economic support measures are ambiguous.

While I find that governments successfully sheltered smaller, highly levered, and more employment-intensive companies with their economic support measures, I show that these policies also benefited firms in financial difficulties already before the financial crisis and, in particular, Zombie firms.

Regarding its contribution, this essay builds on the literature in several aspects. While numerous studies have documented the severe and unprecedented impact of the Corona outbreak on stock and bond markets (cf. among others Baker et al. (2020), Bannigidadmath et al. (2021), Bretscher et al. (2020), Gormsen and Koijen (2020), Kargar et al. (2021), Ramelli and Wagner (2020)), only a limited number of studies analysed the impact of Government policy interventions on stock markets or on the corporate sector more generally. For instance, Bannigidadmath et al. (2021) find inconclusive evidence on the impact of specific government interventions on stock prices, while Zaremba et al. (2020)

conclude that stringency policies significantly increase market volatility and, therefore, add to the already prevailing uncertainty on the market. This essay adds further evidence to the interaction of Government crisis responses and stock market reactions by identifying the relative impact of different levels of government intervention intensities on stock price performance. Moreover, and even more importantly, I can study the impact of government interventions depending on firm characteristics. To the best of my knowledge, this is the first paper to address this second question based on such a broad firm-level dataset.

In the final *third essay*, I analyse whether more active equity mutual funds can use chaos as a ladder to achieve superior returns during economic uncertainty employing a large international dataset. Here, I measure fund activity using the tracking error to the respective benchmarks, while I mainly measure economic uncertainty using the VIX.

First, I show robust evidence that the effect of fund activity on performance is positively moderated by economic uncertainty in a statistically and economically significant manner. Second, this performance moderation is not stable over time but can only be detected in times of severe economic uncertainty. Third, the level of activity generally has a negative impact on fund performance when comparing the performance across mutual funds with varying degrees of activity. However, it again holds that in times of severe economic turmoil, more active fund managers can utilise economic uncertainty as the aggregated effect of fund activity on performance turns positive during such crises. Fourth, while cash flows and holdings are a determinant of tracking error and, hence, fund activity, they cannot solely explain active funds profiting from economic uncertainty.

The *third essay* contributes to the ongoing academic discussion of mutual fund performance in several ways by reassessing the while popular also still controversially discussed hypotheses that the underperformance of active mutual funds is at least to some degree outweighed by their superior performance when it matters most for investors. First, I build on the existing literature, which mainly focuses on US domestic mutual funds by building a large international dataset and, therefore, providing new evidence for the relationship between fund activity and performance during economic uncertainty. Second, I employ a granular measure of general economic uncertainty instead of the common simplification of classifying a period only as a recession or expansion period (e.g. Kosowski (2011)). Third, to the best of my knowledge, this essay is the first to focus on the interrelated effect of the level of economic uncertainty and fund activity on performance within the universe of active mutual funds.

To conclude, the three essays of this dissertation address research questions on mutual funds and economic uncertainty, whose findings motivate several avenues for future research. The *first essay* suggests that European equity mutual funds trade derivatives to economise on transaction costs and to mitigate risk. While these findings are based on a highly granular trade-level dataset, the observation period only covers six months. As the availability of the employed reporting data is steadily increasing, it would be interesting to examine whether the results could be expanded by employing a more extended observation period spanning multiple years. The *second essay* assesses the impact of COVID-19-related government policies on the corporate sector by employing aggregated stringency and economic support indices. Especially as the results for the economic support measures were mixed and showcasing some undesired side effects, such as Zombie firms particularly profiting from the offered support, a more in-depth analysis of the various economic measures seems necessary. This could then serve as the basis for a more differentiated and targeted government response in similar crises in the future. Finally, the *third essay* assessed the impact of fund activity on performance in the context of economic uncertainty. As the activity level was approximated using the funds' tracking error, future studies could focus on the underlying mechanism of how fund activity leads to superior performance in crisis periods by, for instance, examining changes in the fund portfolios as a reaction to market volatility.

A Chapter 1

Table A. 1
Definition of variables

Variable	**Description**
Derivatives trading variables	
derivatives trading fund	Dummy which equals one if a fund traded at least one derivative in the second half of 2016. Source: Own calculation.
derivatives trading	Dummy which equals one if a fund made at least one derivative trade on the respective execution date. Source: Own calculation.
notional	Natural logarithm of the sum of the traded notional of derivative contracts per day. Source: Own calculation.
#trades	Number of derivative trades per day. Source: Own calculation.
Fund characteristics	
fund size	Fund net asset value in million Euro at the beginning of 2016. Source: Morningstar.
family size	Number of funds that belong to the same fund family. Source: Morningstar.
net flow	Absolute value of the sum of net flows over five preceding trading days divided by the mean of net assets over this period. Net flows on a day are estimated by Morningstar using yesterday's assets under management (AUM_0), today's assets under management (AUM_1), and the daily total return of the share class (R) ($AUM_1 - AUM_0 * (1 + R)$). Source: Morningstar.
pos. net flow	Sum of positive net flows over five preceding trading days divided by the mean of net assets over this period. Source: Morningstar.
neg. net flow	Absolute value of the sum of negative net flows over five preceding trading days divided by the mean of net assets over this period. Source: Morningstar.
currency risk	Daily standard deviation of the exchange rates of a share class's base currency to the base currency of the respective benchmark measured on the basis of 20 preceding trading days aggregated to fund level using the weighted average calculated on the basis of the net assets of the respective share classes. Source: Own calculation.
fund risk	Daily standard deviation of fund returns measured on the basis of 20 preceding trading days. Source: Morningstar.
tracking error	Daily standard deviation of differences between fund and benchmark return measured on the basis of 20 preceding trading days. Source: Morningstar.
return	Cumulative daily fund returns over 20 preceding trading days. Source: Morningstar.
return-benchmark	Cumulative daily fund returns over 20 preceding trading days minus cumulative daily discrete benchmark returns over 20 preceding trading days. Source: Morningstar.
return-family	Cumulative daily fund returns over 20 preceding trading days minus average cumulative daily discrete returns of other fund family members. Source: Morningstar.

Appendix A.2 EMIR data reporting and aggregation levels

Under Article 9 of the European Market and Infrastructure Regulation all entities executing derivatives transactions located in the European Economic Area (EEA) have to submit and update their derivative data to (privately owned) trade repositories (TRs). These TRs then filter and redistribute the derivative information to the authorities. ESMA handles the registration and authorisation process of the TRs and supervises them while national competent authorities supervise the individual reporting of the counterparties in their jurisdiction.

We use the most granular trade activity data, which is collected from the six relevant TRs in 2016, that is, CME, DTCC, ICE, KDPW, Regis-TR, and Unavista. The next level of aggregation is the trade-state data, which is an aggregate from trade activity data. For this dataset the TR applies all trade activity messages to the outstanding transactions. Thus, it provides the most recent information on outstanding transactions at the end of the day. Important to note is that intraday transactions (i.e. transactions that opened and closed within the same day) are filtered out. As we want to focus also on intraday trading activity we use trade-flow data.

Table A. 3

Derivatives trading funds and fund characteristics

This table presents the percentage of derivatives trading funds by various fund characteristics along with the percentage of derivatives trading and non-derivatives trading funds in the respective group. In Panel A, funds are grouped by the size of their fund family into terciles. Panel B shows the aggregation by the sample's three most important base currencies. In Panel C, funds are grouped by their size defined as the first reported value of net assets in 2016 into terciles. Panel D distinguishes funds by the three most frequent investment areas. Panel E the interaction of the three most frequent base currencies and investment areas in the sample. In Panel F, groups are created based on the funds' six most frequent domiciles.

	% of trading funds	% of all funds
Panel A: Terciles of fund family size		
1	30.17%	35.61%
2	31.03%	32.14%
3	38.80%	32.25%
Total	100.00%	100.00%
Panel B: Top 3 base currencies		
Euro	45.08%	48.91%
US Dollar	31.41%	24.96%
Pound Sterling	15.54%	15.89%
Total	92.04%	89.77%
Panel C: : Fund size terciles		
1	26.00%	32.89%
2	31.99%	32.89%
3	41.10%	32.89%
na	0.91%	1.34%
Total	100.00%	100.00%
Panel D: Top 3 investment areas		
Global	29.64%	25.36%
Europe	13.14%	14.82%
United States of America	11.51%	9.35%
Total	54.29%	49.53%
Panel E: Investment area and base currency		
Global/EUR	12.23%	12.23%
Global/USD	11.51%	7.57%
Global/GBP	4.32%	3.40%
Europe/EUR	12.37%	13.22%
Europe/USD	0.29%	0.26%
Europe/GBP	0.14%	0.37%
USA/EUR	2.64%	2.41%
USA/USD	7.15%	5.27%
USA/GBP	1.44%	1.14%
Total	52.09%	45.88%

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Table A. 3 continued

	% of trading funds	% of all funds
Panel F: Fund domicile		
Luxembourg	45.32%	38.24%
France	10.26%	15.89%
United Kingdom	12.81%	13.87%
Ireland	15.88%	12.12%
Sweden	2.69%	3.49%
Germany	1.92%	3.34%
Total	88.87%	86.96%

Table A. 4

How do fund flows affect derivatives trading?

Variation of the measurement period

This table presents estimates from linear probability models of the daily derivatives trading dummy on measures of fund flows lagged by one day calculated over a differing number of days following Equation 1.2. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. In Panel A, rolling net flows are used. In Panel B, rolling positive net flows are looked at and in Panel C rolling negative net flows are included. The sample consists of derivatives trading funds. All models account for day and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)	(4)
Panel A: Net flow				
Calculation days	2	3	4	10
net flow	0.790***	0.586***	0.492***	0.177***
	(7.12)	(6.83)	(6.92)	(4.23)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	240,805	243,453	245,510	254,162
Adj. R^2	0.529	0.528	0.528	0.528
Panel B: Positive net flow				
Calculation days	2	3	4	10
pos net flow	1.014***	0.733***	0.655***	0.262***
	(5.30)	(5.09)	(5.54)	(3.92)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	240,805	243,453	245,510	254,162
Adj. R^2	0.529	0.528	0.528	0.528
Panel C: Negative net flow				
Calculation days	2	3	4	10
neg net flow	0.902***	0.668***	0.501***	0.168**
	(4.89)	(4.79)	(4.33)	(2.54)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	240,805	243,453	245,510	254,162
Adj. R^2	0.528	0.528	0.528	0.528

Table A. 5

How do fund risks and returns affect derivatives trading?

Variation of the measurement period

This table presents estimates from linear probability models of the daily derivatives trading dummy on lagged measures of fund risk and fund return calculated over a differing number of days following Equation 1.2. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. In Panel A, we use rolling currency risk. The standard deviation of returns is analysed in Panel B. Panel C includes the rolling tracking error. In Panel D, we look at rolling fund returns and in Panel E the rolling relative return to the benchmark is assessed. Panel F shows the rolling relative return to the fund family. The sample consists of derivatives trading funds. All models account for day and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)	(4)
Panel A: Currency risk				
Calculation days	5	10	15	30
currency risk	1.391	3.706**	5.524***	2.910**
	(1.00)	(2.22)	(3.14)	(1.99)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	198,973	198,973	198,973	198,973
Adj. R^2	0.534	0.534	0.534	0.534
Panel B: Standard deviation of fund return				
Calculation days	5	10	15	30
sd(return)	0.549*	0.436	0.112	-0.113
	(1.96)	(1.21)	(0.29)	(-0.25)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	270,578	270,578	270,578	270,578
Adj. R^2	0.534	0.534	0.534	0.534
Panel C: Tracking error				
Calculation days	5	10	15	30
tracking error	0.339	0.100	0.335	0.523
	(1.25)	(0.27)	(0.86)	(1.19)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	243,660	243,975	244,284	244,406
Adj. R^2	0.533	0.533	0.532	0.532

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Table A. 5 continued

	(1)	(2)	(3)	(4)
Panel D: Cumulative fund return				
Calculation days	5	10	15	30
return	-0.076	-0.042	-0.059	0.059
	(-1.14)	(-0.75)	(-1.14)	(1.40)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	271,585	271,585	271,585	271,585
Adj. R^2	0.533	0.533	0.533	0.533
Panel E: Cumulative fund return relative to benchmark				
Calculation days	5	10	15	30
return-benchmark	0.006	-0.007	-0.018	0.047
	(0.10)	(-0.13)	(-0.34)	(0.97)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	243,660	243,975	244,284	244,406
Adj. R^2	0.533	0.533	0.532	0.532
Panel F: Cumulative fund return relative to family				
Calculation days	5	10	15	30
return-family	-0.103	-0.144**	-0.088*	0.031
	(-1.46)	(-2.45)	(-1.67)	(0.71)
Day FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	271,585	271,585	271,585	271,585
Adj. R^2	0.533	0.533	0.533	0.533

Table A. 6

How do fund flows affect derivatives trading?

Conditional logit model

This table presents estimates from conditional logistic regressions of the daily derivatives trading dummy on measures of fund flows lagged by one day. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. The measures of fund flows are the rolling 5-day net flows (Column 1), the rolling 5-day positive net flows (Column 2) and the rolling 5-day negative net flows (Column 3). The sample consists of derivatives trading funds. All models include day and fund fixed effects. Z-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels,respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)
	net flow	pos. net flow	neg. net flow
flow	3.150***	4.177***	3.002***
	(6.32)	(5.31)	(3.59)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	245,058	245,058	245,058
Pseudo R^2	0.063	0.063	0.063

Table A. 7

How do fund risks and returns affect derivatives trading?

Conditional logit model

This table presents estimates from conditional logistic regressions of the daily derivatives trading dummy on lagged measures of fund risk in Panel A and fund return in Panel B. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. In Panel A, we measure fund risk by the rolling one-month currency risk (Column 1), the one-month standard deviation of returns (Column 2) and the one-month rolling tracking error (Column 3). In Panel B, we measure fund return by three proxies for the fund performance. These are the rolling one-month fund return (Column 1), the rolling one-month relative return to the benchmark (Column 2) and the rolling one-month relative return to the family (Column 3). The sample consists of derivatives trading funds. All models include day and fund fixed effects. Z-statistics based on Huber/White robust standard errors clustered by firms are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels,respectively. A detailed description of all variables can be found in Table A. 1.

	(1)	(2)	(3)
Panel A: Fund risks			
	currency	sd(return)	tracking error
risk	47.178***	-2.862	4.438
	(3.32)	(-0.74)	(1.17)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	193,355	269,268	243,227
Pseudo R^2	0.052	0.064	0.066
Panel B: Fund returns			
	return	return-benchmark	return-family
return	-0.275	-0.303	-0.429
	(-0.64)	(-0.65)	(-0.97)
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	270,269	243,227	270,269
Pseudo R^2	0.064	0.066	0.064

B Chapter 2

Table B. 1
Definition of variables

Variable	**Description**
Country characteristics	
case growth	The natural logarithm of national cumulative COVID-19 cases in t-1 divided by the cumulative cases in t-2. Source: Ritchie et al. (2020), own calculation.
esi	OxCGRT economic Support Index, capturing the governmental economic policy measures. Normalised and scaled from 0-100 for aggregate assessment and data of policy measures. Source: Hale et al. (2021)
si	OxCGRT stringency Index, capturing the restrictive government policy measures. Normalised and scaled from 0-100 for aggregate assessment and data of policy measures. Source: Hale et al. (2021)
Firm characteristics	
c4	Daily abnormal stock return measured by a Carhart 4-factor model. Source: Refinitiv Datastream, Kenneth French[1], own calculation.
bl	Dummy which equals one if a firm was in the top quintile of firms with the highest book leverage ratio in the previous year and zero otherwise. Source: Thomson Reuters Worldscope, own calculation.
ei	Dummy which equals one if a firm was in the quintile of firms with the highest employee intensity, i.e. the lowest ratio of revenues over the number of employees, in the previous year and zero otherwise. Source: Refinitiv Worldscope, own calculation.
ff3	Daily abnormal stock return measured by the Fama-French-3-factor model. Source: Refinitiv Datastream, Kenneth French[2], own calculation.
icr	Dummy which equals one if a firm was in the bottom quintile of firms with the lowest interest coverage ratio in the previous year and zero otherwise. The interest coverage ratio is defined as EBIT divided by total interest expense. Source: Refinitiv Worldscope, own calculation.
size	Dummy which equals one if a firm was in the top quintile of firms with the highest revenues in the previous year and zero otherwise. Source: Refinitiv Worldscope, own calculation.
zombie	Dummy which equals one if a firm had above median leverage and an interest coverage ration below one in the previous year as well as negative sales growth over the preceding three years. Source: Refinitiv Worldscope, own calculation.

continued on next page

[1] Cf. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, last accessed 13 January 2023.
[2] Cf. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, last accessed 13 January 2023.

Appendix B. 1 continued

Variable	**Description**
Controls	
oil	West Texas Intermediate price of oil. Source: U.S. Energy Information Administration.[3]
ur	Monthly unemployment rate in percentage terms. Source: OECD (2021).
inflation	Monthly inflation rate measured by consumer price index expressed in percentage terms. Source: OECD (2021).
bci	Business confidence index. Source: OECD (2021).
cci	Consumer confidence index. Source: OECD (2021).
fdi_in	Quarterly Foreign Direct Investment inward flows measured in million USD. Source: OECD (2021).
fdi_out	Quarterly Foreign Direct Investment outward flows measured in million USD. Source: OECD (2021).
labor	Quarterly relative unit labor cost measured as an index relative to 2010. Source: OECD (2021).

[3] Cf. https://www.eia.gov/dnav/pet/hist/RWTCD.htm, last accessed 13 January 2023.

C Chapter 3

Table C. 1
Definition of variables

Variable	**Description**
Fund characteristics	
cash-adjusted tracking error	Rolling 12-month tracking error in percentage terms adjusted for the impact of previous fund flows over 24 months (cf. Equation 3.4). Source: Morningstar, own calculation.
flow	Sum of monthly net flows divided by net assets. Unless stated otherwise, the sum of net flows is calculated over the preceding three months. Source: Morningstar, own calculation.
net return	Monthly benchmark-adjusted net return in percentage terms. This variable is calculated by deducting the respective benchmark return (Prospectus Benchmark, S&P Dow Jones Benchmark, or FTSE/Russell Benchmark) from the total fund return, net of fees. By default, net return is calculated using the Prospectus Benchmark. Source: Morningstar, own calculation.
normal flow	Unadjusted monthly net flow. Source: Morningstar.
tracking error	Rolling 12-month tracking error in percentage terms, defined as the standard deviation of the preceding 12 monthly net returns relative to the Prospectus Benchmark, S&P Dow Jones Benchmark, or FTSE/Russell Benchmark. By default, tracking error is calculated using the Prospectus Benchmark. Source: Morningstar, own calculation.
return	Monthly total fund return, net of fees, in percentage terms. Unless stated otherwise, this variable is calculated over the preceding three months. Source: Morningstar.
Economic uncertainty measures	
move	Mean of Merrill Lynch Option Volatility Estimate Index. Unless stated otherwise, this variable is calculated over the preceding three months. Source: Refinitiv, own calculation.
ovx	Mean of Cboe Crude Oil ETF Volatility Index. Unless stated otherwise, this variable is calculated over the preceding three months. Source: CBOE, own calculation.
risk level	Categorical variable, indicating the overall risk level within a month. It equals *calm* if the month's average VIX is smaller or equal to the overall average VIX in the observation period plus one standard deviation; *uncertain* if its VIX is greater than the average VIX in the observation period plus one standard deviation and is smaller or equal to the average VIX in the observation period plus two standard deviations; and *crisis* if its VIX exceeds the average VIX in the observation period plus two standard deviations. Source: CBOE, own calculation.
vix	Mean of the CBOE Volatility Index. Unless stated otherwise, this variable is calculated over the preceding three months. Source: CBOE, own calculation.
vstoxx	Mean of EURO STOXX 50 volatility index. Unless stated otherwise, this variable is calculated over the preceding three months. Source: Refinitiv, own calculation.

Table C. 2

Is the performance moderation stable over time?

Robustness test using multiple benchmark measures.

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. The regressions are estimated separately on 5-year subsets of the overall observation period: Column 1 reports the results for 2001-2005, Column 2 for 2006-2010, Column 3 for 2011-2015, and Column 4 for 2016-2020. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Panel A, the Prospectus Benchmark in Panel B, and the S&P Dow Jones Benchmark in Panel C. *flow*, *return*, and *vix* are calculated over the preceding three months. All models include month and fund fixed effects. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
Panel A: FTSE/Russell				
	2001 - 2005	2006 - 2010	2011 - 2015	2016 - 2020
te	0.0493***	-0.0504***	0.0148***	-0.0552***
	(7.23)	(-16.11)	(4.24)	(-16.74)
flow	-0.0690***	-0.0267	-0.0421***	0.0328**
	(-2.67)	(-1.47)	(-2.92)	(2.07)
return	0.00776***	0.00973***	0.000272	0.00265***
	(8.84)	(15.33)	(0.56)	(5.00)
te × vix	-0.00139***	0.000743***	-0.00128***	0.00240***
	(-5.83)	(8.99)	(-7.88)	(16.68)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	331,031	760,122	899,394	911,310
Adj. R^2	0.0446	0.0478	0.0494	0.0411
Panel B: Prospectus				
	2001 - 2005	2006 - 2010	2011 - 2015	2016 - 2020
te	0.0131*	-0.0582***	-0.00697	-0.0950***
	(1.66)	(-16.08)	(-1.59)	(-20.71)
flow	-0.113***	-0.111***	-0.0194	-0.0492***
	(-4.13)	(-5.78)	(-1.27)	(-2.79)
return	0.00508***	0.00534***	0.00621***	0.00266***
	(5.58)	(7.84)	(11.24)	(4.54)
te × vix	-0.000228	0.00123***	-0.000289	0.00409***
	(-0.87)	(12.47)	(-1.45)	(20.98)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	280,349	550,951	611,567	583,527
Adj. R^2	0.0398	0.0411	0.0466	0.0463

Continued on next page

Table C. 2 continued

	(1)	(2)	(3)	(4)
Panel C: S&P Dow Jones				
	2001 - 2005	2006 - 2010	2011 - 2015	2016 - 2020
te	-0.0368***	-0.0915***	0.0208***	-0.0618***
	(-2.66)	(-17.43)	(3.27)	(-9.82)
flow	-0.0298	-0.0368	0.0226	-0.0235
	(-0.69)	(-1.24)	(1.04)	(-0.95)
return	-0.00351**	0.00898***	-0.0125***	-0.0155***
	(-2.12)	(7.80)	(-11.99)	(-12.82)
te $\times$ vix	0.00128***	0.00210***	-0.00140***	0.00253***
	(2.93)	(16.60)	(-4.77)	(9.35)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	137,943	299,475	344,596	355,611
Adj. R^2	0.0380	0.0552	0.0629	0.0459

Table C. 3

Do active funds generate higher returns than their more passive peers in times of economic uncertainty?

Robustness test using multiple benchmark measures.

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*) following Equation 3.3. The interaction term of tracking error and mean of VIX ($te \times vix$) is added in Column 2. Column 3 additionally includes relative fund flow ($flow$) and total fund return, net of fees, ($return$). Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Panel A, the Prospectus Benchmark in Panel B, and the S&P Dow Jones Benchmark in Panel C. $flow$, $return$, and vix are calculated over the preceding three months. All models include month fixed effects. Domicile, investment-area, and strategy fixed effects are added in Column 4. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
Panel A: FTSE/Russell				
	net return	net return	net return	net return
te	-0.00445***	-0.0167***	-0.0147***	-0.0184***
	(-9.73)	(-13.03)	(-11.01)	(-13.39)
flow			0.0917***	0.0994***
			(11.94)	(12.93)
return			0.0142***	0.0138***
			(49.07)	(47.63)
te × vix		0.000573***	0.000504***	0.000609***
		(10.45)	(8.81)	(10.59)
Month FE	Yes	Yes	Yes	Yes
Domicile FE	No	No	No	Yes
Investment-area FE	No	No	No	Yes
Strategy FE	No	No	No	Yes
Fund FE	No	No	No	No
N	3,895,133	3,895,133	3,239,341	3,239,341
Adj. R^2	0.0314	0.0315	0.0336	0.0358

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Table C. 3 continued

	(1)	(2)	(3)	(4)
Panel B: Prospectus				
	net return	net return	net return	net return
te	-0.00188***	-0.0310***	-0.0304***	-0.0350***
	(-3.16)	(-18.06)	(-16.93)	(-19.47)
flow			0.0838***	0.0969***
			(9.93)	(11.47)
return			0.0134***	0.0131***
			(39.79)	(38.85)
te × vix		0.00135***	0.00136***	0.00147***
		(18.80)	(18.04)	(19.59)
Month FE	Yes	Yes	Yes	Yes
Domicile FE	No	No	No	Yes
Investment-area FE	No	No	No	Yes
Strategy FE	No	No	No	Yes
Fund FE	No	No	No	No
N	2,730,275	2,730,275	2,225,969	2,225,969
Adj. R^2	0.0263	0.0269	0.0285	0.0302
Panel C: S&P Dow Jones				
	net return	net return	net return	net return
te	-0.0142***	-0.0462***	-0.0458***	-0.0454***
	(-17.50)	(-20.72)	(-19.37)	(-18.60)
flow			0.0939***	0.0965***
			(7.81)	(8.07)
return			0.0127***	0.0113***
			(19.94)	(17.66)
te × vix		0.00147***	0.00149***	0.00153***
		(16.21)	(15.54)	(15.97)
Month FE	Yes	Yes	Yes	Yes
Domicile FE	No	No	No	Yes
Investment-area FE	No	No	No	Yes
Strategy FE	No	No	No	Yes
Fund FE	No	No	No	No
N	1,543,087	1,543,087	1,274,826	1,274,826
Adj. R^2	0.0351	0.0358	0.0372	0.0401

Table C. 4

Do more active equity mutual funds perform better in times of economic uncertainty? Robustness test using multiple benchmarks and additional fixed effects

This table reports estimates from linear regressions of monthly net returns on tracking error (*te*), relative fund flow (*flow*), total fund return, net of fees, (*return*), and the interaction term of tracking error and mean of VIX ($te \times vix$) following Equation 3.1. Benchmark-sensitive variables are based on the FTSE/Russell Benchmark in Panel A, the Prospectus Benchmark in Panel B, and the S&P Dow Jones Benchmark in Panel C. *flow*, *return*, and *vix* are calculated over the preceding three months. Starting with month and fund fixed, benchmark × month, domicile × month, and investment-area × month fixed effects are included stepwise. T-statistics based on Huber/White robust standard errors clustered by funds are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Table C. 1.

	(1)	(2)	(3)	(4)
Panel A: FTSE/Russell				
	net return	net return	net return	net return
te	-0.0223***	-0.0401***	-0.0387***	-0.0392***
	(-13.38)	(-22.95)	(-21.79)	(-21.91)
flow	0.0323***	0.0299***	0.0262***	0.0268***
	(4.01)	(4.14)	(3.67)	(3.79)
return	0.00936***	0.00605***	0.00950***	0.0103***
	(32.37)	(11.08)	(17.93)	(19.30)
te × vix	0.000731***	0.00144***	0.00146***	0.00149***
	(11.99)	(22.01)	(21.36)	(21.51)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Benchmark × Month FE	No	Yes	Yes	Yes
Domicile × Month FE	No	No	Yes	Yes
Inv. Area × Month FE	No	No	No	Yes
N	3,239,262	3,238,179	3,236,923	3,235,672
Adj. R^2	0.0397	0.299	0.334	0.353

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Table C. 4 continued

	(1)	(2)	(3)	(4)
Panel B: Prospectus				
	net return	net return	net return	net return
te	-0.0439***	-0.0475***	-0.0466***	-0.0471***
	(-20.46)	(-20.30)	(-19.70)	(-20.00)
flow	0.0208**	0.00299	-0.000529	-0.00320
	(2.37)	(0.34)	(-0.06)	(-0.37)
return	0.00916***	0.0129***	0.0146***	0.0146***
	(27.90)	(18.28)	(20.77)	(21.04)
te × vix	0.00163***	0.00182***	0.00181***	0.00183***
	(20.57)	(21.33)	(20.88)	(21.14)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Benchmark × Month FE	No	Yes	Yes	Yes
Domicile × Month FE	No	No	Yes	Yes
Inv. Area × Month FE	No	No	No	Yes
N	2,225,923	2,087,868	2,086,783	2,085,116
Adj. R^2	0.0362	0.232	0.250	0.257
Panel C: S&P Dow Jones				
	net return	net return	net return	net return
te	-0.0501***	-0.0541***	-0.0517***	-0.0527***
	(-16.21)	(-17.83)	(-16.72)	(-16.67)
flow	0.0409***	0.0369***	0.0209*	0.0248**
	(3.23)	(3.13)	(1.83)	(2.21)
return	0.00394***	0.00107	0.00920***	0.0103***
	(6.18)	(1.19)	(10.65)	(11.91)
te × vix	0.00171***	0.00175***	0.00174***	0.00178***
	(16.48)	(16.95)	(15.87)	(15.73)
Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Benchmark × Month FE	No	Yes	Yes	Yes
Domicile × Month FE	No	No	Yes	Yes
Inv. Area × Month FE	No	No	No	Yes
N	1,274,790	1,274,144	1,272,629	1,270,279
Adj. R^2	0.0453	0.216	0.291	0.315

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