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Equity Funds and Derivatives: Evidence from Linked Fund-Trade Data[☆]

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Abstract

Building on data collected under the EMIR framework, we provide new insight into the type of derivatives that are traded by UCITS equity funds, why some of them trade derivatives whilst others do not, what makes some more active traders and to what extend the trading in derivatives is a reaction to daily changes in the market. 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 behavior 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, which suggests that derivatives are used for transaction costs or risk reduction purposes.

Keywords: UCITS funds, derivatives trading, fund families, flows, risks
JEL: G10, G20, G23

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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 Proposed Rule Release 18f-4 of the Investment Company Act[1], the SEC aims at putting new limitations on derivatives usage by mutual funds. Notwithstanding the recognized positive effects of these instruments, such as risk mitigation and economizing on transaction costs, the SEC was concerned about how these instruments might build up leverage, illiquidity, and counterparty risks. Interestingly, this proposal 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 UCITS 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

[1]The SEC published a first proposal in 2015 (IC-31933, file no. S7-24-15) and published an amended proposal (IC-33704) in November 2019; cf. https://www.sec.gov/rules/proposed.shtml. Among others, this rule says that a mutual fund is not allowed to increase its Value at Risk (VaR) by more than 50 percent relative to the hypothetical VaR of an otherwise equal, but unleveraged fund.

[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.

(iii) and (iv) is very limited.[3]

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 U.S. equity funds hold derivatives positions in their portfolio.

We first analyze 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. Long and short trades are equally important for currency forwards. 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 analyze which fund characteristics can explain the decision to trade derivatives and the trading behavior. 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 economize 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, by 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). By taking into account the currency of the net flows and relating them to the

[3] For a detailed review of the relevant literature refer to Section 2.

fund's base currency, we find a similar pattern also for currency forwards. The more inflows funds receive in currencies that are not the base currency the larger the number currency forward trades hedging the associated currency risk.

Second, we investigate the role of the 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 to trade derivatives. The fund's return risk, as well as the tracking error, does 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 analyze 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 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 economizing 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 as well as 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 economizing 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 organized as follows. In Section 2, we provide an overview on the relevant literature. In Section 3, we outline our empirical strategy. Section 4 describes the linked fund-trade dataset. Section 5 presents the results. Finally, Section 6 concludes.

2. Literature review

As it has been already pointed out, there is already literature which deals with questions (i) and (ii). However, these papers had to rely on low-frequency reporting data, and mostly on US data. Evidence at 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) report that in their sample of US equity UCITS funds, almost 90% are allowed to trade derivatives, but only a tenth of them is 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% are using 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 is using derivatives, and the most important determinants for doing so are the 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 has an impact on 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.

Regarding 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 that derivatives allow to reduce 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 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, the question of why funds are trading a given volume of derivatives on any specific day. This question has not yet been analyzed in the literature.

An important question is, of course, to learn more about the motives of why funds are trading derivatives. This is the question (iv) analyzed in this paper. In principle, there are three reasons for doing so. First, equity funds might want to economize 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 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 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

[4] A more detailed exposition of regulatory concerns on derivatives usage by UCITS funds can be found in the document supporting the Proposed Rule Release 18f-4 of the Investment

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.

Since data is not readily available, there have only been few papers analyzing 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 via the use of protective puts or covered calls. Guagliano et al. (2019) show 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 rather weak or even statistically not detectable.

Company Act by the SEC (IC-33704) published on November, 25, 2019; cf. https://www.sec.gov/rules/proposed.shtml.

3. Empirical strategy

3.1. Derivatives trading behavior 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 analyze the role of the fund family and other fund characteristics. According to the results in the literature, our conjecture is 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:

$$\begin{aligned} DerivativesFund_i = \alpha + \lambda_{familysize} + \lambda_{family} + \lambda_{invarea} + \lambda_{currency} + \\ \lambda_{domicile} + \lambda_{benchmark} + \lambda_{size} + \epsilon_i, \end{aligned} \tag{1}$$

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 analyze 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 to also 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,

$$DTD_{i,t} = \alpha + \beta x_{i,t-1} + \lambda_t + \lambda_i + \epsilon_{i,t}, \tag{2}$$

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.

3.2. Derivatives trading behavior and fund returns

To uncover motives for derivatives trading, we are interested in analyzing 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 economizing 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 emphasize that the observed excess return of a fund could be written as follows:

$$r_{i,t} = \alpha_{i,t} r_{mm,t} + \beta_{i,t} r_{b,i,t} + (1 - \alpha_{i,t} - \beta_{i,t})(r_{d,i,t}) + \epsilon_{i,t}. \tag{3}$$

The return index i stands for the fund, mm the money market rate, b the fund's benchmark, and d 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

$$r_{i,t} - r_{mm,t} = \beta_{i,t}(r_{b,i,t} - r_{mm,t}) + (1 - \alpha_{i,t} - \beta_{i,t})(r_{d,i,t} - r_{mm,t}) + \epsilon_{i,t}. \tag{4}$$

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

$$r_{d,i,t} - r_{mm,t} \approx \Omega_{i,t}(r_{b,t} - r_{mm,t}) + \Gamma_{i,t}\kappa_{i,t}(r_{b,t} - r_{mm,t})^2 + \nu_{i,t}. \tag{5}$$

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 5 into Equation 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:

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

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 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:

$$r_{i,t} - r_{mm,t} = \beta^k_i + \beta^m_i(r_{b,t} - r_{mm,t}) + \beta^n_i(r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t} \tag{7}$$

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 inference on the betas and, as a consequence,

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

on the impact of derivatives trading on returns and their distribution.

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:

$$\begin{aligned} r_{i,t} - r_{mm,t} = \beta_i^k + \beta_i^n (r_{b,t} - r_{mm,t}) \\ + \beta_i^p bot_{b,t} (r_{b,t} - r_{mm,t})^2 + \beta_i^q top_{b,t} (r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t} \end{aligned} \tag{8}$$

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.

4. Data

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 benchmark, and funds that have a benchmark inception date after December 31, 2015. Moreover, we obtain funds' Legal Entity Identifier (LEI) from Bloomberg. We disregard funds with missing LEI since the LEI is 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 Dollar to deal with the incubation bias (Evans, 2010). We end up with a comprehensive sample of 4,555 European equity UCITS funds.

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

estimations for each beta-factor

[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

granularity to the authorities. The highest level of granularity is the trade activity data (also referred as flow data). This data provides various messages to track the life cycle of a derivative transactions. 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 standardized during our sample period. Therefore, we rely on a methodology developed and tested by the European Securities and Markets Authority to categorize derivatives using a variety of other codes, for example, exchange or 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.

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 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. It should be noted that all variables are winsorized at the 1% and 99% level.

Descriptive statistics of the derivatives trading funds are given in Panel A of Table 1. The average fund trades on 40% of the days and makes about

[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.

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. Non-trading funds tend to be smaller, to belong to smaller fund-families, and to have slightly higher return volatility and tracking errors.

— Table 1 about here —

5. Derivatives trading of equity funds

5.1. Which types of derivatives are traded by equity funds?

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 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.

— Figure 1 about here —

Table 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.

— Table 2 about here —

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 summarized in Figure 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 2 about here —

Figure 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 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.

— Figure 3 about here —

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 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

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

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 certain 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 for its own can explain between 3.6% and 7.7% of the overall variation, they are only able to 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 to trade derivatives 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 3 about here —

A detailed comparison of derivatives trading and non-trading funds in terms of their fixed characteristics can be found in Appendix C, 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 have a preference for choosing Luxembourg or Ireland as their domicile. Overall, these differences are rather small, 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.

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 plus fund fixed effects, which now we can be used since there is variation in a fund's derivative use over time.

Table 4 presents the results. In Panel A, the dependent variable is the natural logarithm of a fund's traded notional per day. Not surprisingly, 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. The addition of 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 to be important since it can explain by its own 12.9% of the overall variance. However, the largest part in explained variation is added by including a fund fixed effect. This increases the overall adjusted R-squared to 56.0%, which is almost equal to the adjusted R-squared if we would use the fund fixed effect as the only explanatory variable. 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%, which again is almost equal to the adjusted R-squared of the fund fixed effect alone.

Overall, this evidence can be interpreted as follows. The decision to become active on the derivatives market is embedded in the overall environment the investment company running the whole fund family is delivering. This might be related to the trading infrastructure, the specific derivatives know-how available in the company, the existence of a general policy on how to handle derivatives contracts, and, of course, the specific 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 4 about here —

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 economize 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 speculating on specific price movements.

To shed more light on this question, we conduct three different analyzes 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 analyze 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 at detecting whether derivatives trading is associated with risk-adjusted returns as well as with the fund's delta and gamma risk.

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 hypothesize 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 behavior arises. Nevertheless, according to the transaction cost hypothesis, there should be a relationship between a fund's net flows and its equity futures trading behavior.

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 visualized in Figure 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 4 about here —

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 analyze 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 5 visualizes 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).

— Figure 5 about here —

5.4.2. Derivatives trading and time-varying fund characteristics

In this section, we analyze 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 behavior 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 5 presents the results for fund flows, whereas Table 6 shows the ones for fund risk and return.

— Table 5 about here —

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.

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.

— Table 6 about here —

In Panel A of Table 6 we analyze 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 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.

In Panel B, we analyze 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 D and fund risks and returns in Appendix E. Using alternative measurement periods, we find similar results. Second, instead of the linear probability model we estimate a conditional logit model. The results in in Appendix F and Appendix G confirm our finding that fund flows and currency risk are positively related to the propensity to trade.

5.4.3. Derivatives trading and a funds' risk-profile

Finally, after having dissected derivatives trading behavior of equity UCITS funds, we will analyze 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. For this purpose we estimate Regression 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 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 realizations derivatives using funds have superior returns. In other words, in the downward case, they display less correlation with benchmark returns. 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.

— Table 7 about here —

To better understand the implications of the results displayed in Table 7, Figure 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.

— Figure 6 about here —

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 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, making the risk-adjusted returns being less risky for derivatives trading funds.

— Figure 7 about here —

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 behavior.

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 funds' decision use of 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 behavior only for a six month period. These limitations make it difficult to causally infer the motives of funds to trade derivatives. We hope that these limitations can be addressed by future research.

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Figure 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 winsorized at the 1% and 99%-level.

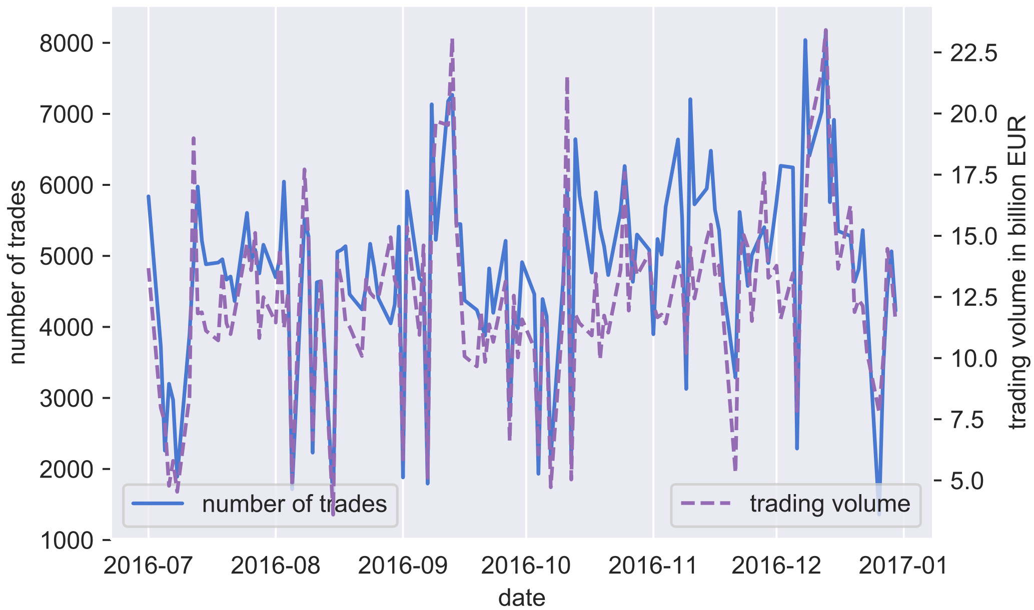
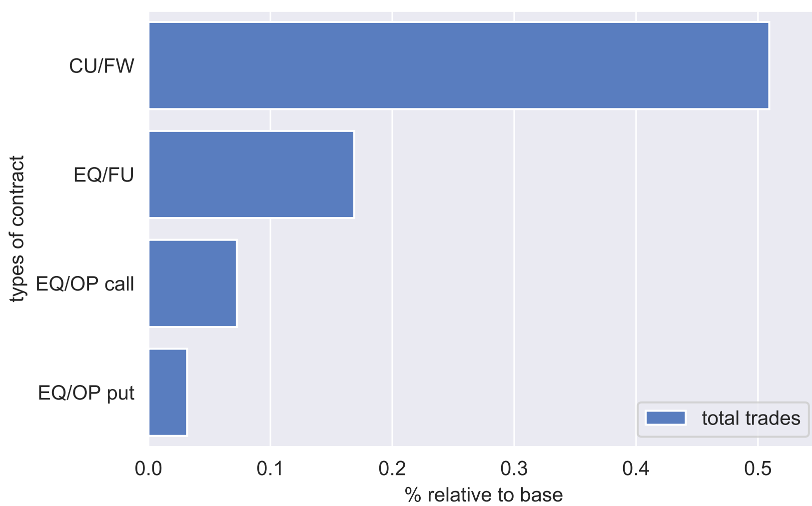


Figure 2

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) visualizes 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 2.

(a) Total trades



(b) Total notional

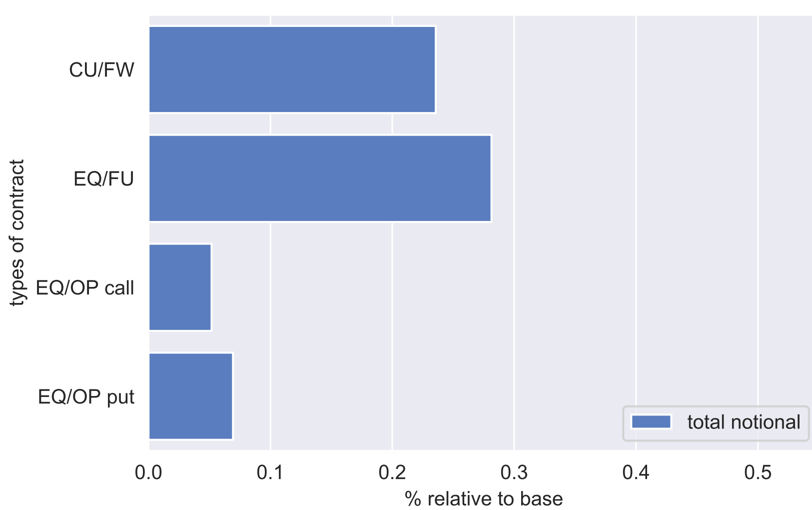


Figure 3
Most important derivative contract types: long and short trades
This figure illustrates how the total number of trades of the three major derivatives contract types are distributed across long and short trades. The three most important contract types are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP). For the options on equity, we report trades of call and put options separately.

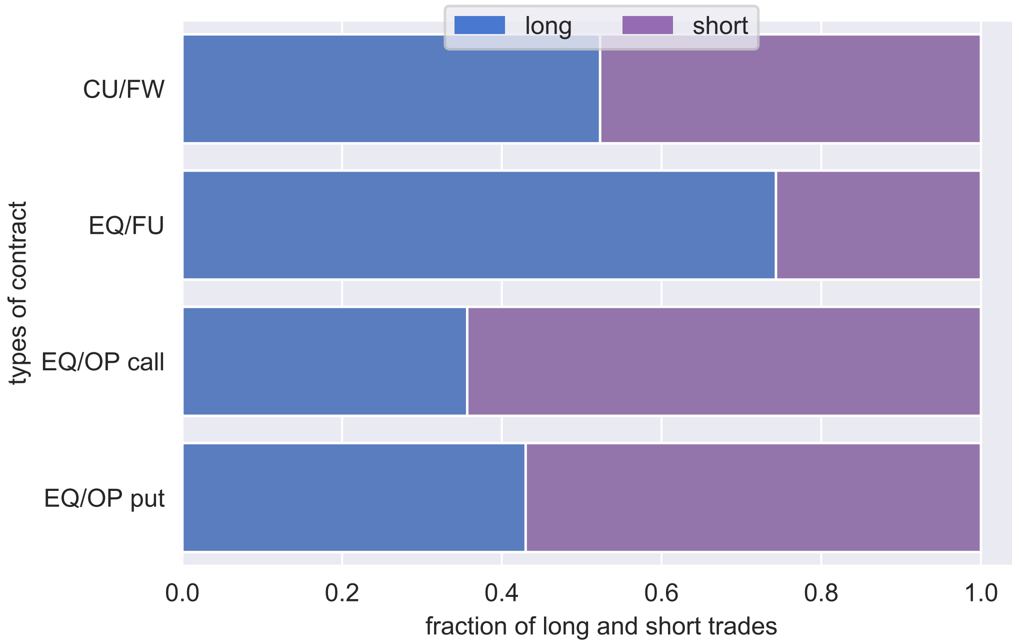
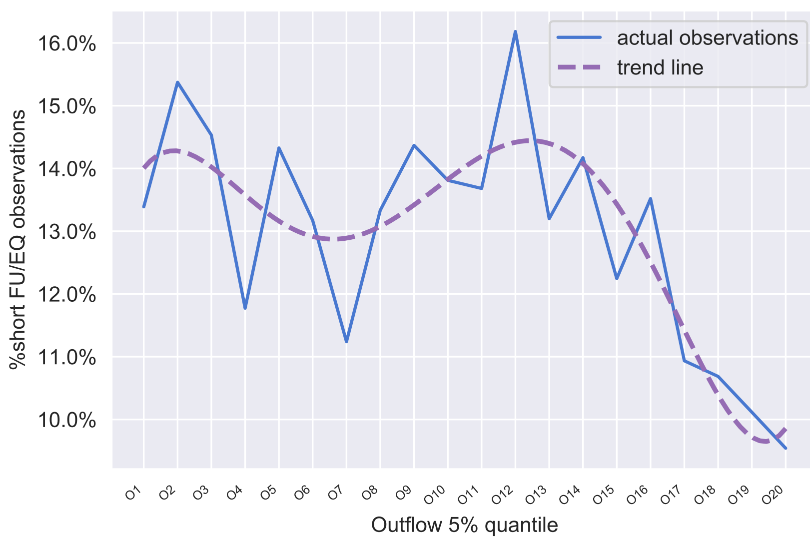


Figure 4
How do fund flows affect the trading of equity futures?
This figure illustrates the relation between daily fund flows and trades of equity futures in the following days. Daily flow observations are split into mainly outflows or inflows using the direction of the relative net flow. Subfigure (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

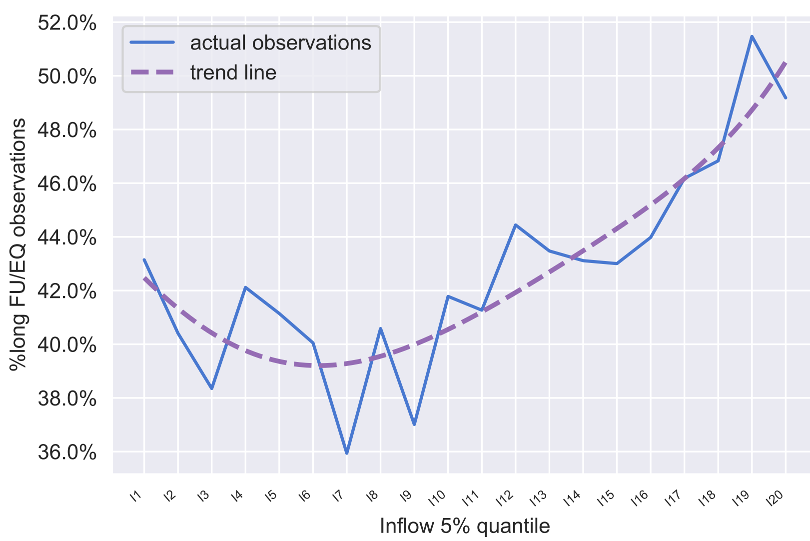
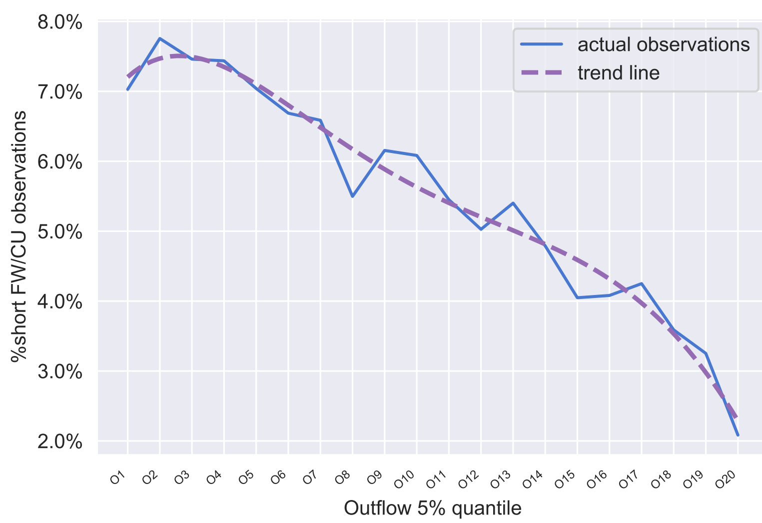


Figure 5
How do fund flows in non-base currencies affect trading of currency forwards?
This figure illustrates the relation between daily fund flows and trades of currency forwards in the following days. Daily flow observations are split into mainly outflows or inflows using the direction of the relative 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

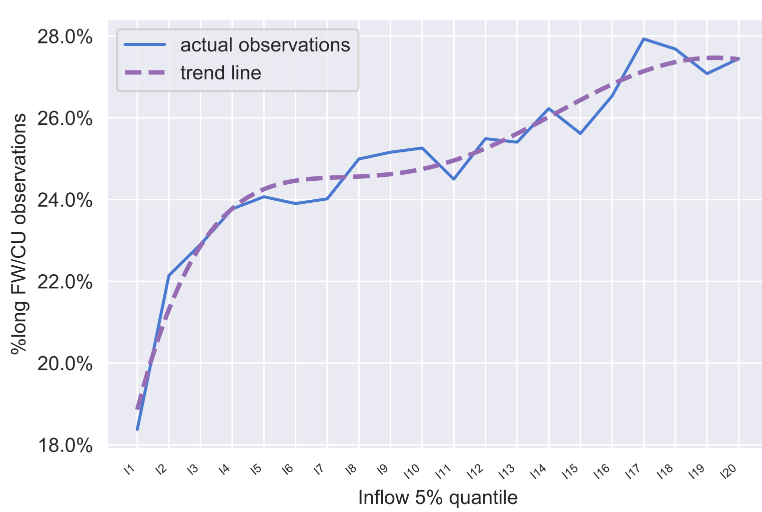


Figure 6

Do actively derivatives trading funds outperform non-trading funds?

This figure illustrates the predicted 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 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.

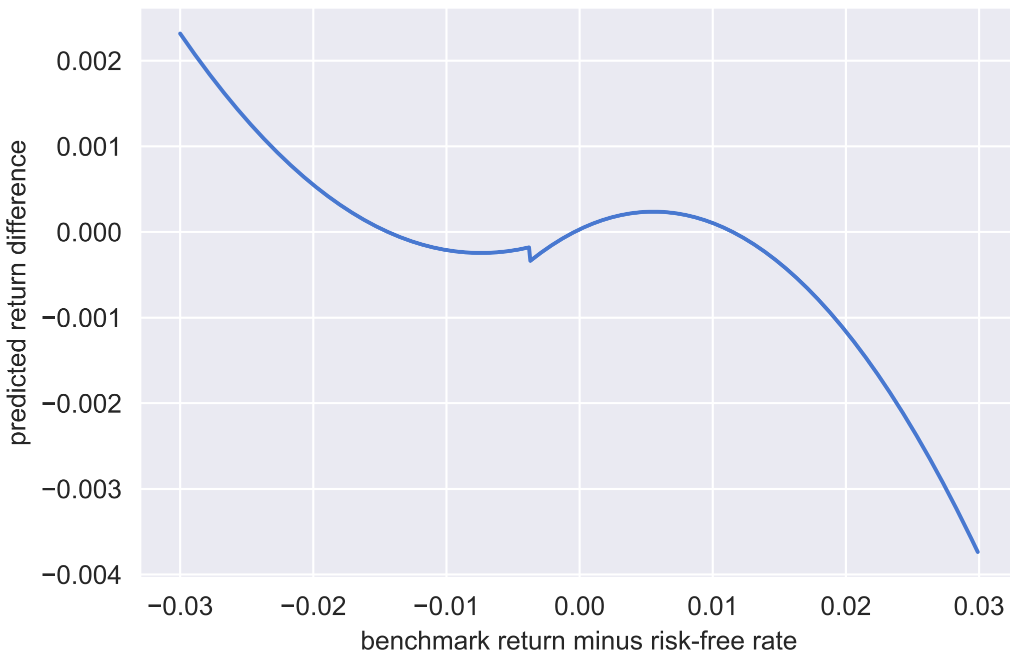


Figure 7
Are risk-adjusted returns of actively derivatives trading and non-trading funds different? This figure shows the kernel density of the estimated risk-adjusted returns by the funds' trading activity according to Equation 8, i.e. the kernel density of the estimated β_i^k. Trading funds only include 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.

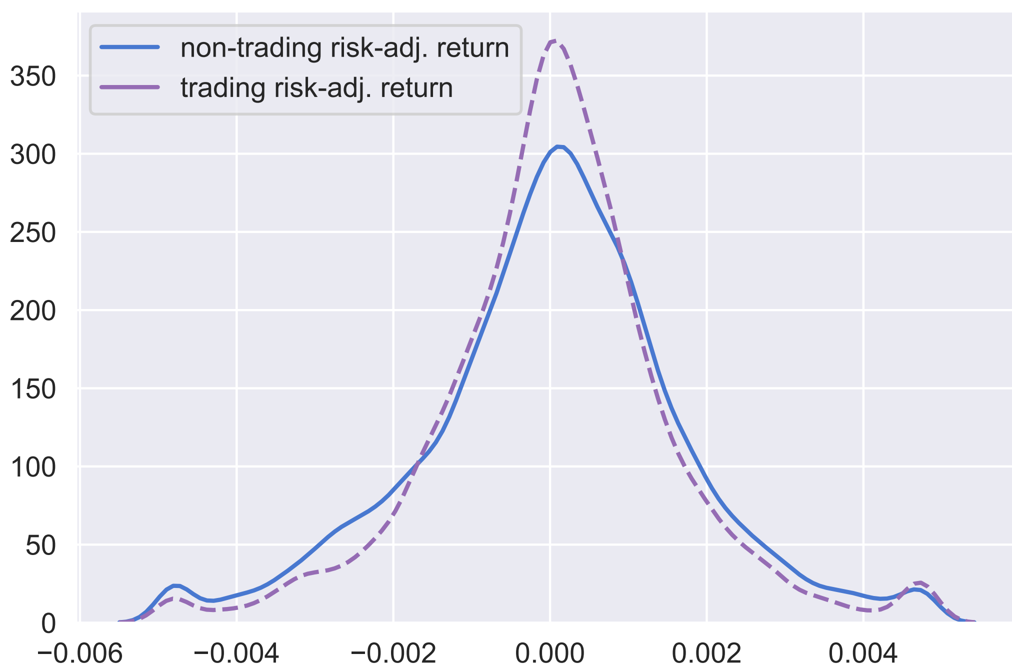


Table 1
Summary statistics of funds

This table presents summary statistics of derivatives trading in Panel A and non-trading funds in Panel B funds. 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.

	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

Table 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 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 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. 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.

	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

Table 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.

	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

Table 5
How do fund flows affect derivatives trading?

This table presents estimates from linear probability models of trading dummies on on measures of fund flows lagged by one day, Equation 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 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)	(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

Table 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, Equation 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 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)	(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

Table 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 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, $r_{b,i,t}$ for the return of fund i's benchmark b on day t and $d_{i,t}$ is a dummy variable indicating whether a fund i traded at least one derivative in the month of t. $bot_{i,t}$ and $top_{i,t}$ 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	

Appendix A
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.
fund risk	Daily standard deviation of discrete fund returns measured on the basis of 20 preceding trading days. Source: Morningstar.
tracking error	Daily standard deviation of differences between discrete fund and benchmark return measured on the basis of 20 preceding trading days. Source: Morningstar.
return	Cumulative daily discrete fund returns over 20 preceding trading days. Source: Morningstar.

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Appendix A continued

Variable	**Description**
return-benchmark	Cumulative daily discrete fund returns over 20 preceding trading days minus cumulative daily discrete benchmark returns over 20 preceding trading days. Source: Morningstar.
return-family	Cumulative daily discrete fund returns over 20 preceding trading days minus average cumulative daily discrete returns of other fund family members. Source: Morningstar.

Appendix B EMIR data reporting and aggregation levels

Under Article 9 of the European Market and Infrastructure Regulation all entities 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 authorization 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.

Appendix C
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%

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Table C continued

	% of trading funds	% of all funds
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%
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%

Appendix D
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, Equation 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 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)	(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

Appendix E
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, Equation 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 analyzed 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, and 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 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)	(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

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Table E continued

	(1)	(2)	(3)	(4)
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
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

Appendix F
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)	(2)	(3)
Panel A: Fund flows			
	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

Appendix G

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)	(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

esma European Securities and Markets Authority