Mutual Funds and Derivatives: Evidence from Linked Fund-Trade Data☆

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Abstract

By using a novel data set of mandatory derivatives trades' filings under the EMIR regulation, we analyze the trading behavior of 4,555 European equity mutual funds. 46% of these funds execute a total of more than 600,000 trades over our sample period. About 80% of these trades are related to either currency forwards, equity futures or equity options. We find that the decision to trade is to a large extent embedded in the fund-family affiliation, while the trading frequency is driven by other fund-fixed characteristics. Size, geographic focus, base currency, or domicile of the fund play a minor role. When it comes to the motives for trading derivatives, our results support the transaction cost savings and risk mitigation hypothesis. In fact, we find evidence that net flows are driving the likelihood for trading equity futures, while currency flows as well as currency risk are driving the likelihood of trading currency futures. We also show that derivatives trading funds have significantly less downward risk but also less upward potential. The risk adjusted returns are slightly higher, even though statistically not discernible.

Keywords: Mutual funds, derivatives trading, fund families, net flows, tracking error

JEL: G10, G20, G23

☆The usual caveats apply. The corresponding author is Daniel Bias, E-Mail: daniel.bias@tum.de

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1. Introduction

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 somewhat limited empirical evidence since, hitherto, research on derivatives usage by mutual funds had to rely, at best, on low-frequency holding or survey data.

In this paper, we use large scale derivatives trading data from the mandatory reporting of any derivative contract under the European Markets Infrastructure Regulation 648/2012 (EMIR). This allows us to sketch the anatomy of derivatives trading by European equity funds. In detail, we are interested in understanding (i) what types of derivatives are traded by mutual 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 (i) and (ii), research on (iii) and (iv) is very limited.[2]

Our comprehensive fund sample consists of 4,555 European equity mutual funds. We link the fund sample with data on derivatives trades in the period from July 1 to December 31, 2016. We find that 46% of these funds do at least one derivatives transaction over our observation period.[3] Interestingly, three types of contracts account for about 80% of all trades, with forward contracts on currencies being responsible for more than 50% and future or option contracts on equities for the remaining less than 30%. For currency

[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 VaR by more than 50 percent relative to the hypothetical VaR of an otherwise equal, but unleveraged fund.

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

[3]This percentage is very close to the what is reported by (Benz et al., 2019) for US mutual funds and slightly above other results in the literature so far (cf. Koski and Pontiff, 1999; Cao, Ghysels and Hatheway, 2011; Cici and Palacios, 2015).

forwards, long and short trades are almost equal. While more than 70% of the equity future trades are long trades, it turns out that more than 60% of the equity call option trades are short trades. Moreover, regarding option strategies we find that the majority of those trades we are able to classify, are premium and synthetic trades.

Next, we analyze which characteristics can explain the decision to become a derivative using fund. We show that the by far most important characteristic is the fund-family affiliation. In fact, a fund-family fixed-effect explains more than 34% of the cross-sectional variation in the likelihood of being a derivatives trader. Compared to that, all other variables, i.e. the fund-family size, the investment area, the investment strategy (measured by the fund's benchmark), the fund's base currency, domicile, or size, are almost negligible as these variables increase the adjusted R-squared of our model only by an additional 5 percentage points.

For the derivatives using funds, we analyze their trading volume and trading frequency, i.e. the daily traded notional and the probability that a fund trades on a particular day. The fund fixed-effect, on a stand-alone basis, can explain 56% of the cross-sectional variation. A part from fund-family affiliation, which is still important, it also turns out that the choice of a particular benchmark has a strong predictive power with respect to trading volume and frequency. These results indicate that the trading infrastructure provided by the fund-family as well as the predetermined investment strategy are an important determinant for the usage of derivatives.

Other fund-fixed characteristics, such as investment area, currency, domicile or size, play only a minor role. Overall, this model can explain close to 60% of cross-sectional variation. The result of this combined model indicates that there must be some fund-fixed characteristics not covered by the fixed-effects mentioned before, that drive equity funds' derivatives activities. Most importantly, these might be related to fund managers' personal traits or incentive schemes in place. We do not have data to further investigate this.

In the next step, we analyze the likely motives for derivatives usage. Funds might use derivatives in order to economize on transaction cost, for risk management purposes, or for return enhancing strategies, like increasing the economic leverage.

For this purpose, we exploit the granular nature of our data in order to uncover patterns in derivatives usage. By aggregating net fund flows on a daily basis and grouping them in 5% quantiles based on daily net flows, we find a clear 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 fund's base currency, we find a similar pattern also for currency forwards. The larger the inflow in currencies which are not the base currency, the larger the currency forward trades aimed at hedging the associated currency risk.

Next, 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 to trade 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 to execute 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 the funds. Even thought the beta of derivatives using funds with respect to the benchmark is slightly higher, i.e. 0.65 as compared to 0.58, these funds have less convexity for high benchmark returns, and more convexity for low benchmark returns. This is to say that these funds have less downside risk. In fact, the kernel density of the risk-adjusted return 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 statistical significant difference, even though it is higher by 75 bp/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 use by mutual funds in multiple ways. First, by exploiting our daily trade data we are able to provide an anatomy of derivatives trading by equity mutual funds. To the best of our knowledge, this is the first paper using such granular data. Hitherto, the literature had to rely on 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 is to a large extent embedded in fund-fixed characteristics. The trading infrastructure provided by the fund-family, i.e. 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 funds 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 give an overview on the relevant literature. In Section 3 our empirical test strategy is explained in more detail, while Section 4 describes the data set. Afterwards in Section 5 we present the results with respect to questions (i) to (iv) mentioned above. Finally, Section 6 concludes.

2. Literature review

As it has been already pointed out, there is a decent number of papers dealing with questions (i) and (ii). However, these papers had to rely on low frequency reporting data. It is therefore interesting to see how the results reported there 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 dealing with mutual 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 mutual funds are allowed to use derivatives. Natter et al. (2016) report that in their sample of US equity mutual 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 mutual funds (Benz et al., 2019) find that 40% are using derivative instruments. While this number is close to our finding, the other numbers reported in the literature are by far lower. It could well be that derivatives usage has changed over time, leading to a larger fraction of derivatives using funds in more recent studies.

With respect to question (i), i.e. what type of derivatives are traded by mutual 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), i.e. the question 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 mutual funds are 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. The latter result is also confirmed by Deli and Varma (2002). What seems to be more important in this regard is whether a fund is focused on specific asset classes, with debt funds being the most heavy 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.

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 these findings in the literature. However, because of our granular daily data we are able to say more on the relative impact of these different variables. This is especially true when it comes to question (iii), i.e. the question 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 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 used for betting on specific price movements adding idiosyncratic risk to the fund. A part from the return risk implications derivatives usage might have, regulators are also concerned about the fact that these contracts could add liquidity or

[4]A more detailed exposition of regulatory concerns on derivatives usage by mutual funds can be found in the document supporting the Proposed Rule Release 18f-4 of the Investment Company Act by the SEC (IC-33704) published on November, 25, 2019; cf. https://www.sec.gov/rules/proposed.shtml.

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.

Due to the fact that data is not easily 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 about 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 mutual 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. In a comprehensive analysis of US mutual funds Benz et al. (2019) show that exposures coming from derivatives are very small, i.e. 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.

3. Empirical strategy

In this paper we analyze the funds' trading behavior in the derivatives space by means of three different approaches. First, we simply group this trading behavior according to certain fund and trading characteristics. Second, we regress the trading activity on fund characteristics. Third, by using a non-linear regression approach we aim at detecting whether derivatives trading has an impact on risk-adjusted returns as well as on the fund's delta and gamma risk. The latter two approaches deserve a more detailed description, which is given in the following.

3.1. Trading determinants

Using trading data from mandatory reporting allows us to observe derivative trading and non-derivative trading equity mutual 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 ($DerivativesFund_i$), i.e. a dummy which is set to one, if the fund trades derivatives during our sample period, on the following fund-family and fund-specific fixed effects:

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

Here, i denotes a fund, ϵ_i is the error term, $\lambda_{familysize}$ 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. 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 overall variation in the funds' decision to use or not use derivatives can be explained by these characteristics.

To analyze the propensity and extent of a fund's derivative use, we aggregate the trade-level data on 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 dependent variable of the fixed effects approach to identify fund characteristics that can explain the propensity and 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 a reaction to changing 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 $x_{i,t-1}$. All models include day and fund fixed effects. 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 in order to alleviate simultaneity concerns.

3.2. Return Analysis

In order 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, delta risk (volatility) of the fund portfolio should decrease. By using non-linear derivatives, also the gamma risk of the fund, i.e the convexity of the payoff profile, would be reduced.

Of course, 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.

Now, disentangling these effects is not an easy task. However, because of the daily trading data at hand, we are able to propose an approach, where the different impact types described above could somehow be isolated. For this purpose, we first emphasize that the observed excess return of a fund could be written as follows:

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

Here, the return indexes i, mm, b, and d stand for the fund i, the money market rate, the fund's benchmark index and its 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:

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

Now, we recall that by using a second-order Taylor approximation the return of the derivatives position can be written as:

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

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

Now, substituting the second equation into the first, 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 or not. In this way we get for each fund 6 estimations for each beta-factor, which makes a total of more than 25,000. We can then make inference on the betas and, as a consequence, 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 mutual 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 disregard funds with missing information about their Legal Entity Identifier (LEI), as counterparties of a derivative trade are identified by this variable in the 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). These criteria are fulfilled by 4,555 equity funds.

We identify 2,085 of the 4,555 equity funds in the EMIR data, i.e. 45.8% of the equity funds make at least one derivative trade.

4.2. Data on derivatives trades

We make use of a proprietary regulatory data set collected under Article 9 of the European Market Infrastructure Regulation (EMIR). The data itself is collected from trade repositories (TRs) which collect the data from the reporting counterparties. ESMA handles the registration and authorisation process of the TRs and supervises them while national competent authorities supervise the reporting of the counterparties. The reporting obligation applies to all counterparties executing derivatives transactions located in the European Economic Area and needs to be fulfilled within a working day of the execution of the trade.

EMIR-originated data is provided at different levels of granularity to the authorities. The highest level of granularity is trade activity (also referred to as flow data), which provides various messages to update the status of open transactions. Each message has a certain action type that defines the content and consequently the status of the transaction (e.g., new trade, modified, cancelled/terminated). The next level of aggregation is the trade-state data which provides information on outstanding transactions at the end of day (most of the time excluding intraday trading activity). In this paper we use trade-flow data, as trade-state data has not yet been processed.

We obtain flow data in the period from July 1 to December 31, 2016. The data set is collected from the six relevant TRs in 2016, i.e., CME, DTCC, ICE, KDPW, Regis-TR and Unavista. We filter out only new transactions, i.e. transactions of action type N. EMIR data provides a variety of fields to describe the complex universe of derivative transactions. We extract the main EMIR fields to identify the central properties of these contracts: asset class, contract type, counterparty side (buy/sell), and notional amount. For the exchange traded derivatives the reporting of asset class and contract type is not standardized, thus we use a methodology developed and tested by ESMA to populate this information. Further, we apply various cleaning steps to filter out unrealistic or unexpected values.

4.3. Descriptive statistics of sample

Our main sample 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. Descriptive statistics of the derivatives trading funds are given in Panel A of Table 1. There, it can be seen that the average fund trades on 40% of the days and makes about 2.3 trades per day.

— Table 1 about here —

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. A detailed definition of all variables can be found in Appendix A.1. It should be noted that all variables are winsorized at the 1% and 99% level. The average (median) 5-day net flow of a fund is 0.84% (0.22%) of the net asset value, the rolling monthly return is 0.51% (0.60%), which on average (in the median) is 0.76 (0.37) percentage points below the benchmark. The rolling annualized standard deviation of the fund return is 15.02% (12.65%). The average (median) annualized tracking error of a derivatives trading fund is 12.33% (9.49%). We measure the currency risk 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. The average (median) annualized currency risk is 3.00% (0.63%).

A comparison with the characteristics of non-trading funds 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.

A more detailed comparison can be found in Table 2, where again it can be seen that both groups are similar, however with some systematic, but rather small differences. For instance, trading funds tend to belong to larger fund families and tend also to be larger themselves. In terms of base currency distribution, 49% of all funds have the Euro as their base currency, while for trading funds this ratio is a little bit smaller at 45%. Also, in terms of the investment area the differences are rather small, as 15% of all sample funds are focused on Europe, while this is still true for 13% of the trading funds.

The most significant difference can be found for the the group of funds which have a global investment focus and the US-dollar as a base currency. Overall, 7.6% of the funds belong to this group, while among the trading funds this ratio is 11.5%. Another systematic difference relates to the fund domicile, where it turns out that derivatives trading funds have a preference for choosing Luxembourg or Ireland. In fact, 50% of all the funds are domiciled in one of these two countries, while for the derivatives trading funds this ratio is 61%.

— Table 2 about here —

5. Derivative use by equity funds

5.1. What 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. Over our sample period, we do not observe any time trend or other systematic trading pattern in funds' daily trading activities. Rather, we only observe several peaks in both the number of trades and the trading volume.

— Figure 1 about here —

Table 3 presents the relative distribution of derivative trading activities across asset classes and derivative types. The underlying asset class of a trade is identified by an algorithm. 16% (23%) of the trades (notional) cannot uniquely be assigned to one asset class and are, therefore, classified as undefined. 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 or 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, can be neglected.

— Table 3 about here —

Panel B presents the relative distribution of the notional. Here, the three types of contracts mentioned above still account for 65% of the overall trade volume and 84% of the classified trade volume. However, the relative importance among these three contract types changes. While the fraction of forward contracts on currencies decreases to 24%, the share of future equity contracts increases to 28%. Options on equity remain almost unchanged with 13%. The importance of the three major derivatives contract types is summarized in Figure 2 and in Figure 3. In doing so, 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 about here —

Figure 4 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 mutual funds write a call option in 64% and a put option in 57% of the trades. Hence, short positions on calls are the prevailing contract type when it comes to option trading, representing about 62% of those trades.

— Figure 4 about here —

Finally, we want to shed some more light on the equity option positions. The fact that equity option trades are short (call) positions in the majority of the cases could be taken as a first indication that options are not primarily used for increasing the fund's gamma. However, as options could be integrated in different strategies this is a rather vague statement.

Therefore, we try to identify whether the sample funds stick to specific option strategies. In order to do so, we have first to collect all necessary information on every single option trade. There are a total of 66,591 option trades in the sample executed by 154 funds. However, only for 21,783 trades we have all necessary information for classifying them, as can be seen in Table 4.

— Table 4 about here —

Next, we classify these trades into spread trades, straddle trades, synthetic trades, premium trades and protective puts. 38% of the trades belong to one of these strategies. The remaining are unclassified. It could be that these are simply stand-alone trades of one single option contract; it might also be that some of these trades make part of a larger option strategy, but could not be uncovered by the algorithm we were using for identifying the strategies.

The breakdown of these trades is shown in Table 5. Interestingly, the largest part, i.e. 42% of the classified trades, are premium trades. These are short positions in out of the money puts or calls. According to yet unverified results, in the majority of these trades call options are sold. If a short call is combined with holding the underlying stock, the overall position has less downside risk, however at the price of losing upside potential. In this case the premium trade is reducing the convexity of the return profile, or more technically speaking, reducing the gamma risk of the fund. If, however, put options are used in premium trades, the fund is increasing its downside risk. With respect to option spreads, which account for 17% of all classified trades, the vast majority are bullish call spreads. This again is a way to reduce the downside risk of the fund.

The second most important strategy are synthetic trades accounting for 26% of the classified trades. These trades could be interpreted as synthetically buying or selling the underlying. Hence, they should be motivated by transaction cost savings.

— Table 5 about here —

5.2. Which equity funds use 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 tell us which part of the overall variation can be explained by these fund characteristics.

Table 6 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 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 6 about here —

5.3. Which funds are active derivatives users?

In this chapter we would like to better understand why some funds are active derivatives traders, while others only execute trades infrequently. For this, we apply again a fixed effects approach. However, the dependent variable is now the daily observation on 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 7 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 slice 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 we get, 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 7 about here —

5.4. What is the rationale for trading derivatives?

As has already been explained we can think of three fundamental economic rationales for an equity mutual 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 in order 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 with respect to 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 longer periods. Therefore, significant noise in the 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.

In order 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 which are not trading at all.

The results are given in Table 8. 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. This relationship is visualized in Figure 5 and Figure 6.

— Table 8 about here —

— Figure 5 about here —

— Figure 6 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. In order 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, while 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 otuflows 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). Table 9 gives the results, while Figure 7 and Figure 8 are visualizing them. As it 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).

— Table 9 about here —

— Figure 7 about here —

— Figure 8 about here —

5.4.2. Derivatives trading and time-varying fund characteristics

Here we analyze the role of 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. With respect to 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. All models include day and fund fixed effects to control for unobserved time-varying characteristics. Table 10 presents the results.

— Table 10 about here —

In Panel A, we use 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. It should be noted, moreover, that the result is robust with respect to the measurement period of the funds' flows. As one can see in Table A.2 in the Appendix, varying the measurement period from 2 to 10 days does not undermine the statistical significance of the coefficients.

Additional support for this hypothesis is delivered in Table 11. 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 11 about here —

Coming back to Table 10, in Panel B we analyzes 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 rises the probability of a trade by 1.24 percentage points. Again, the result seems to be robust with respect to the measurement period of the currency risk. As one can see in Table A.2 in the Appendix, varying the measurement period from 5 to 30 days does not undermine the statistical significance of the coefficients with the exception of the 5 day period. 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 B of Table 10, we use the rolling one-month standard deviation of the fund return and the rolling one-month tracking error. Both coefficients are statistically insignificant. They remain insignificant also when we use different measurement periods, as can be seen in Table A.2 in the Appendix.

In Panel C, we analyze the relation 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 relation between a fund's past performance and the decision to use derivatives. Again, the results seem not to depend on the choice of the measurement period.

5.4.3. Derivatives trading and a fund's risk-profile

Finally, after having dissected derivatives trading behavior of equity mutual funds, we will analyse whether we see any relation to the risk-/return profile of the funds. Evidently, we cannot say anything on 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 12. 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. Once could also say that they have a lower upward convexity. The differences of the coefficients are statistically highly significant. Overall, this finding is in line with the notion that derivatives are used for risk mitigation purposes.

— Table 12 about here —

In order to better understand the implications of the results displayed in Table 12, Figure 9 exemplifies the predicted return difference of 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 9 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 because of 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 a statistical analysis.

Figure 10 displays the kernel density function of the risk-adjusted return of trading vs. non-trading funds. The results discussed above are again corroborated here. The probability mass is shifted towards the middle, making the risk-adjusted returns being less risky for derivatives trading funds.

— Figure 10 about here —

6. Conclusion

In this paper, we use a novel trade-level data set from mandatory reporting under the EMIR regulation to shed light on the derivative use by equity mutual funds. In detail, we provide new insights into the questions (i) what type of derivatives are traded by mutual funds, (ii) why some of them trade derivatives, while others do not, (iii) what makes some funds being more active traders, and (iv) what are the motives for trading derivatives.

First, we have shown that equity funds 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 affiliation with a given fund family is by far the most important determinant for the use of derivatives. It explains more than 34% of the overall variation of being a derivatives trader. This is in line with the presumption that the parent investment company, by providing the necessary infrastructure, know-how and processes, enables the fund manager to make use of derivatives.

Third, when it comes to explain why some funds are heavy derivative users, while others only trade infrequently, we show that the relevant drivers must be embedded in fund specific characteristics. Actually, the fund fixed effect, on a stand-alone basis, can explain 56% of the overall variation in a funds daily traded notional and the propensity to trade. Moreover, it also turns out that the investment strategy (measured by the fund's benchmark) has a strong predictive power. It can be concluded from this that a fund's investment strategy, the incentive schemes as well as personal traits of the fund manager play an important role here.

Fourth, uncovering the predominant reasons why funds trade derivatives turned out to be a difficult task. Nevertheless, we were able to uncover some robust findings. For instance, there is a strong and economically purposeful relationship between daily fund flows and the trading of equity futures. Similar is also true when we account for the currency risk embedded in such fund flows and relate this to the trading of currency forwards. All of this is in line with the presumption that funds trade derivatives for transaction cost and risk mitigation purposes. This is finally also corroborated in a regression analysis which shows that derivatives using funds are significantly less exposed to downward movements in the benchmark, but they also profit less from upward movements. Hence, our evidence so far does not indicate that funds are using derivatives predominantly for speculative reasons.

Finally, even though we were able to exploit a very granular data-set on derivatives trading by equity mutual funds, it has to be said that at this point there are also relevant limitations. Most importantly, we do not know the overall derivatives position of a fund at any point in time during our observation period. This is adding unexplained variation to our analysis, making our results less robust. Also, our time period is rather limited making causal inference on the motives for derivatives usage very hard. We hope that this limitations can be addressed in further research.

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Figure 1
Total 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.

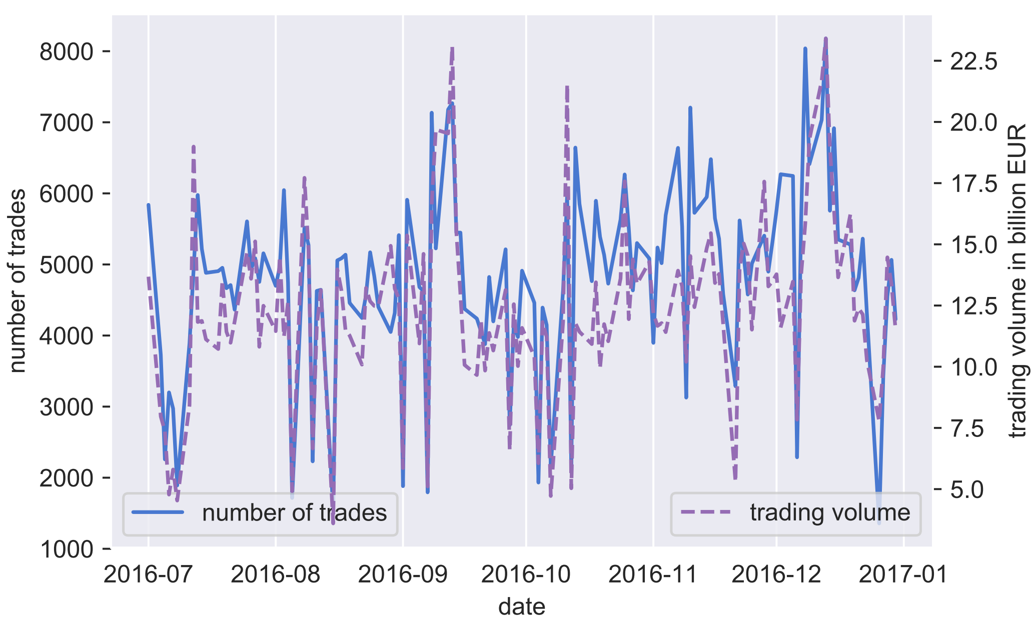

Figure 2
Derivatives contract types relative to total number of trades
This figure illustrates the share of the three major derivatives contract types that are traded by European mutual equity funds relative to the total number of trades. These contracts are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP). For the relative importance of all traded contract types, please refer to Table 3.

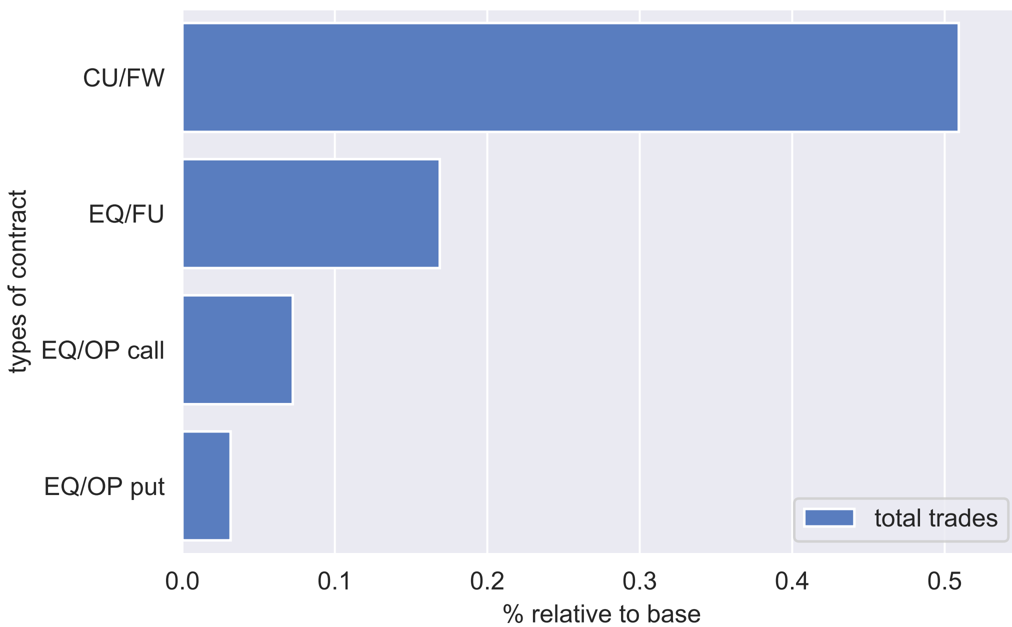

Figure 3
Derivatives contract types relative to total notional volume of trades
This figure illustrates the share of the three major derivatives contract types that are traded by European mutual equity funds relative to the total notional of trades. These contracts are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP). For the relative importance of all traded contract types, please refer to Table 3.

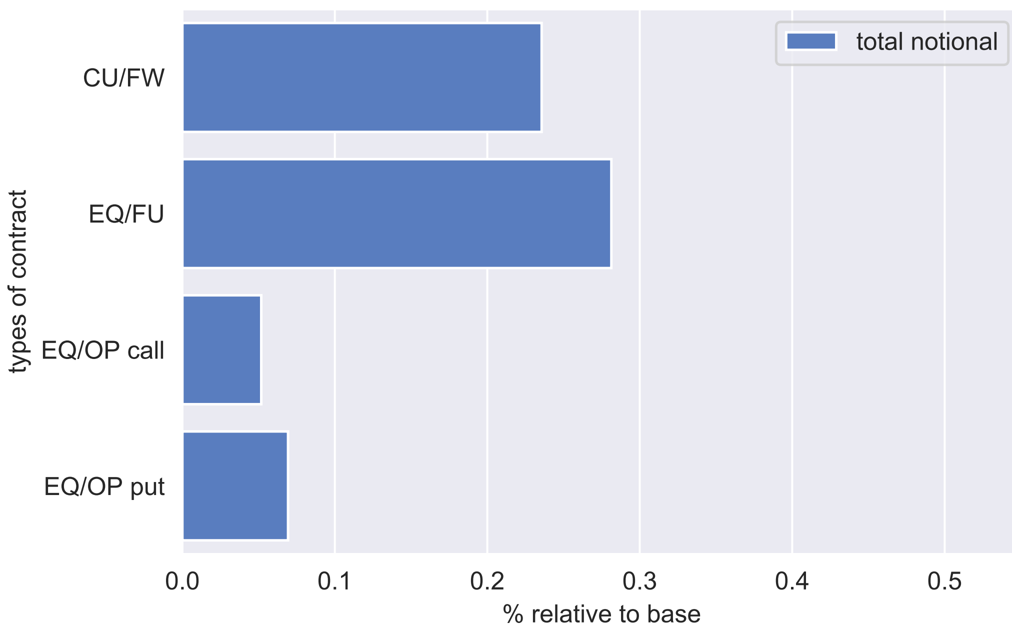

Figure 4
Share of long and short trades for the three major contract types
This figure illustrates how the total number of trades of the three major derivatives contract types are distributed across long and short trades. The three major derivatives contract types are forwards on currencies (CU/FW), futures on equities (EQ/FU), and options on equities (EQ/OP).

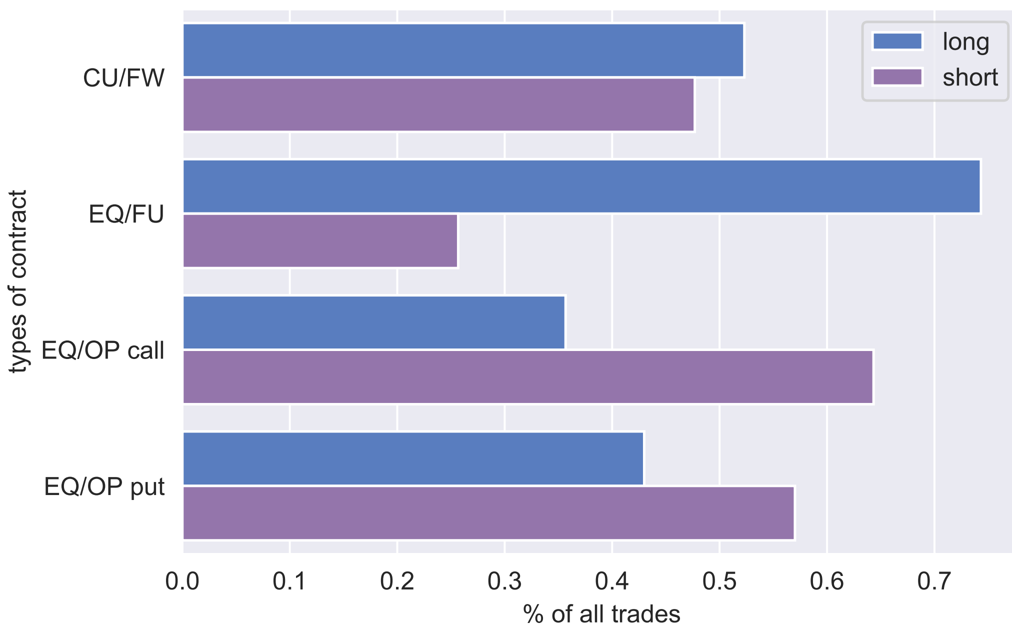

Figure 5

Equity Future Trades by Fund Outflow: Daily Quantiles

This figure 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. The percentage also takes into considerations 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.

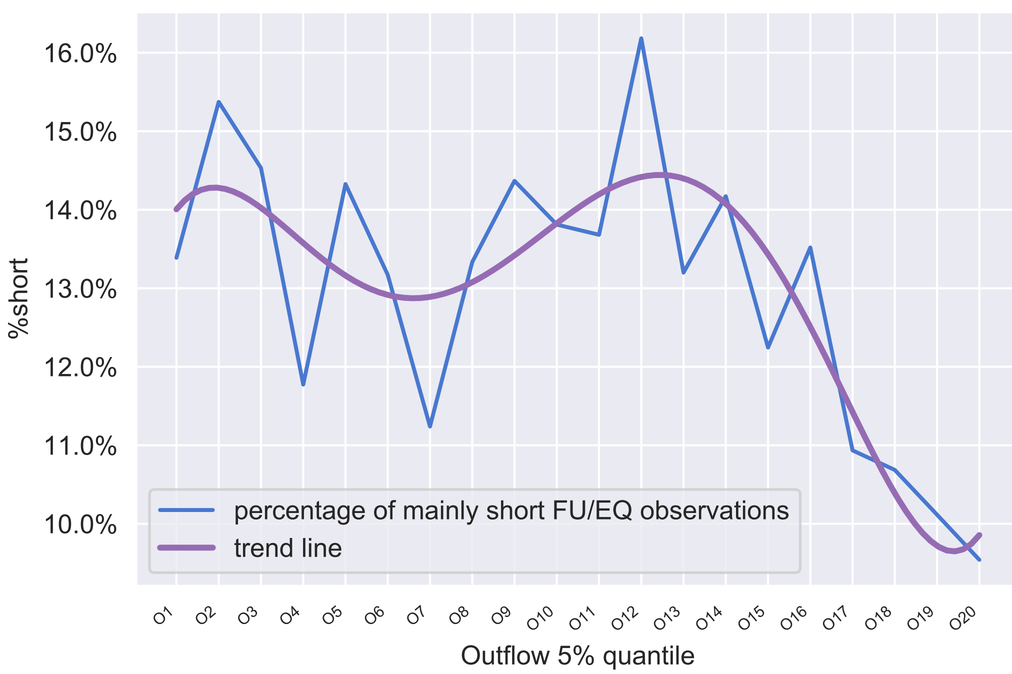

Figure 6
Equity Future Trades by Fund Inflow: Daily Quantiles
This figure shows the percentage of fund day observations with more long FU/EQ trades than short ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund inflow in t = 0. The percentage also takes into considerations 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.

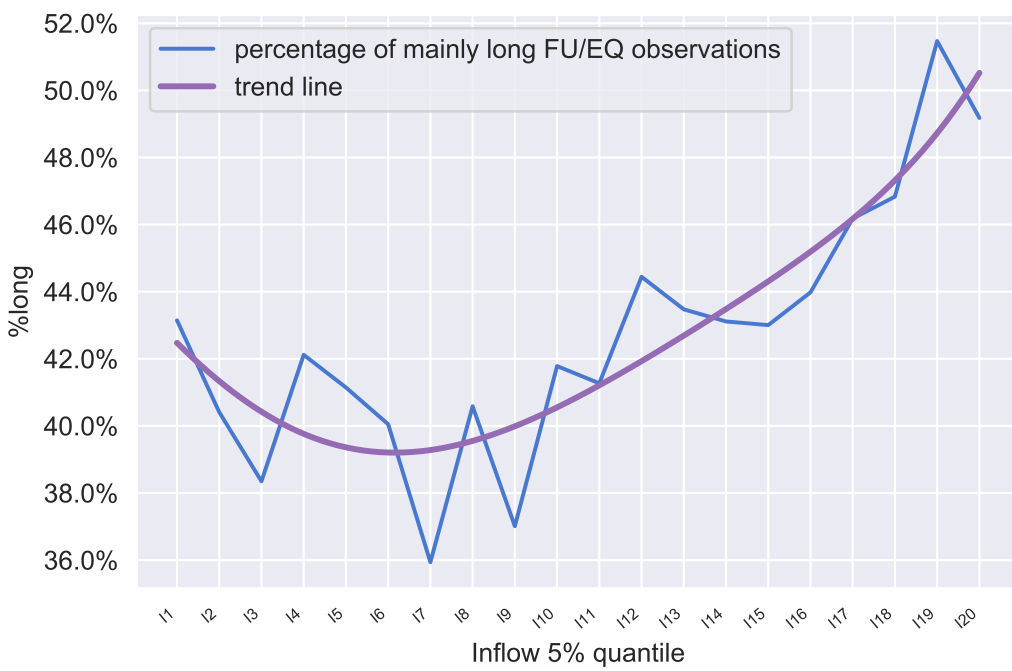

Figure 7
Currency Forward Trades by Fund-Currency Outflow: Daily Quantiles
This figure shows the percentage of fund-base currency-day observations with more short FW/CU trades than long ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund-base currency outflow in t = 0, whereby multiple share classes of a fund with the same base currency are aggregated to a single fund-base currency observation. The percentage also takes into considerations 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.

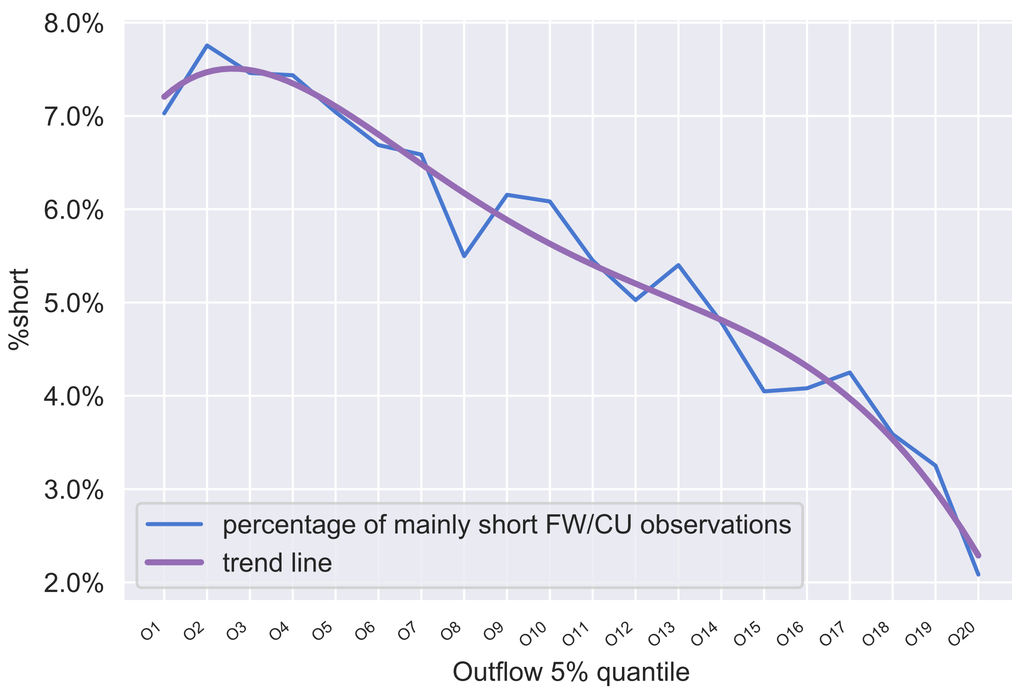

Figure 8
Currency Forward Trades by Fund-Currency Inflow: Daily Quantiles
This figure shows the percentage of fund-base currency-day observations with more long FW/CU trades than short ones in terms of the traded notional aggregated over t = 0 to 4 by 5% quantiles of the relative fund-base currency inflow in t = 0, whereby multiple share classes of a fund with the same base currency are aggregated to a single fund-base currency observation. The percentage also takes into considerations 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.

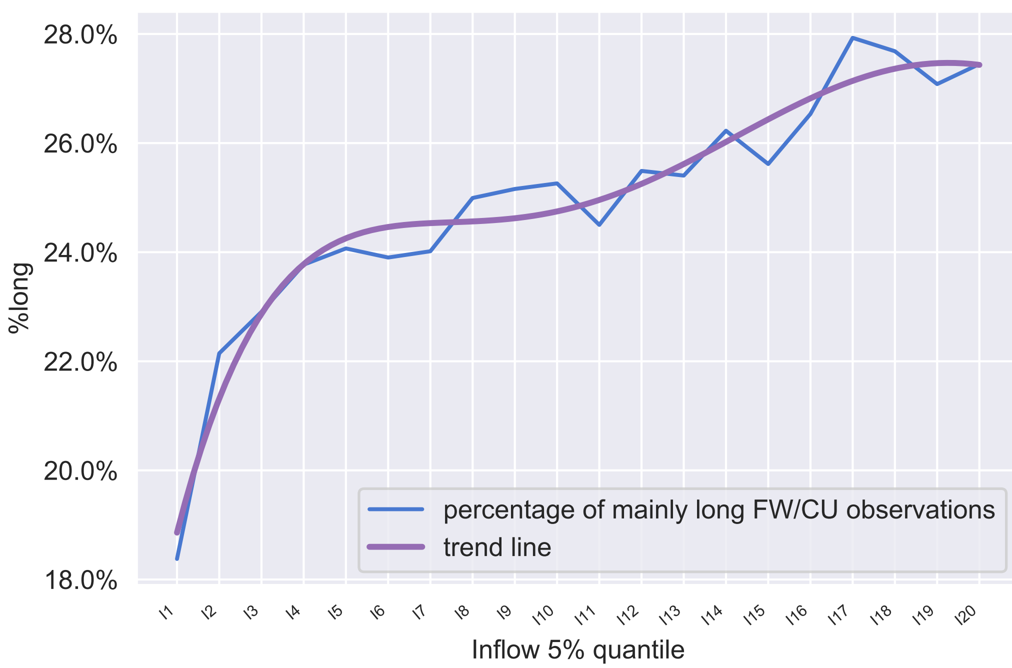

Figure 9

Outperformance of derivative trading funds

This figure shows the predicted return of derivatives trading funds (TF) versus non-trading funds (NTF) according to the regression:

$r_{i,t} - r_{f,t} = \beta^0_{i,t} + \beta^1_{i,t} d_{i,t} + (\beta^2_{i,t} + \beta^3_{i,t} d_{i,t})(r_{b,t} - r_{f,t}) + (\beta^6_{i,t} + \beta^7_{i,t} d_{i,t}) bot_{b,t} (r_{b,t} - r_{f,t})^2 + (\beta^8_{i,t} + \beta^9_{i,t} d_{i,t}) top_{b,t} (r_{b,t} - r_{f,t})^2 + \epsilon_{i,t}$,

where $r_{i,t}$ stands for the return of fund i on day t, $r_{f,t}$ for the risk-free 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. Trading funds only include funds in the top four deciles in terms of the number of reported trades.

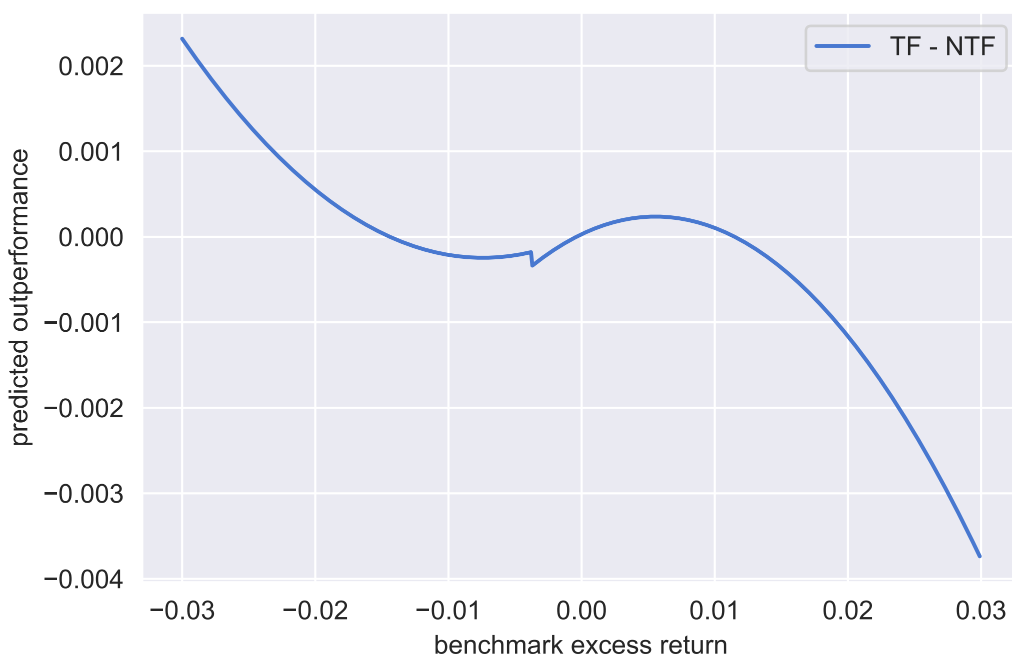

Figure 10
Kernel density of trading and non-trading funds' estimated alpha.
This figure shows the kernel density of the estimated constant by the funds' trading activity in the regression:
$r_{i,t} - r_{f,t} = \beta^0_{i,t} + \beta^1_{i,t} d_{i,t} + (\beta^2_{i,t} + \beta^3_{i,t} d_{i,t})(r_{b,t} - r_{f,t}) + (\beta^6_{i,t} + \beta^7_{i,t} d_{i,t}) bot_{b,t}(r_{b,t} - r_{f,t})^2 + (\beta^8_{i,t} + \beta^9_{i,t} d_{i,t}) top_{b,t}(r_{b,t} - r_{f,t})^2 + \epsilon_{i,t}$,
where $r_{i,t}$ stands for the return of fund i on day t, $r_{f,t}$ for the risk-free 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. Trading funds only include funds in the top four deciles in terms of the number of reported trades.

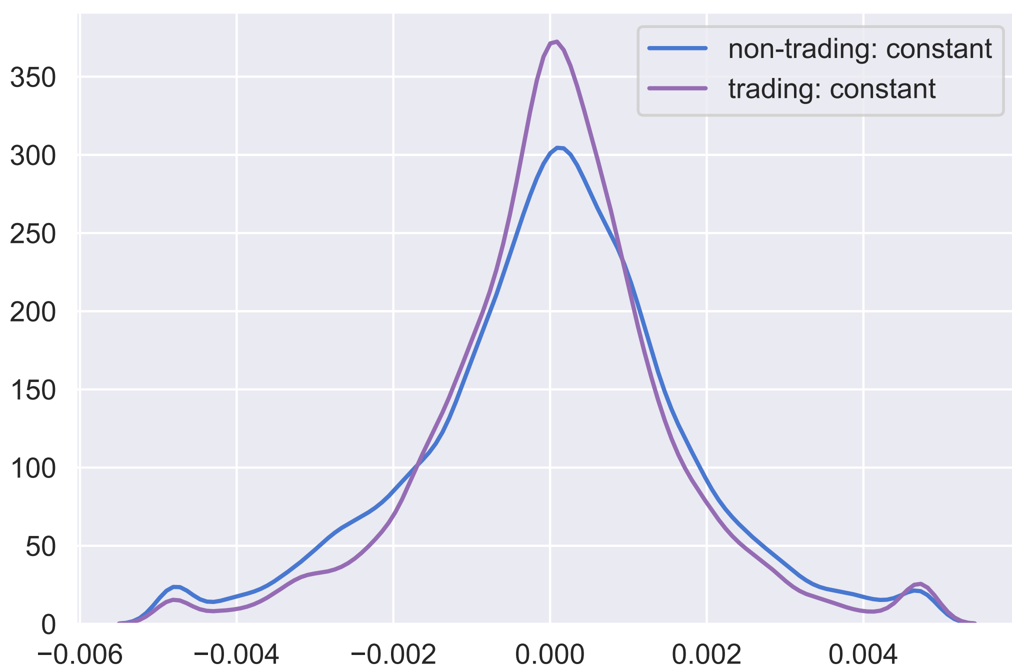

Table 1
Summary statistics of derivatives trading funds

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

	Obs	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
currency risk	198,975	0.0019	0.0025	0.0000	0.0004	0.0035
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
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
Panel B: Derivatives non-trading funds						
fund size	253,386	234.84	408.43	31.10	88.79	240.72
family size	298,292	11.56	12.61	3.00	8.00	15.00
net flow	273,373	0.0067	0.0161	0.0002	0.0015	0.0053
pos. net flow	273,373	0.0040	0.0102	0.0000	0.0004	0.0025
neg. net flow	273,373	0.0041	0.0100	0.0001	0.0008	0.0031
currency risk	212,699	0.0017	0.0025	0.0000	0.0000	0.0036
fund risk	297,480	0.0099	0.0060	0.0067	0.0082	0.0105
tracking error	259,134	0.0085	0.0064	0.0046	0.0071	0.0106
return	298,292	0.0034	0.0391	-0.0200	0.0050	0.0309
return-benchmark	259,134	-0.0087	0.0283	-0.0218	-0.0049	0.0074
return-family	298,292	-0.0003	0.0262	-0.0125	0.0000	0.0127

Table 2
Relative number of traders by 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. The used criterion in Panel B is the stated base currency. 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 investment area. In Panel E, the classification is based on investment area as well as base currency of the funds. Funds are distinguished by style in Panel F. In Panel G, groups are created based on the funds' domicile.

	% 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		
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%

Continued on next page

Table 2 continued

	% of trading funds	% of all funds
USA/USD	7.15%	5.27%
USA/GBP	1.44%	1.14%
Total	52.09%	45.88%
Panel F: Fund style		
small_cap	0.96%	0.86%
mid_cap	0.62%	0.50%
mid_small_cap	4.56%	8.19%
large_cap	59.86%	56.82%
value	1.10%	1.14%
growth	1.87%	1.60%
blend	6.95%	5.23%
Panel G: 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 3
Derivative trades by asset class and derivative type

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 is based on the total number of trades and Panel B on the total notional of all trades.

Panel A: 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: 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 4
Sample of Equity Option Trades

This table summarizes the construction of the equity option trade sample. In addition to the remaining number of trades, the number of funds conducting these trades is presented. We start with all equity option trades in the second half of 2016 that were matched with Morningstar's fund data. As further analyses of the trading strategy require detailed information regarding the trades, we exclude all trades with missing information about the underlying, the strike and the option style as well as type. Furthermore, only trades, for which a match with the respective underlying price on the basis of the provided data in the trade report was possible, are kept.

Step	Remaining trades	Remaining funds
OP/EQ trades	66,591	154
Underlying not missing	27,845	131
Strike price not missing	27,845	131
option style and type not missing	27,845	131
Match with underlying prices	21,783	83

Table 5
Classification of Equity Option Trades

This table shows the classification of the equity option trade sample into various trading strategies. The classification is conducted consecutively in the presented order. A spread is defined as two equity option trades by the same fund, on the same date, on the same underlying with the same option type but taking different positions. A straddle is defined as two equity option trades by the same fund, on the same date, on the same underlying, taking the same position but with different option types. A synthetic trade is defined as two equity option trades by the same fund, on the same date, on the same underlying, with different option types taking different positions. In case of ambiguous matches of a trade with several others, only the constructed pairs with the smallest difference in their execution times are kept. Premium trades are short trades, which are at least 10 percent out of the money. A protective put is a long put, which is at least 10 percent out of the money.

Type	Trades	Funds	Share of all trades
total sample	21,783	83	
spread trades	1,364	29	6.26%
straddle trades	1,071	13	4.92%
synthetic trades	2,173	15	9.98%
premium trades	3,503	37	16.08%
protective puts	152	11	0.70%
unclassified	13,520		

Table 6
Fund characteristics and the decision to use 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 size of the fund family, fund family, investment area, currency, domicile, 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.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

Table 7

Fund characteristics and active derivatives users

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 size of the fund family, fund family, investment area, currency, domicile, benchmark, deciles of fund size, and 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

Table 8
Equity Future Trades by Fund Flow: Daily Quantiles

This table shows the percentage of fund day observations conducting a FU/EQ trade strategy by 5% quantiles of the relative flow in t = 0. Buy is defined as more long FU/EQ trades than short ones in terms of the traded notional aggregated over t = 0 to 4 and sell vice versa. The quantiles are calculated separately for in- and outflows per day. The sample consists of funds, which reported at least one FU/EQ trade in the second half of 2016.

Panel A: Outflow 5% quantiles

5% quantiles	Buy	No FU/EQ	Sell	Total
1	45.00%	41.61%	13.39%	1,449
2	42.28%	42.35%	15.37%	1,379
3	41.80%	43.67%	14.53%	1,390
4	40.04%	48.18%	11.77%	1,376
5	35.53%	50.14%	14.33%	1,382
6	36.65%	50.18%	13.17%	1,397
7	34.80%	53.96%	11.24%	1,388
8	33.84%	52.83%	13.33%	1,380
9	32.83%	52.80%	14.37%	1,392
10	34.79%	51.40%	13.81%	1,354
11	34.84%	51.48%	13.68%	1,418
12	34.83%	48.98%	16.18%	1,378
13	35.58%	51.22%	13.20%	1,394
14	39.26%	46.57%	14.17%	1,383
15	38.48%	49.27%	12.24%	1,372
16	38.56%	47.93%	13.52%	1,398
17	42.30%	46.76%	10.94%	1,390
18	41.59%	47.73%	10.69%	1,385
19	39.67%	50.22%	10.12%	1,384
20	41.47%	48.99%	9.54%	1,331
Total	38.21%	48.80%	12.99%	27,720

Continued on next page

Table 8 continued

Panel B: Inflow 5% quantiles				
5% quantiles	Buy	No FU/EQ	Sell	Total
1	43.15%	47.04%	9.81%	1,233
2	40.41%	50.86%	8.73%	1,168
3	38.35%	52.13%	9.52%	1,176
4	42.12%	46.86%	11.02%	1,161
5	41.15%	47.05%	11.80%	1,169
6	40.05%	47.11%	12.84%	1,176
7	35.94%	49.02%	15.04%	1,177
8	40.58%	46.43%	12.98%	1,163
9	37.01%	49.49%	13.50%	1,178
10	41.78%	46.59%	11.63%	1,144
11	41.27%	45.61%	13.12%	1,197
12	44.44%	42.98%	12.58%	1,161
13	43.47%	45.00%	11.53%	1,180
14	43.11%	45.94%	10.95%	1,169
15	43.00%	44.12%	12.88%	1,165
16	43.98%	43.38%	12.64%	1,171
17	46.18%	41.17%	12.65%	1,178
18	46.83%	40.75%	12.41%	1,168
19	51.47%	37.87%	10.66%	1,191
20	49.18%	37.68%	13.14%	1,096
Total	42.66%	45.38%	11.96%	23,421

Table 9

Currency Forward Trades by Fund Flow: Daily Quantiles

This table shows the percentage of fund-base currency-day observations conducting a FW/CU trade strategy by 5% quantiles of the relative flow in t = 0, whereby multiple share classes of a fund with the same base currency are aggregated to a single fund-base currency observation. Buy is defined as more long FU/EQ trades than short ones in terms of the traded notional aggregated over t = 0 to 4 and sell vice versa. The quantiles are calculated separately for in- and outflows 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.

Panel A: Outflow 5% quantiles

5% quantiles	Buy	No FU/EQ	Sell	Total
1	25.67%	67.30%	7.03%	12,194
2	26.18%	66.06%	7.76%	11,669
3	28.04%	64.50%	7.46%	11,407
4	27.29%	65.28%	7.44%	10,973
5	26.65%	66.31%	7.04%	10,581
6	26.33%	66.98%	6.69%	10,078
7	26.42%	66.99%	6.59%	10,158
8	26.01%	68.49%	5.50%	10,296
9	25.73%	68.12%	6.15%	10,756
10	24.86%	69.06%	6.08%	11,244
11	24.40%	70.15%	5.45%	11,449
12	24.71%	70.26%	5.03%	11,638
13	24.33%	70.27%	5.40%	11,756
14	23.43%	71.78%	4.79%	12,549
15	23.47%	72.48%	4.05%	13,834
16	23.09%	72.83%	4.08%	14,605
17	23.91%	71.84%	4.25%	14,800
18	23.45%	72.96%	3.59%	15,635
19	22.20%	74.55%	3.25%	16,482
20	18.77%	79.14%	2.08%	19,101
Total	24.41%	70.36%	5.24%	251,205

Continued on next page

Table 9 continued

Panel B: Inflow 5% quantiles				
5% quantiles	Buy	No FU/EQ	Sell	Total
1	18.38%	79.71%	1.91%	17,800
2	22.15%	74.84%	3.01%	15,213
3	22.91%	73.62%	3.48%	14,407
4	23.77%	72.47%	3.76%	13,731
5	24.07%	71.47%	4.46%	13,528
6	23.90%	71.62%	4.48%	13,095
7	24.02%	71.32%	4.66%	12,437
8	24.99%	69.57%	5.43%	11,555
9	25.16%	69.44%	5.40%	11,181
10	25.26%	68.83%	5.91%	11,021
11	24.50%	69.31%	6.19%	10,910
12	25.49%	68.31%	6.20%	10,722
13	25.40%	68.08%	6.51%	10,392
14	26.23%	66.89%	6.89%	9,845
15	25.62%	67.57%	6.82%	9,857
16	26.53%	66.12%	7.35%	10,153
17	27.93%	64.26%	7.81%	10,344
18	27.68%	64.16%	8.15%	10,685
19	27.08%	65.32%	7.60%	10,775
20	27.45%	65.23%	7.32%	11,458
Total	24.60%	70.00%	5.40%	239,109

Table 10
Role of fund flows, risks and returns for derivatives use

This table presents estimates from linear probability models of the daily derivatives trading dummy on lagged fund characteristics. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. The sample consists of derivatives trading funds. In Panel A, we use 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). In Panel B, we look at the 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 C, we rely on 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). 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.

	(1)	(2)	(3)
Panel A: Fund flows			
	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: 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

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Table 10 continued

	(1)	(2)	(3)
Panel C: 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 11
Impact of Flow on FU/EQ Trades

This table presents estimates from linear probability models of daily FU/EQ dummies on flow. In Panel A, the respective long dummy equals one if a fund buys at least one equity future trade on a day and zero otherwise. In Panel B, the short dummy equals one if a fund sells at least one equity future trade on a day and zero otherwise. The sample consists of derivatives trading funds. We use 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). 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.

	(1)	(2)	(3)
Panel A: 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 B: 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 12
Disentangling of fund returns

This table shows summary statistics of the estimated coefficients by the funds' trading activity in the regression:
$r_{i,t} - r_{mm,t} = \beta^0_{i,t} + \beta^1_{i,t} d_{i,t} + (\beta^2_{i,t} + \beta^3_{i,t} d_{i,t})(r_{b,t} - r_{mm,t}) + (\beta^6_{i,t} + \beta^7_{i,t} d_{i,t}) bot_{b,t}(r_{b,t} - r_{mm,t})^2 + (\beta^8_{i,t} + \beta^9_{i,t} d_{i,t}) top_{b,t}(r_{b,t} - r_{mm,t})^2 + \epsilon_{i,t}$, where $r_{i,t}$ 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. Summary statistics for derivatives trading funds only include funds in the top four deciles in terms of the number of reported trades. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively.

	Trading	Mean	SD	Skew.	t-stat
constant	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.

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.
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.1 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.

Table A.2
Robustness: measurement period of fund flows, risks and returns

This table presents estimates from linear probability models of the daily derivatives trading dummy on lagged fund characteristics calculated over a differing number of days. This dummy equals one if a fund makes at least one derivative trade on a day and zero otherwise. The sample consists of derivatives trading funds. All models account for day and fund fixed effects. 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. In Panel D, we use rolling currency risk. The standard deviation of returns is analyzed in Panel E. Panel F includes the rolling tracking error. In Panel G, we look at rolling fund returns and in Panel H the rolling relative return to the benchmark is assessed. 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.

	(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

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Table A.2 continued

	(1)	(2)	(3)	(4)
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
Panel D: 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 E: 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 A.2 continued

	(1)	(2)	(3)	(4)
Panel F: 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 G: 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 H: 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

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Table A.2 continued

	(1)	(2)	(3)	(4)
Panel I: 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