Synthetic Leverage and Fund Risk-Taking

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Abstract

Mutual fund risk-taking via active portfolio rebalancing varies both in the cross-section and over time. In this paper, I show that the same is true for funds' off-balance sheet risk-taking, even after controlling for on-balance sheet activities. For this purpose, I propose a novel measure of synthetic leverage, which can be estimated based on publicly available information. In the empirical application, I show that German equity funds have increased their risk-taking via synthetic leverage from mid-2015 up until early 2019. In the cross-section, I find that synthetically leveraged funds tend to underperform and display higher levels of fragility.

Keywords: leverage; risk-taking; derivatives; securities lending; mutual funds.

JEL classification: G11; G23; E44.

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1 Introduction

It is well-established that mutual fund risk-taking varies both in the cross-section and over time (e.g., Huang, Sialm, and Zhang (2011)). An increased risk-taking is of concern for policymakers, regulators, and market participants due to its potential to amplify structural run and liquidity risks within the fund sector (e.g., Goldstein, Jiang, and Ng (2017)). Prior work on fund risk-taking mainly focuses on active portfolio rebalancing (e.g., reach-for-yield behavior as in Choi and Kronlund (2018)). In this paper, I acknowledge the fact that funds may engage in risk-taking by other means and I investigate risk-taking via off-balance sheet activities (which I refer to as *synthetic leverage*). I show that funds' synthetic leverage also displays substantial time-series and cross-sectional variation, even after controlling for their on-balance sheet activities.

Fundamentally, mutual funds can increase their risk exposures not only by active portfolio rebalancing but also by means of leverage. While it is well-documented that *financial leverage* does not play an important role for the typical fund, since investment funds generally make very limited use of debt financing[1], there is, however, a long-standing policy discussion as to whether funds engage in risk-taking via *synthetic leverage* (e.g., ECB (2014); IMF (2018)). Broadly speaking, synthetic leverage refers to (mainly off-balance sheet) activities that tilt an investor's risk-return profile (Breuer (2002)). The two most prominent examples of such activities are derivatives trading and, albeit to a lesser extent, securities financing transactions (SFTs, i.e., repurchase agreements and securities lending). In line with the idea that fund managers respond to incentives (e.g., Chevalier and Ellison (1997, 1999)), anecdotal evidence suggests that both competition and the current macro-financial environment may induce fund managers to engage in such activities to take additional risks.[2]

[1] Almazan et al. (2004); Boguth and Simutin (2018); Fricke and Wilke (2020).

[2] See "Securities lending proves lucrative as investors aim for alpha", FT, April 23rd 2018; "Fund groups challenged over securities lending practices", FT, May 11th 2019, and "Mutual funds hit back at SEC proposal to limit derivative use", FT, March 30th 2016. Market pracitioners, however, generally dispute the idea that SFTs could be used for increasing leverage. See "Securities lending: the facts", BlackRock, May 2015.

While questions on synthetic leverage of investment funds have been widely discussed in policy circles, the academic literature on the topic remains sparse. Two aspects in particular have impeded a structured investigation of the effects of synthetic leverage usage: first, data availability issues.[3] In particular, data confidentiality aspects make it difficult, if not impossible, for market participants and fund investors to assess the structure of a fund's granular derivatives portfolio. Second, there remains a lack of a consensus on an economically meaningful measure of synthetic leverage. To fill these gaps, I propose a measure of synthetic leverage, which can be estimated based on publicly available data and does not require detailed data on funds' derivatives/SFT activities.

The fundamental idea of my framework is that a fund's unobserved actions will affect the distribution of its realized returns. By finding a suitable benchmark to compare the realized return (distribution) against, we can uncover the economic effect of a fund's unobserved actions. In this regard, the *return gap* (Kacperczyk, Sialm, and Zheng (2008)), denoted as Δ, turns out to be very useful. The return gap is the difference between a fund's realized gross return (R) and its hypothetical holdings-based return (R^H). The holdings-based return, R^H, is the return on the fund's most recently disclosed asset portfolio. The return gap is a measure of the net effect of a fund's unobserved actions, since the realized return includes all unobserved actions of a fund, while the holdings-based return does not. My methodology identifies synthetically leveraged funds by comparing the distributions of R^H and R: in the absence of any unobserved actions, I expect the two returns to align ($\Delta \approx 0$). On the other hand, if a fund manager engages in unobserved actions to hedge or take risks (such as derivatives trading), this should have a measurable impact on the fund's realized return distribution and lead to systematic differences between R and R^H. For example, for funds that follow a hedging (risk-taking) strategy, the distribution of R has less (more) probability mass in the tails of the distribution relative to R^H. In light of the broad definition of synthetic leverage given above, risk-taking funds would be those

[3] Following the global financial crisis, regulators around the world introduced various regulations with the aim to increase the transparency and robustness of SFT and derivatives markets. For example, the EU adopted the securities financing transactions regulation (SFTR), which requires investors to submit regular reports on their trading activites to centralized trade repositories.

that make use of synthetic leverage, since their unobserved actions *increase* the variance of realized returns relative to the holdings-based benchmark. Effectively, this comparison aims at uncovering the effect of unobserved actions on a fund's market risk, relative to the market risk of the fund manager's underlying asset portfolio.

This simple idea can be brought to the data via dynamic regressions of Δ on R^H. The estimated coefficient on R^H, denoted as β^H, makes it possible to place funds on the spectrum of hedging ($\beta^H < 0$) and risk-taking ($\beta^H > 0$). I propose β^H as a natural indicator for fund-level synthetic leverage usage. Of course, a major concern is that systematic differences between R and R^H could be driven by unobserved actions that are unrelated to the concept of synthetic leverage, most importantly fund managers' active portfolio rebalancing. I tackle this issue in two ways: first, I explicitly control for such actions in my estimation of β^H. For example, I include a fund's contemporaneous portfolio turnover and its flows as control variables. Second, I decompose Δ into its rebalancing/non-rebalancing components and explicitly adjust Δ for a fund manager's active portfolio rebalancing. To the best of my knowledge, this is the first paper to investigate such a decomposition of the return gap. Interestingly, I find that active portfolio rebalancing between month $t-1$ and t captures only 11% of the overall variation of Δ. In other words, the vast majority of the (variation of the) return gap cannot be explained by funds' active portfolio rebalancing.

Using a unique dataset on German equity funds for the period September 2009 to May 2020, I show that my measure of synthetic leverage mainly picks up the effects of funds' derivatives usage. Of lesser importance are securities lending activities, which is in line with the idea that SFTs should mainly affect the first moment of the return distribution, not necessarily the second moment. For my sample, I find that the share of funds that make use of derivatives and/or securities lending is relatively stable over time. What does vary strongly is the economic purpose of such activities. In fact, in line with the above-mentioned anecdotal evidence, I find a relatively steady increase in funds' risk-taking via synthetic leverage from 2015 onwards, which suggests that funds' risk-taking behavior depends on the macro-financial environment. In the cross-section, I find that synthetically leveraged funds (those that make use of risk-taking strategies) differ from other funds across various characteristics. For example, they tend to show higher expense ratios and larger downside risk compared with other funds. In addition, synthetically leveraged funds show larger cash ratios, but less liquid asset portfolios (based on their small-minus-big factor loading). Regarding performance, I find that the returns of synthetically leveraged funds tend to be negative on a risk-adjusted basis and that they underperform significantly relative to other funds. This echoes the findings of Huang et al. (2011), who showed that funds that increased their risk-taking via shifting towards more risky assets also tend to underperform (see Choi and Kronlund (2018) as well). Lastly, while synthetically leveraged funds displayed substantially larger outflows during the COVID-19-induced market stress period in March 2020, I find that their flow-performance sensitivity does not differ systematically from that of other funds. However, I provide evidence that synthetically leverage funds show larger flow externalities, which seems to be concentrated on periods with high levels of market volatility (as proxied by the VIX). Overall, these results indicate that synthetic leverage should be closely monitored in the future and that more work is needed to assess whether and how synthetic leverage adds systemic fragility to the financial sector.

The remainder of this paper is structured as follows: section 2 reviews the related literature. Section 3 introduces the methodological framework for measuring synthetic leverage. Section 4 describes the dataset and presents the summary statistics. Section 5 analyzes synthetic leverage both in the cross-section and over time. Section 6 analyzes differences in fund performance. Section 7 takes a closer look at synthetic leverage and fund fragility. Section 8 summarizes the main results and concludes.

2 Related Literature

My paper contributes to different streams of the literature. Most importantly, my paper adds to the existing literature on fund risk-taking. It is widely accepted that performance pressure due to both competition and the macro-financial environment may incentivize risk-taking behavior (e.g., Chevalier and Ellison (1997); Chevalier and Ellison (1999); Feroli, Kashyap, Schoenholtz, and Shin (2014); Chodorow-Reich (2014)). Such risk-taking behavior has the potential to amplify structural risks in the fund sector (e.g., Chen, Goldstein, and Jiang (2010); Goldstein et al. (2017)). Following Kacperczyk et al. (2008), however, much of this literature is concerned with risk-taking via active portfolio rebalancing (e.g., Huang et al. (2011)).[4] My paper adds to this literature by investigating risk-taking not via portfolio rebalancing, but by means of (synthetic) leverage. Since it is widely documented that investment funds tend to refrain from using financial leverage (e.g., Boguth and Simutin (2018); Fricke and Wilke (2020)), I concentrate on quantifying funds' synthetic leverage. Specifically, my measure of synthetic leverage explicitly focuses on the (sizeable) residual variation of the return gap that is left after controlling for fund managers' portfolio rebalancing. This novel methodological approach differs substantially from previous work identifying (synthetically) leveraged funds (e.g., Molestina Vivar, Wedow, and Weistroffer (2020)). In particular, my return gap-based methodology offers a natural framework that could also be used to place other kinds of institutional investors on the risk-taking/hedging spectrum.

Relatedly, my paper adds to the literature on unobserved actions of investment funds. In their seminal paper, Kacperczyk et al. (2008) introduce the return gap as a measure of the net effect of a given fund's unobserved actions.[5] This literature typically views the return gap as a measure of skill due to informed portfolio rebalancing. In this paper, I decompose the return gap to show that the contribution of this (active) rebalancing component is indeed positive. Overall, however, it explains only a small share of the

[4]Naturally, much of the reach-for-yield literature focuses on corporate bond funds (e.g., Choi and Kronlund (2018)). In line with reach-for-yield behavior, Banegas, Montes-Rojas, and Siga (2016) provide evidence that equity funds receive aggregate inflows when interest rates are low. These inflows are concentrated on high-income funds, which the authors interpret as reach-for-income behavior. As noted by Daniel, Garlappi, and Xiao (2021), the reach-for-income hypothesis posits that demand for assets with high current income, which are not necessarily riskier, increases when interest rates fall.

[5]Other papers have used the return gap, or variations thereof, to identify window dressing (Meier and Schaumburg (2006); Agarwal et al. (2011)), changes in fund's trading costs (Bollen and Busse (2006)), and differences in indirect expenses between retail-institutional twins (Evans and Fahlenbrach (2012)).

variation of the return gap.

This paper also contributes to the literature on SFT/derivatives trading of asset managers, in the sense that my measure of synthetic leverage could capture the economic effects of such activities. A number of recent papers explore the implications of SFTs of institutional investors. For example, Kaplan, Moskowitz, and Sensoy (2013) examine the impact of short selling on asset prices and market quality. Based on a randomized stock lending experiment with a large, anonymous money manager, the authors find that supply shocks significantly reduce market lending fees and raise quantities, but have no impact on asset prices or market liquidity. Focusing on passively managed mutual funds (including ETFs), Blocher and Whaley (2014) find that these funds can earn significant revenue from securities lending. The authors also report that fund managers tend to tilt their portfolios towards stocks with higher lending fees. Similarly, Greppmair, Jank, Saffi, and Sturgess (2020) find that funds make use of information acquired in equities lending markets in their portfolio allocation decisions. In particular, funds that lend shares are more likely to exit positions relative both to stocks they do not lend and to funds that do not lend. Evans, Ferreira, and Prado (2017) find that funds that lend equities underperform otherwise similar funds, which is driven by investment restrictions set by the fund family that keep funds from selling the stocks.

Regarding funds' derivatives trading, most of the early literature was concerned with identifying characteristics that distinguish derivatives users from non-users. In particular, much attention has been devoted to the question of whether derivatives users tend to outperform non-users, with most of the evidence suggesting that the returns of these two groups are not significantly different from each other (e.g., Koski and Pontiff (1999); Almazan et al. (2004)). More recently, the literature has focused on derivatives trading of bond funds, in particular how U.S. corporate bond funds positioned themselves in the credit default swap market before and during the global financial crisis (e.g., Stulz (2010); Aragon, Li, and Qian (2017); Jiang, Ou, and Zhu (2019)). In a recent paper, Kaniel and Wang (2020) use a novel granular dataset from the SEC to show that mutual funds mainly use derivatives (in particular, swaps) to amplify market exposure, but less for hedging purposes. In terms of performance, they find that funds that used derivatives for hedging purposes tended to outperform other funds during the COVID-19 episode.

3 Measuring Synthetic Leverage

The following section lays out the novel framework for measuring synthetic leverage, which allows me to place funds on the spectrum of hedging versus risk-taking. I should note that there is, to date, no consensus view on what constitutes a usfeul economic measure of synthetic leverage. Importantly, in contrast to existing regulatory measures, my approach has the advantage that it does not require detailed information on derivative/SFT activities. This is important because, due to confidentiality, such data are generally not available to market participants and fund investors.

3.1 Institutional Background

Mutual funds are subject to tight regulatory constraints regarding financial leverage. For European funds, Directive 2009/65/EC relating to undertakings for collective investment in transferable securities (UCITS) limits funds' debt financing to 10% of total net assets. For the U.S., the Investment Company Act of 1940 limits funds' debt financing to 50% of a fund's total net assets. It is widely documented that most funds remain well below these regulatory thresholds, in many cases even using a zero financial leverage strategy (e.g., Almazan et al. (2004); Boguth and Simutin (2018); Fricke and Wilke (2020)).

However, funds could lever up their investments by other means, for example by entering derivatives positions (see Internet Appendix A for a summary of existing regulations regarding funds' derivatives exposures in the EU). In fact, derivatives contracts are often considered a relatively cheap way to express investment views, since such products often involve only small upfront costs and can also be more liquid than some of the underlying products. One standard textbook example is a synthetic long position in a stock through the combination of put and call options. While showing exactly the same payoff structure as the underlying stock, this is a levered strategy in the sense that entering the derivatives positions likely involves substantially lower upfront costs. A similar argument can be made for other kinds of derivatives (such as futures and swaps), which also allow an investor to take large positions with relatively small initial outlay.

The two main types of SFTs are repurchase agreements and securities lending, which essential for market participants' funding and collateralization needs. In an SFT a fund earns interest (and potentially also appreciation on the collateral) on the loaned securities (Evans et al. (2017)). SFTs are often reported to be attractive for investment funds, as they potentially allow funds to generate incremental returns at relatively low risk. In principle, SFTs can also be used to take leveraged positions, for example, by taking a long position in one instrument and a short position in another in the expectation of changes in the yield spread of the two instruments (IOSCO (1999); Committee of European Securities Regulators (2010)).[6] Market pracitioners, however, generally dispute the idea that SFTs could be used for increasing leverage.[7] While the regulatory framework for UCITS' leverage acknowledges that SFTs are being used to create leverage, most of the existing literature concentrates almost exclusively on synthetic leverage via funds' derivatives exposures.

3.2 Unobserved Actions and the Return Gap (Δ)

My framework draws upon the return gap, Δ, of Kacperczyk et al. (2008):

$$\Delta_{t,f} = \underbrace{R_{t,f}}_{\text{Realized gross return}} - \underbrace{R^H_{t,f}}_{\text{Return on portfolio in t-1}} \tag{1}$$

[6]Effectively, SFTs extend the balance sheet by the amount of (cash) collateral involved, since the asset ownership remains with the lender.

[7]See "Securities lending: the facts", BlackRock, May 2015.

where the actual return, $R_{t,f}$, is the total return (including dividend payments) before expenses.[8] The holdings-based return on fund's holdings, R^H, is the total return of a hypothetical buy-and-hold portfolio that invests in the most recently disclosed asset positions[9]:

$$R^H_{t,f} = \sum_{j}^{J+1} w_{t-1,f,j} r_{t,j} = \mathbf{w}'_{t-1,f}\mathbf{r}_t \tag{2}$$

where $w_{t-1,f,j}$ is the weight of asset j in fund f's portfolio at the end of month $t-1$ and $r_{t,j}$ is the relative return of asset j over the previous month.[10] Note that I always include cash as asset $(J+1)$, where $r_{t,J+1}$ equals the 1-month Euribor.

As noted by Kacperczyk et al. (2008), the return gap captures funds' unobserved actions and includes hidden costs and benefits. One example is a fund's interim trades, which can create or destroy value. Hidden benefits can result from securities lending as well. Hidden costs can include, among other things, trading costs and commissions, agency costs, and investor externalities. Derivative exposures can result in costs and benefits, depending on the performance of individual contracts and the market environment. In the spirit of Grinblatt and Titman (1993), Kacperczyk et al. (2008) interpret the return gap as a measure of outperformance: a positive return gap indicates that a given fund outperformed relative to the benchmark of its most recent portfolio holdings.[11] I discuss additional advantages of using R^H as the benchmark in subsection 3.4.

[8] Fund managers can subtract management fees and other expenses on a regular basis from the assets under management, which reduces the investor's net return. Since R^H does not include any of these these expenses, I use the gross return in Eq. (1). Equivalently, I could use the net return and add expenses to the holding-based return.

[9] Note that Kacperczyk et al. (2008) define this measure only for (actively-managed) U.S. equity funds, due to the fact that they obtain data on funds' asset portfolios from CDA/Spectrum, which includes only common stock positions and excludes other non-equity holdings.

[10] Equity returns include dividend payments and are adjusted for stock splits. Bond returns include both coupon payments and accrued interest (as in Bai, Bali, and Wen (2019)).

[11] Using data on actively managed U.S. equity mutual funds during 1984–2003, Kacperczyk et al. (2008) find that the average Δ is close to zero and thus the aggregate magnitude of unobserved actions is relatively small in the aggregate. At the same time, there is substantial cross-sectional variation in Δ, indicating that hidden costs are more important for some funds, while hidden benefits are more pronounced for others. Moreover, there is evidence that the fund-level Δ is very persistent, both for the best and worst performers, and thus likely driven by systematic factors. As such, Δ helps predict future performance.

3.3 Hedging Versus Risk-Taking

Depending on the net effect of the above-mentioned unobserved actions, the distribution of a given fund's actual returns R can differ systematically from its holdings-based return R^H. Fundamentally, my framework looks at systematic deviations between R and R^H in order to identify synthetically leveraged funds. In fact, the return gap provides a useful framework in terms of classifying funds into those that appear to use a hedging strategy (possibly involving derivatives and/or SFTs), a risk-taking strategy (again possibly involving derivatives and/or SFTs), or neither of these two. For example, in the latter case with no hedging/risk-taking, R_i and R_i^H would be closely aligned, so the actual strategy corresponds to the disclosed portfolio holdings.

Basic idea. Suppose that the fund's realized return R is the sum of the holdings-based return R^H and the return due to its unobserved actions R^U:

$$R = R^H + R^U, \text{ with } R^H \sim iidN(0, \sigma^H). \tag{3}$$

To allow for a general correlation structure between the two components, I specify a linear relationship:

$$R^U = b^U \times R^H + \epsilon \text{ with } \epsilon \sim iidN(0, \sigma). \tag{4}$$

Thus, the fund's realized return is a noisy version of the holdings-based return:

$$R = b^H \times R^H + \epsilon, \tag{5}$$

where $b^H = (1 + b^U)$ can be interpreted as a holdings-beta, similar to a standard market-beta in asset pricing: a value of $b^H = 1$ corresponds to realized returns and holdings-based returns moving exactly in tandem, while $b^H > 1$ ($b^H < 1$) would indicate that realized returns vary more (less) than proportionally. In the absence of other factors, differences between R and R^H will be due to a fund manager's unobserved actions. This is the key idea of my methodology.

For convenience, Eq. (5) can be written in terms of the return gap

$$R - R^H = \Delta = \underbrace{(b^H - 1)}_{\beta^H} \times R^H + \epsilon, \tag{6}$$

such that a fund's strategy can be assessed based on the sign of β^H.[12]

An illustrative example. The left panel of Figure 1 shows the corresponding distributions for $\beta^H = -0.4$ (green) and $\beta^H = 1$ (red). Based on these distributions, the strategy shown in green corresponds to a hedging strategy, since the distribution of R is squeezed relative to the distribution of R^H. Similarly, the strategy shown in red corresponds to a risk-taking strategy: the realized return distribution has more probability mass on more extreme outcomes. For the symmetric cases shown here, the right-hand panel plots the expected relationship between Δ and R^H for the two cases: for hedging (risk-taking) funds, I expect a significantly negative (positive) relationship. For funds where R does not differ systematically from R^H, the relationship between Δ and R^H would be flat. A linear regression of Δ against R^H yields slope parameter $\beta^H = (b^H - 1)$, shown as dotted lines in the right-hand panel.

Estimation details. For each fund f, I estimate the dynamic β^H parameter using the following regression:

$$\Delta_{t,f} = \alpha_f + \beta^H_f \times R^H_{t,f} + \gamma_i \times X_{t,f} + \epsilon_{t,f},$$

with $X_{t,f}$ as a $T \times K$ matrix that includes the set of control variables (more on this below). Of course, systematic deviations between R and R^H can be driven by a number of actions

[12]Note that $\text{Corr}(R, R^H) = \frac{(\beta^H+1)}{\sqrt{(\beta^H+1)^2+v}}$ with $v = (\sigma/\sigma^H)^2$. The correlation is therefore driven both by β^H and the (relative) variance of ϵ and the holdings-based return. Note that v can play an important role, since $\lim_{v\to\infty} \text{Corr}(R, R^H) \to 0$. Intuitively, ϵ is the innovation term of a given fund's unobserved actions. The larger the variance of this term, the less correlated the two return series will be.

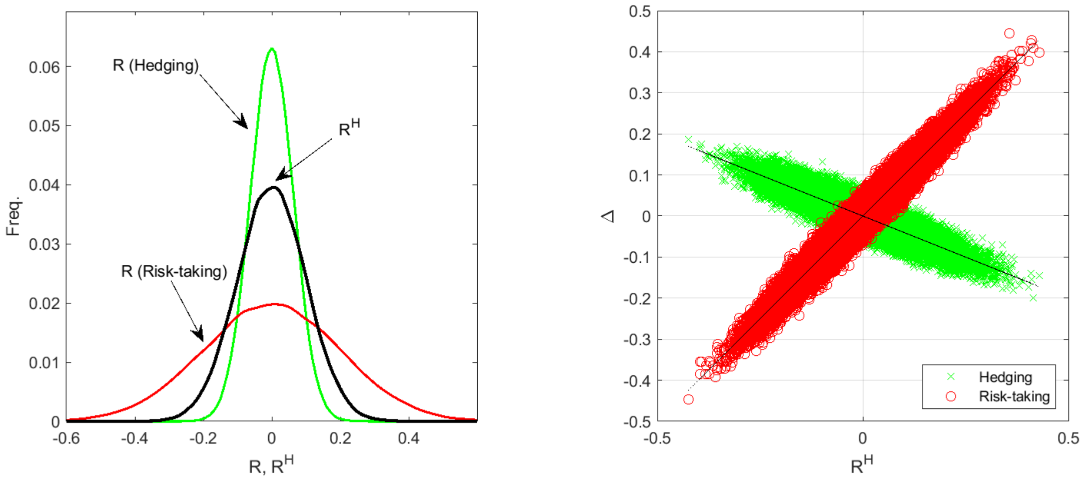

Figure 1: Illustration of hedging, risk-taking, and the return gap. Left: distributions for R^H and R for different β^H. Right: relationship between Δ and R^H. Parameters: $\sigma^H = 0.1$, $\sigma = 0.02$, $\beta^H = -0.4$ (green) and $\beta^H = 1$ (red).

which are unrelated to the idea of synthetic leverage.

In order to interpret β^H as a measure of synthetic leverage, I aim to control for these actions and restrict my attention only on the residual variation of Δ. In this regard, previous work on the return gap (e.g., Kacperczyk et al. (2008)) suggests that the key aspect that may contaminate the estimated β^H is a fund manager's portfolio rebalancing. The idea is that, when a fund manager has shifted a large part of the asset portfolio during month $t-1$ and t, R may not be close to R^H, because the latter is based on an outdated portfolio.[13] I therefore control for a fund manager's active trading during a given month (which may or may not induce systematic deviations between R and R^H) in two ways. First, I exclude the effect of portfolio rebalancing on Δ itself. Given that I observe funds' granular asset portfolios at the end of each month, I decompose the return gap as follows (cf. Choi and Kronlund (2018) and Barbu, Fricke, and Moench (2020)):

$$\Delta_{t,f} = \underbrace{(R_{t,f} - R^{H_t}_{t,f})}_{\Delta^{\text{Contemp.}}} + \underbrace{(\mathbf{w}_{t,f} - \mathbf{w}^b_{t-1,f})'\mathbf{r}_t}_{\Delta^{\text{Active}}} + \underbrace{(\mathbf{w}^b_{t-1,f} - \mathbf{w}_{t-1,f})'\mathbf{r}_t}_{\Delta^{\text{Passive}}}, \tag{7}$$

[13] In fact, a skilled fund manager may be able to consistently beat its holdings-based benchmark by means of intra-month securities trading, which would be picked up by the intercept.

where $R_{t,f}^{H_t} = \mathbf{w}_{t,f}'\mathbf{r}_t$ is the holdings-based return based on the portfolio in t, $\mathbf{w}_{t-1,f}^b$ denotes fund f's portfolio weights from month $t-1$ evaluated at prices in t, and bold-face letters indicate vectors. The first component ($\Delta^{\text{Contemp.}}$) is the return gap with the portfolio in t as the benchmark. Note that $\Delta^{\text{Contemp.}}$ correponds to the negative of the backward-holdings return gap of Agarwal et al. (2011), who use this component to identify funds engaging in window dressing. The second component (Δ^{Active}) corresponds to active rebalancing: it is the return difference of the fund's portfolio in t and the portfolio in $t-1$, both evaluated at prices in t. The third component (Δ^{Passive}) corresponds to passive rebalancing: it is defined as the difference of the portfolio in $t-1$ evaluated at prices in t and of the same portfolio evaluated at prices in $t-1$. In everything that follows, I use $(\Delta - \Delta^{\text{Active}})$ as the dependent variable and estimate the following regression:

$$(\Delta - \Delta^{\text{Active}}) = \alpha_f + \beta_f^H \times R_{t,f}^H + \gamma_f \times X_{t,f} + \epsilon_{t,f}, \tag{8}$$

As such, I explicitly control for a fund manager's active portfolio rebalancing between month $t-1$ and t, and focus only on the remaining variation.

Second, I also include contemporaneous fund flows, both raw and squared (Flows_t and Flows_t^2), and the fund's contemporaneous portfolio turnover (Turnover_t) in the set of controls X in regression (8). Since potential trading costs and flow externalities should be proportional to the fund's porfolio liquidity, I also include the lagged portfolio Hirschmann-Herfindahl-Index (HHI_{t-1})[14] and the lagged cash ratio (CashRatio_{t-1}) as proxies for funds' portfolio liquidity. I also include the VIX (lagged and contemporaneous) to control for the general market environment and market illiquidity. Lastly, I include lagged financial leverage (Leverage_{t-1}), the lagged fund TNA ($\log(\text{TNA}_{t-1})$), and the lagged return gap (Δ_{t-1})

In everything that follows, the baseline approach consists of estimating β^H based on 36-month rolling-windows using ordinary least squares (OLS). For all cross-sectional

[14] Pastor, Stambaugh, and Taylor (2020) suggest that more diversified portfolios should be more liquid. Goldstein et al. (2017) interpret the HHI as a measure of potential externatilities.

comparisons, I sort funds into quintiles based on their estimated β^H separately for each month t. This allows me to compare the characteristics of risk-taking funds (those in Quintile 5) or hedging funds (those in Quintile 1) with other funds. Given that funds in the intermediate groups (in particular those in Quintile 3) are those for which $R \approx R^H$, they serve as the natural reference group, since their performance is consistent with the reported underlying asset portfolios.

3.4 Discussion

My methodology identifies funds that follow risk-taking or hedging strategies, with the main information coming from funds' asset portfolios and their realized returns. Clearly, risk-taking funds are of particular interest, since their unobserved actions *increase* the variance of realized returns relative to their own holdings-based benchmark. Conceptually, these are the funds that make particular use of synthetic leverage. On the other hand, significant hedgers could be interpreted as using negative synthetic leverage in the sense that their unobserved actions tend to *reduce* the variance of realized returns relative to their holdings-based benchmark.

My methodology shares some similarities with previous attempts to identify (synthetically) leveraged funds. For example, Molestina Vivar et al. (2020) assume that funds which both make use of derivatives and display a market beta above one are likely candidates. However, their approach neither controls for funds' portfolio rebalancing, nor takes the holdings-based return as the benchmark. This could possibly hamper the empirical identification of synthetically leveraged funds.[15]

While it would be possible to estimate β^H using alternative benchmark returns, R^H is a rather attractive measure for a number of reasons: first, by using each fund's holdings-based return series as the benchmark, my methodology explicitly accounts for on-balance sheet risk-taking. In other words, my measure of synthetic leverage focuses on additional

[15] Across all fund-month observations, I find a Pearson-correlation of 0.31 between my baseline β^H and an alternative β that does not include any controls, does not account for active rebalancing, and uses the market return as the benchmark.

risk-taking that cannot be explained by the fund manager's reported asset portfolios or the portfolio rebalancing activities. Second, granular data on individual funds' asset portfolios are available to policymakers and regulators. These data are of very high quality due to regular quality/consistency checks.[16] For example, a fund that is registered as an emerging market fund should report portfolio holdings consistent with its investment mandate. From a consumer-protection perspective, R^H therefore serves as a reasonable benchmark that the realized returns R can be compared against. My approach allows me to identify cases where the realized fund returns are very different from this benchmark. Of course, such deviations may be consistent with a fund's communicated strategy (e.g., the use overlay techniques), but it is important to document such deviations. Third, not all funds have specific benchmarks that they wish to track/outperform. For example, a fund with an absolute performance goal is aiming to provide its investors with stable and positive returns across different market periods. In these cases, differences between the realized performance and the holdings-based benchmark would still help in uncovering a fund's unobserved actions. Third, regulatory data on whether a given fund targets the relative outperformance of a specific benchmark is not always available. While this information could be taken from different market databases (e.g., Morningstar), data coverage may be problematic, which is not the case for R^H. Using R^H as the relevant benchmark has the additional advantage that it explicitly takes into account a fund's most recent actual portfolio holdings, which may not always replicate exactly the fund's desired benchmark index. Lastly, my return gap-based methodology explicitly accounts for a fund manager's active portfolio rebalancing. This is important, because a fund whose portfolio manager trades very actively should, in the absence of other unobserved actions, not be classified as being synthetically leveraged.

My approach is also related to the regulatory VaR approach for estimating a fund's global derivatives exposure (see Internet Appendix A), since it is also based on differences between realized returns and those of a benchmark portfolio. One major difference is that

[16] In contrast, some studies have raised doubts about the portfolio holdings data reported in popular market databases, e.g., Chen, Cohen, and Gurun (2021).

my approach makes use of the full distribution of Δ (or the individual components R and R^H) and models the conditional mean, $E(\Delta|R^H, X)$, which treats positive and negative returns symmetrically. However, my framework is general enough to accommodate asymmetric modeling approaches. One example would be to use quantile regressions, which model a conditional lower percentile of the distribution of Δ (or its adjusted version). This would be particularly relevant if policymakers and fund investors are more interested in large negative realizations of Δ, in which case realized returns would be substantially lower than the holdings-based benchmark. I leave such an extension for future research.

4 Data and Summary Statistics

4.1 Data

The dataset consists of all open-ended funds reporting to the investment fund statistics (IFS) of the Deutsche Bundesbank. In principle, my methodology can be applied to a wide variety of fund types. Here, I restrict my analysis to equity mutual funds, which make up roughly 37% of the German mutual fund sector's TNA.[17] I use monthly data and conduct my analysis at the fund level. Fund level data are obtained by aggregating data across share-classes, with all fund characteristics that vary across share classes (e.g., expense ratios) calculated as the TNA-weighted averages across the fund's share classes. Following Kacperczyk et al. (2008), I explicitly keep passively managed funds (both index funds and exchange-traded funds, ETFs) which make up 14% of the funds in my final sample. Hence, the vast majority of funds are actively managed. I drop sector funds, emerging market funds, and funds with unknown investment region. The vast majority of funds in my sample have investment region Europe (57%) or global (32%). The remaining

[17] Compared with the U.S., the German investment fund sector is peculiar in the sense that it consists of two very different sub-sectors: first, *Publikumsfonds* are akin to traditional open-ended mutual funds, which are open to both private and institutional investors. Second, *Spezialfonds* are specialized investment vehicles for institutional investors, which are generally not available to retail investors. These institutional funds are typically tailored to the specific needs of a very small number of large investors, such that run risks should be less relevant for these institutional funds. As of end-2019, institutional funds made up roughly 77% of the German fund sector's total assets under management (see Fricke and Wilke (2020)).

funds focus on Asia (6%) and North America (5%). The vast majority of funds in my sample (82%) focus on large caps and the remainder focuses on small/mid caps (10%) or does not specify the focus (8%). Following the literature, I drop very young (younger than two years) and very small funds (TNA $<$ €5 mllion). I apply the TNA reversal filter of Pastor, Stambaugh, and Taylor (2015) and winsorize flows at the 1st/99th percentile.

The IFS contains information on funds' granular portfolio holdings from September 2009 onwards. The IFS also contains time-varying (aggregated) information on funds' derivatives and securities lending activities, which is crucial for validating my methodology. Funds report two items that are related to the aggregated assets and liabilities from derivatives (in Euros). From these variables, I construct a weighted indicator, $\text{ShareDerivatives}_{t,f}$, which is the sum of the aggregated derivatives assets and liabilities relative to a fund's TNA. I also construct a binary indicator whether fund f uses derivatives in month t, $\text{I}(\text{Derivatives}_{t,f})$. These two indicators can be seen as the intensive and the extensive margin of funds' derivatives usage and are available for the full sample. From December 2014 onwards, the IFS also contains information on funds' securities lending activities, and I construct a binary indicator on whether fund f is active in securities lending market in month t, $\text{I}(\text{SecLending}_{t,f})$.

I augment the IFS data with several other datasets: first, I collect fund-specific information from Morningstar. Most importantly, the IFS does not contain information on expense ratios, which are available in Morningstar. I also use information on gross and net returns, flows, and a number of other fund-specific characteristics from Morningstar. Second, I use granular information on the individual securities in funds' asset portfolios from the Eurosystem's Centralized Securities Database (CSDB). Third, I use the German Securities Holdings Statistics (SHS) to obtain information on the ownership composition for each investment fund over time at the sectoral level based on the European System of Accounts (ESA).

My sample covers 465 funds over the period September 2009 to May 2020. The sample is rather representative, since I cover an average of 89% of the TNA of German equity mutual funds. I lose the first three years of data (and a number of funds with insufficient observations) since I estimate β^H over rolling-windows of 36 months, such that most analyses start in October 2012. Overall, I end up with 20,838 fund-month β^H observations for 327 unique funds.

4.2 Summary Statistics

Panel A of Table 1 shows the summary statistics for the main variables of interest. The first row shows that synthetic leverage, β^H, is slightly positive at 0.03 but close to zero on average. This is not surprising given that the raw correlation between R and R^H is 0.97 across all fund-month observations. I will take a closer look at the cross-sectional and time series variation of β^H in the next subsection.

Δ Components. In line with the statistics reported by Kacperczyk et al. (2008), the average return gap Δ tends to be small, and in fact, as shown in Panel B, not significantly different from zero (the results are based on the time series of the cross-sectional equal-weighted/TNA-weighted means of Δ). Moreover, in line with Agarwal et al. (2011), $\Delta^{\text{Contemp.}}$ is negative on average but not significantly different from zero. This suggests that funds tend to rebalance their portfolios from month $t-1$ to t towards stocks that tend to perform well. In fact, the active rebalancing component (Δ^{Active}) is significantly positive at all standard significance levels, which suggests that fund managers' rebalancing may display some level of skill, or at the very least, evidence of trend-following behavior. The last row of Panel B shows that the return gap adjusted for active portfolio rebalancing ($\Delta - \Delta^{\text{Active}}$) is indistinguishable from zero.

As discussed in Section 3, to address concerns that my measure of synthetic leverage could pick up funds' (active) portfolio rebalancing, I use ($\Delta - \Delta^{\text{Active}}$) as the dependent variable in regression (8). An obvious question is how much the three components in Eq. (7) contribute to the overall variation of Δ. As a first step, Panel C of Table 1 reports the cross-correlations between these components across all fund-months: Δ is strongly

A - Summary Statistics		Mean	Std. dev.	Median	Q25	Q75
β^H		0.03	0.11	0.01	-0.08	0.16
R	(%)	0.77	4.15	1.19	-4.36	5.12
R^{net}	(%)	0.66	4.14	1.07	-4.48	5.01
R^H	(%)	0.74	4.02	1.11	-4.19	5.03
Δ	(%)	0.03	0.83	0.04	-0.81	0.90
$\Delta^{\text{Contemp.}}$	(%)	-0.40	0.95	-0.32	-1.42	0.55
Δ^{Active}	(%)	0.06	0.47	0.00	-0.25	0.45
Δ^{Passive}	(%)	0.37	0.28	0.30	0.15	0.62
Age	(years)	18.98	12.50	16.00	7.42	37.67
CashRatio	(%)	3.38	4.72	1.69	0.17	8.81
I(ETF / index fund)		0.15	0.35	0.00	0.00	1.00
Flows	(%)	-0.08	3.78	-0.16	-2.38	2.35
HHI	(%)	2.57	1.59	2.33	0.84	4.58
Leverage	(%)	100.09	0.60	100.00	100.00	100.10
TNA	(× million €)	493.51	1240.54	113.15	17.98	1200.37
Turnover	(%)	4.42	8.10	1.95	0.00	10.19
ShareDerivatives	(%)	27.24	90.83	0.00	0.00	74.23
I(Derivatives)		0.44	0.50	0.00	0.00	1.00
I(SecLending)		0.23	0.42	0.00	0.00	1.00

B - Significance test		Time series average (s.e.)
Δ (%)	Mean	0.02
		(0.02)
	TNA-weighted Mean	0.05*
		(0.03)
$\Delta^{\text{Contemp.}}$ (%)	Mean	-0.42
		(0.12)
	TNA-weighted Mean	-0.33
		(0.09)
Δ^{Active} (%)	Mean	0.06***
		(0.01)
	TNA-weighted Mean	0.04***
		(0.01)
$(\Delta - \Delta^{\text{Active}})$ (%)	Mean	-0.04
		(0.03)
	TNA-weighted Mean	0.01
		(0.03)

C - Correlation matrix	Δ	$\Delta^{\text{Contemp.}}$	Δ^{Active}	Δ^{Passive}
Δ	1	0.865***	0.108***	-0.030***
$\Delta^{\text{Contemp.}}$	-	1	-0.341***	-0.260***
Δ^{Active}	-	-	1	-0.029***
Δ^{Passive}	-	-	-	1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Panel A shows the summary statistics, based on all fund-month observations during the period 2009/09-2020/05. Shown are the mean, standard deviation, median, and the bottom and top quartile for the following characteristics: β^H is the coefficient on R^H from the fund-specific, 36-month rolling window regression (8); R is the realized gross return; R^{net} the realized net return (after expenses and trading costs); R^H the holdings-based return; Δ is the return gap. $\Delta^{\text{Contemp.}}$, Δ^{Active}, and Δ^{Passive} are the three components of the return gap as defined in Eq. (7). All return-based indicators are shown as monthly percentages. Age is fund age in years; CashRatio is the share of cash holdings relative to a fund's assets under management; Flows are monthly net flows; HHI is the Hirschmann-Herfindahl Index based on funds' portfolio weights; Leverage is the ratio of total assets to TNA; Turnover is a fund's portfolio turnover rate as defined in Pastor et al. (2020). ShareDerivatives is the sum of the reported derivatives position (in Euros) on both the asset and liability side of the balance sheet, relative to the fund TNA. Panel B reports standard significance tests (using Newey-West standard errors with 36 lags) for the time averages of the (weighted) cross-sectional Δ, $\Delta^{\text{Contemp.}}$, and Δ^{Active}, respectively. Panel C shows the cross-correlations between the individual Δ components across all fund-months.

positively correlated with $\Delta^{\text{Contemp.}}$, but the correlation with the two rebalancing components is much smaller and, in the case of Δ^{Passive}, even slightly negative. Interestingly, the correlation between $\Delta^{\text{Contemp.}}$ and the two rebalancing components is around -0.3 in both cases.

(a) Cross-section **(b)** Time series

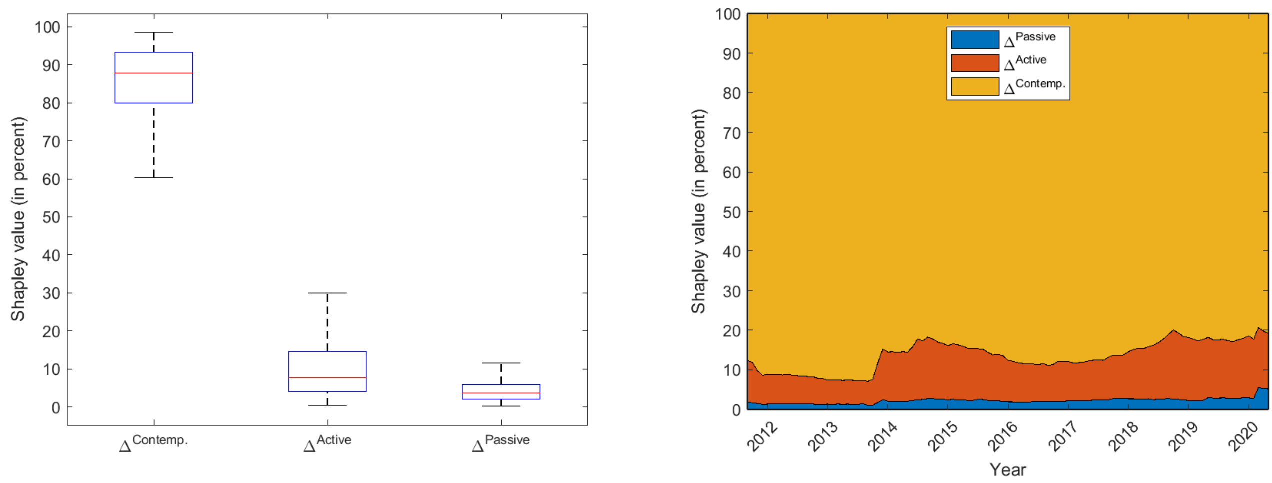

Figure 2: Shapley values in the cross-section (left) and in the time series (right). Panel (a) shows the cross-sectional distribution of the relative contribution for the three components of Δ (as measured by the Shapley value), using standard boxplots. For each fund f with at least 36 monthly observations, I estimate the corresponding Shapley values over the full sample. Panel (b) shows the results when estimating Shapley values based on pooling observations across all funds over rolling-windows of 24 months.

As a second step, I also explore the relative importance of the different components using Shapley value regressions (see Internet Appendix B for details). Fundamentally, Shapley value regressions quantify how much of the variation of a given variable y is due to its individual components $x_1, x_2, \ldots, x_K$. Pooling across all fund-month observations, I find that $\Delta^{\text{Contemp.}}$ accounts for approximately 86% of the variation of Δ. The remaining variation is largely due to Δ^{Active} (11%), whereas Δ^{Passive} plays only a minor role (3%).[18] Of course, pooling observations may hide both cross-sectional and time series heterogeneity. With regard to the cross-section of funds, Figure 2 (a) shows that the pooled results

[18] These results are robust to using alternative approaches. For example, using a variance decomposition along the lines of Duarte and Eisenbach (2020) yields very similar results. The main advantage of Shapley value regressions is that the (variance) contributions of all variables are non-negative, which is not the case for the variance decomposition.

continue to hold when applying the Shapley value regressions separately for each fund. While the boxplots suggest that there are indeed some funds for which Δ^{Active} plays a more important role (at the expense of $\Delta^{\text{Contemp.}}$), for the vast majority of funds $\Delta^{\text{Contemp.}}$ is by far the dominant component.[19] With regard to the time dimension, Figure 2 (b) shows the dynamic Shapley values, which are estimated based on pooling observations across all funds over rolling-windows of 24 months. Again, it becomes clear that $\Delta^{\text{Contemp.}}$ is by far the dominant component in terms of the overall variation of Δ. However, the relative contribution of the active rebalancing component appears to have increased from 2014 onwards, with values close to 16% at the end of 2019. In other words, over time funds' active portfolio rebalancing explains a larger share of the overall variation of the return gap. In future work, it would be interesting to relate the importance of the different components to the macro-financial environment.

5 Synthetic Leverage of Equity Mutual Funds

5.1 Cross-Sectional and Time Series Variation of β^H

I now take a closer look at synthetic leverage both in the time series and in the cross-section. In this regard, Figure 3 point towards substantial variation along both dimensions: the black line shows the dynamics of the cross-sectional median β^H, and the dark blue (light blue) areas indicate the 25th/75th (10th/90th) percentiles of the distribution.[20] The solid red line (corresponding to the right y-axis) shows the relative number of funds with a positive β^H parameter for each cross-section. Overall, the dynamics of β^H appear to depend on the macro-financial environment: up until 2015, there was a decreasing trend in the share of funds with a positive β^H, dropping to roughly 30% in mid-2015. Afterwards, there was a relatively steady increase with close to 65% of the funds leaning

[19]Reassuringly, Figure 7 in the Internet Appendix B shows that the boxplots look very similar for funds from different β^H quintiles. In particular, the active rebalancing component does not appear to show a systematically higher relative contribution for risk-taking funds.

[20]The goodness-of-fit of regression (8) is also reasonable. Over the full sample, the cross-sectional median R^2 ranges between 36% and 49%, with an average value of 42%.

towards risk-taking strategies in late 2018.

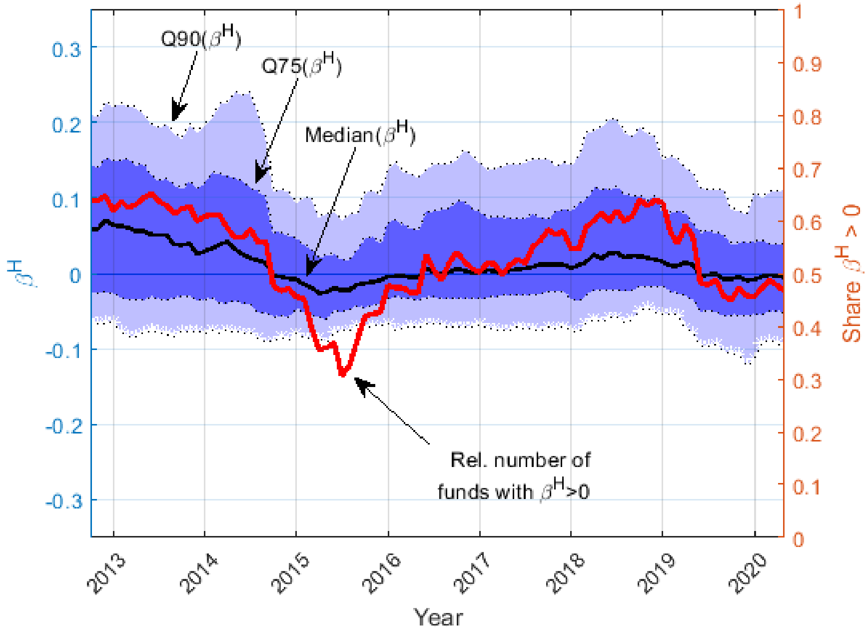

Figure 3: Cross-sectional distribution of β^H over time. Left-hand y-axis: different percentiles of β^H (the median is shown as the black line). Right-hand y-axis: the solid red line shows that relative number of funds with positive β^H (Share $\beta^H > 0$).

Interestingly, most of the time series variation appears to come from changes in the upper tail of the distribution of β^H, whereas the lower tail appears more stable. Note that, while some jumps in the VIX correspond with related movements in β^H, the contemporaneous correlation between the median β^H (black line) and the contemporaneous VIX is in fact negative at -0.15.[21] However, the correlation between the first-differences of the two variables is substantially positive at 0.18, which provides first evidence that changes in β^H are somewhat procyclical.

5.1.1 Characteristics of Synthetically Leveraged Funds

I now turn to cross-sectional analyses regarding synthetic leverage. I will start with showing that fund-level synthetic leverage is rather persistent and then analyse the characteristics of risk-taking funds (those with high levels of synthetic leverage).

[21]While I control for the VIX in the estimation of β^H, this is not a mechanical result and I find a similarly low correlation when excluding the VIX as a control variable in the estimation.

Persistence. By construction, my measure of synthetic leverage is highly persistent at short horizons due to the use of overlapping data. Table 2 illustrates that β^H is also persistent for longer horizons. In particular, it shows that funds in extreme deciles are substantially more likely to stay in these deciles three years later. For example, funds that are in quintile 5 in month t have a 39% probability of being in the same quintile 36 months later. The same can be observed for hedging funds, albeit with a somewhat lower probability of 25%. Note that these probabilities also indicate that funds may not follow the same strategy over time, but appear to adjust these as a function of the prevailing macro-financial conditions. The last column shows that attrition rates are very similar across deciles. For the sake of completeness, Panel B of Table 2 shows similar results using a more coarse-grained classification approach. Overall, despite focusing on off-balance sheet activities, these findings closely match those of Huang et al. (2011) both qualitatively and quantitatively.

Transition probabilities (in %)

A		$t+36$					
	Quintile(β^H)	1 (Hedging)	2	3	4	5 (Risk-taking)	Attrition
	1 (Hedging)	25.1	20.1	20.0	13.8	6.6	14.4
	2	20.1	25.9	23.9	11.0	4.8	14.4
β^H_t	3	16.3	18.7	19.2	17.8	13.6	14.4
	4	9.6	12.7	14.4	22.5	26.4	14.4
	5 (Risk-taking)	5.9	5.7	10.7	23.8	39.4	14.5

B		$t+36$		
		$\beta^H \leq 0$	$\beta^H > 0$	Attrition
t	$\beta^H \leq 0$	53.0	32.9	10.6
	$\beta^H > 0$	25.5	59.8	14.7

Table 2: Persistence of β^H. Panel A shows the transition probability of funds between different quintiles of β^H in month t and $t+36$, respectively. Panel B shows the persistence of the sign of β^H over a 36-month window.

Validation. My methodology seeks to identify funds that, through their unobserved actions, follow risk-taking (or hedging) strategies. The key suspects of such unobserved actions are derivatives usage and, to a lesser extent, securities lending. Market reports indicate that both derivatives usage and securities lending have become more prevalent in the asset management sector over recent years. As shown in Table 1, these two activities are also important for German investment funds: across all fund-month observations, 44% (23%) of funds report making use of derivatives (securities lending). Figure 4 shows the number (left) and the aggregated TNA (right) of funds make use of such activities. Over the full sample, during each month around 43% of funds reported making use of derivatives, 21% of funds reported making use of securities lending, and 13% reported making use of both of these activities. In terms of relative TNA, the average shares of these funds are even larger at 54%, 60%, and 37%, respectively.[22] Hence, funds that make use of these kinds of activities are indeed sizeable.[23] Note that, while Figure 4 does not point towards a notable increase in terms of derivatives usage/securities lending over my sample period, the results in Figure 3 indicate a strong time variation in terms of the purpose for which funds make use of these activities. In fact, from 2015 onwards, risk-taking motives appear to have become more prevalent.

I now take a closer look at the characteristics of funds in the different β^H quintiles. Table 3 shows the results from a univariate analysis, where I show the average characteristics of (TNA-weighted) portfolios of funds in the different quintiles. The first 5 columns show the time series averages (standard errors in parentheses) and the last two columns show significance tests on the differences between funds in quintiles 1 and 3, and funds in quintiles 5 and 3, respectively (based on Newey-West standard errors with 36 lags). All variables denoted with index $t-35:t$ are calculated as averages over 36 monthly observations, with Sd denoting the standard deviation and DownsideRisk the 5%-Value at Risk (in absolute terms), which is a proxy for a fund's tail risk (cf. Agarwal, Ruenzi, and Weigert (2017)).

The results suggest that risk-taking funds (those in quintile 5) indeed differ from other funds along various characteristics. For example, risk-taking funds display higher turnover

[22] These statistics are based on assessing whether a given fund reports making use of derivatives during a specific month. When classifying funds as derivatives users/securities lenders, if they report making use of these activities *at least once* during my sample, the numbers become even larger. In this case 79% of the funds in my sample report making use of derivatives, amounting to an average TNA share of 91%. This suggests that most funds make use of derivatives in one form or another during my sample period.

[23] Interestingly, the number of funds that make use of derivatives is substantially larger than the number of funds using securities lending (left-hand panel of Fig. 4), but their aggregate TNA is roughly the same (right-hand panel). Hence, relatively larger funds tend to be active in the securities lending market.

Characteristics (univariate)	Quintile(β^H) 1 (Hedging)	2	3	4	5 (Risk-taking)	Diff: 1-3	Diff: 5-3
Sd($R_{t-35:t}$)	3.876	4.129	3.780	3.714	4.220	0.096	0.440***
	(.039)	(.058)	(.046)	(.039)	(.069)	(.038)	(.044)
Sd($R^H_{t-35:t}$)	3.951	4.145	3.633	3.458	3.620	0.317**	-0.014
	(.038)	(.058)	(.042)	(.033)	(.056)	(.041)	(.041)
Sd($\Delta_{t-35:t}$)	0.657	0.527	0.701	0.786	1.047	-0.044	0.346***
	(.007)	(.009)	(.021)	(.015)	(.023)	(.022)	(.012)
DownsideRisk($R_{t-35:t}$)	5.755	6.120	5.632	5.649	6.320	0.122	0.687***
	(.073)	(.095)	(.103)	(.116)	(.125)	(.082)	(.071)
DownsideRisk($R^H_{t-35:t}$)	5.844	6.163	5.458	5.320	5.536	0.386**	0.079
	(.071)	(.094)	(.09)	(.089)	(.096)	(.075)	(.072)
DownsideRisk($\Delta_{t-35:t}$)	0.939	0.655	0.960	1.161	1.696	-0.021	0.736***
	(.021)	(.015)	(.022)	(.021)	(.048)	(.033)	(.035)
beta - MKT	1.057	1.155	1.094	1.108	1.249	-0.037	0.154**
	(.006)	(.007)	(.007)	(.006)	(.012)	(.01)	(.009)
beta - HML	0.027	0.014	-0.059	-0.113	-0.100	0.086	-0.041
	(.012)	(.008)	(.011)	(.007)	(.012)	(.02)	(.008)
beta - SMB	-0.097	-0.107	-0.035	-0.004	0.049	-0.062	0.084**
	(.009)	(.011)	(.011)	(.009)	(.014)	(.016)	(.009)
beta - UMD	0.001	0.021	0.015	-0.022	0.007	-0.014	-0.009
	(.005)	(.004)	(.004)	(.005)	(.005)	(.005)	(.005)
Age	19.693	18.812	26.681	34.394	37.934	-6.988	11.253
	(.599)	(.381)	(.631)	(.695)	(.378)	(1.104)	(.851)
CashRatio	1.931	1.296	2.836	4.344	4.851	-0.906	2.015*
	(.045)	(.061)	(.115)	(.13)	(.097)	(.13)	(.152)
Expense Ratio	0.986	0.682	1.173	1.439	1.470	-0.187	0.297**
	(.018)	(.025)	(.023)	(.011)	(.006)	(.032)	(.02)
I(ETF/Index fund)	0.418	0.639	0.282	0.063	0.017	0.136*	-0.265
	(.012)	(.019)	(.017)	(.009)	(.002)	(.023)	(.016)
$\text{Flows}_{t-35:t}$	0.003	0.533	0.352	0.151	0.091	-0.349	-0.261
	(.033)	(.05)	(.042)	(.035)	(.023)	(.061)	(.038)
Sd($\text{Flows}_{t-35:t}$)	2.871	4.436	2.367	1.881	2.132	0.503**	-0.235
	(.073)	(.134)	(.063)	(.052)	(.063)	(.105)	(.09)
$\text{Leverage}_{t-35:t}$	100.066	100.047	100.084	100.099	100.089	-0.018	0.006
	(.003)	(.003)	(.005)	(.004)	(.004)	(.005)	(.006)
I($\text{Leverage}_{t-35:t}$)	0.721	0.856	0.778	0.836	0.920	-0.057	0.142**
	(.01)	(.007)	(.014)	(.01)	(.006)	(.015)	(.016)
MinInvAmount	121.810	36.384	31.004	92.988	22.329	90.806	-8.674
	(6.716)	(6.537)	(4.358)	(12.606)	(4.516)	(7.276)	(6.496)
MorningstarRating	3.022	3.455	3.418	3.481	3.410	-0.396	-0.008
	(.026)	(.027)	(.03)	(.037)	(.027)	(.04)	(.032)
Family TNA	0.109	0.077	0.101	0.085	0.055	0.008	-0.046
	(.004)	(.002)	(.003)	(.006)	(.001)	(.006)	(.003)
TNA	2.247	5.253	2.652	2.950	2.788	-0.406	0.136
	(.155)	(.232)	(.1)	(.119)	(.123)	(.187)	(.151)
$\text{Turnover}_{t-35:t}$	2.882	1.727	2.779	3.548	3.471	0.103	0.693***
	(.083)	(.065)	(.062)	(.047)	(.047)	(.128)	(.063)
$\text{ShareDerivatives}_{t-35:t}$	0.417	0.141	0.231	0.288	0.422	0.185**	0.190**
	(.007)	(.006)	(.014)	(.012)	(.01)	(.012)	(.008)
I($\text{Derivatives}_{t-35:t}$)	0.645	0.630	0.814	0.879	0.943	-0.169	0.129**
	(.016)	(.02)	(.008)	(.007)	(.002)	(.014)	(.009)
I($\text{SecLending}_{t-35:t}$)	0.346	0.480	0.483	0.525	0.626	-0.137	0.143*
	(.022)	(.028)	(.03)	(.031)	(.035)	(.018)	(.015)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Characteristics of risk-taking funds (univariate analysis). The first five columns show the average characteristics of (TNA-weighted) portfolios of funds in the different quintiles, based on the classification in the previous month $t-1$. The last two columns show significance tests on the differences between funds in quintiles 1 and 3, and funds in quintiles 5 and 3, respectively (based on Newey-West standard errors with 36 lags).

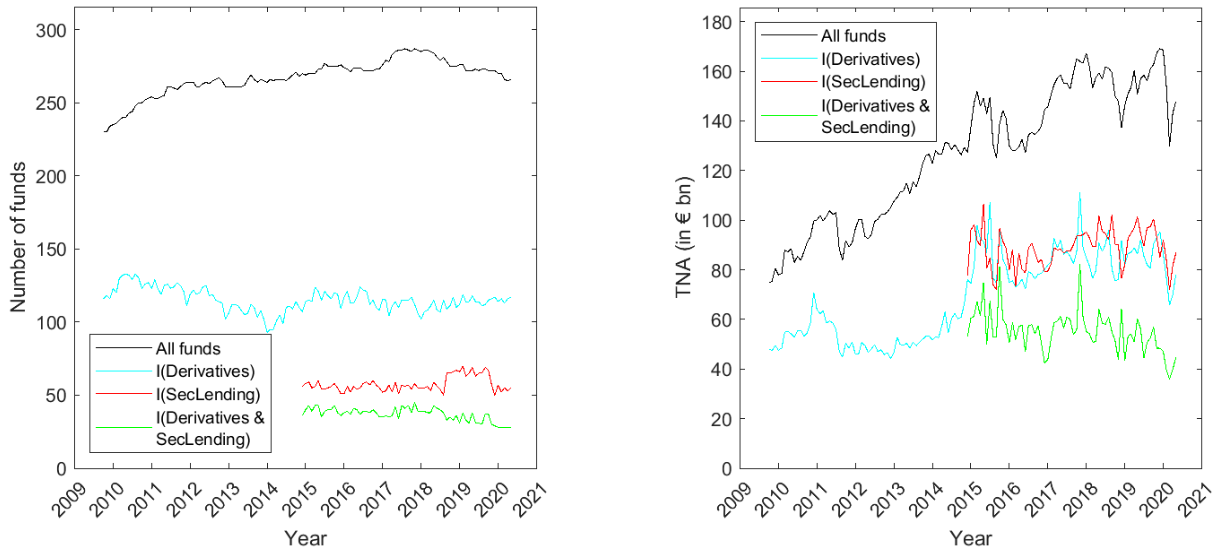

Figure 4: Number of funds (left) and aggregate TNA (right) over time. Results shown for all funds, funds that reported using derivatives, securities lending, or both of these activities, separately for each month. Note: information on securities lending activities is available from December 2014 onwards (based on IFS).

ratios, larger expense ratios (in line with Huang et al. (2011), possibly due to their more complex trading strategies), and slightly larger cash ratios (possibly to meet margin calls and investor redemptions). Risk-taking funds are more likley to make use of financial leverage (extensive margin, I(Leverage)), but not on the intensive margin (Leverage).[24]

Interestingly, compared with funds in quintile 3, risk-taking funds display a larger volatility of their realized returns (but not their holdings-based returns) and their return gap. Similarly, risk-taking funds also display significantly larger downside risk for these two measures, such that the 5% VaR is significantly larger by around 0.7% compared to funds in quintile 3. These results suggest that risk-taking funds' asset portfolios are comparable to those of other funds, since both the volatility and the downside risk of the holdings-based return does not differ systematically. Table 3 also shows the factor loadings for the Carhart (1997) four factor (4F) model, namely excess return on the market (MKT), small minus big (SMB), high minus low (HML), and up minus down (UMD).[25]

[24]As shown in Table 1, financial leverage (total assets/TNA) generally does not appear to play a big role in my sample. For example, the median value is 100%, indicating that most funds show zero leverage. This is in line with Boguth and Simutin (2018).

[25]Data on regional factors come from Ken French's website.

Risk-taking funds display a significantly larger market beta and a larger exposure to small stocks, which are likely to be less liquid.

With regards to funds' unobserved actions, I find that risk-taking funds tend to be significantly more likely to report using both of these activities, with the results on securities lending being somewhat weaker. For example, with regard to the extensive margin, risk-taking funds have a 94% (62%) probability of reporting using derivatives (securities lending), compared with 81% (48%) for funds in quintile 3. Similarly, risk-taking funds also display a larger ratio of derivatives relative to fund TNA (ShareDerivatives), at close to 0.4% compared to funds in quintile 3 (0.2%).[26] However, it should be clear that these numbers are relatively small, which suggests that purely focusing on reported derivatives exposures may be misleading when assessing their economic effect. Overall, my measure of synthetic leverage therefore appears to be mainly driven by funds' derivatives trading, but less by securities lending.[27]

5.1.2 A Closer Look at Fund Style

The results from the previous subsection showed that risk-taking funds differ from other funds across various characteristics. Here I take a closer look at the classification results for different fund categories along several dimensions of fund style. For example, Table 3 shows that risk-taking funds are rarely passively managed funds (which are all ETFs in my sample), even though the difference to the baseline category is not significant. Equity ETFs have grown substantially over my sample period: within the category of equity mutual funds, ETFs had a market share of 16% (in terms of relative TNA) in September 2009, which rose to 22% in December 2019. Similarly, the number of equity ETFs in my sample increased from 29 to 57 over the same period. Interestingly, practically all

[26]As a robustness check, in the Internet Appendix C, I move beyond the univariate approach and estimate a multinominal logistic regression, which confirms the key finding that risk-taking funds are more likely to make use of derivatives. On the other hand, there is no significant difference regarding securities lending.

[27]To assess the relative importance of these activities and their relative contribution to synthetic leverage, additional data would be needed that allow track the performance of a fund's derivatives portfolio over time (e.g., as in Kaniel and Wang (2020)).

equity ETFs/ Index funds report that they are physically-replicating, while synthetically-replicating funds are virtually non-existent. In line with these numbers, I find that the vast majority of ETFs/ Index Funds (85% across the full sample) end up in β^H-quintiles 1-3. In other words, passsively managed funds rarely make use of risk-taking strategies. In line with previous work (e.g., Greppmair et al. (2020)), I find that passively managed funds have a higher propensity to engage in securities lending activities (31% probability across the full sample, compared with 17% for actively managed funds). Interestingly, this is not the case for derivatives usage, where passively managed funds actually have a lower propensity of engagement (probablities of 16% versus 47% across the full sample).

The second dimension of interest with regards to fund style is a fund's Global Category as reported in Morningstar. In line with the dominance of large cap funds, the aggregate pictures are dominated by funds from this category. Interestingly, funds that do not restrict themselves to only large caps or only small/mid caps rarely tend to make use of risk-taking strategies, but rather appear to employ hedging strategies (more than 35% of all fund-month observations for this group are in quintile 1). By contrast, small/mid cap funds have a somewhat higher propensity to end up in quintile 3 (27%), compared with the extreme quintiles 1 (13%) and 5 (18%). In other words, the returns of these funds are broadly in line with their reported asset portfolios.

Lastly, I also explored whether there are differences across funds in terms of their reported investment region. It turns out that funds with focus on Global equity markets or North American equity markets have a higher propensity to end up in quintile 5 (close to 30% across all fund-month observations in both cases) compared with the dominant group of European equity funds (16%). Interestingly, funds that focus on Asian equity markets rarely end up in quintile 5 (2% across all fund-month observations), but often end up in quintile 1 (40% of observations). This suggests that these funds tend to hedge rather than take additional risks via their unobserved actions, which may be driven by higher FX risks that these funds should face.

5.1.3 Investor Composition

Who invests in synthetically leveraged funds? I tackle this question using information from the securities holdings statistics (SHS). For each fund-month, I calculate the share of fund TNA held by banks, ICPFs, investment funds (IFs), households (HHs), non-financial companies (NFCs) and all other investors (Others), respectively.

In order to test whether differences in the ownership structure are statistically significant, Table 4 assesses, separately for each investor group, whether a given group tends to be overrepresented or underrepresented relative to quintile 3. I also include time and style FEs and cluster standard errors by fund and by date.

Dep. var.: Share held by ...	Banks	ICPFs	IFs	HHs	NFCs	Others
Quintile(β^H_{t-1})						
1 (Hedging)	-0.010	-0.016	0.029	-0.020	0.017*	-0.000
	(0.011)	(0.020)	(0.024)	(0.032)	(0.009)	(0.019)
2	0.003	0.005	0.003	-0.055**	0.004	0.038**
	(0.007)	(0.016)	(0.017)	(0.025)	(0.005)	(0.019)
4	-0.021**	0.046**	-0.027*	0.067***	-0.004	-0.063***
	(0.009)	(0.020)	(0.014)	(0.025)	(0.005)	(0.018)
5 (Risk-taking)	-0.021**	0.061*	-0.036*	0.051	0.012	-0.073***
	(0.010)	(0.032)	(0.021)	(0.042)	(0.020)	(0.027)
Constant	0.034***	0.145***	0.122***	0.518***	0.025***	0.160***
	(0.010)	(0.019)	(0.017)	(0.027)	(0.005)	(0.018)
Time FEs	✓	✓	✓	✓	✓	✓
Style FEs	✓	✓	✓	✓	✓	✓
Obs.	18,222	18,222	18,222	18,222	18,222	18,222
adj.-R^2	0.018	0.042	0.072	0.043	0.000	0.064

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Who invests in synthetically leveraged funds? Regression of the relative share of fund TNA held by different investor groups on the different β^H quintiles. All specifications include time FEs (standard errors in parentheses, clustered by fund and by date).

The results indicate that the investor composition of risk-taking funds differs from funds in quintile 3. While both ICPFs and HHs tend to be more invested in funds with high levels of synthetic leverage, both banks and investment funds tend to be underrepresented. It is not implausible that these sophisticated investor groups are especially aware of the differences in R and R^H in risk-taking funds and thus actively avoid investing in them. The finding that risk-taking funds display larger expense ratios (cf. Table 3) indeed suggests that these are catered towards (smaller) retail investors. To what extent these investors are aware of these unobserved fund actions is unclear, in particular whether this raises consumer-protection issues. I leave this as an interesting avenue for future research.

6 Synthetic Leverage and Fund Performance

Why do funds make use of synthetic leverage? An important incentive is that it might boost their performance. This section analyses performance differences between funds with different levels of synthetic leverage.

Note that, a priori, it is unclear whether synthetically leveraged funds should outperform other funds. For example, similar to financial leverage, synthetic leverage may be a means to alter higher-order moments of a fund's return distribution. At the individual fund-level, while synthetic leverage should affect the variance of a fund's return distribution, it might not have a positive effect on the fund's average performance. Moreover, the return gap is a fund-specific performance measure in the sense that it measures how well a given fund performed relative to its *own* holdings-based benchmark. While the raw return gap has indeed been shown to be a valuable predictor of future fund performance (Kacperczyk et al. (2008)), my methodolgy effectively compares the conditional distribution of R versus R^H, after adjusting for other aspects unrelated to the concept of synthetic leverage. It is unclear whether risk-taking funds should outperform other funds, since my methodology treats positive and negative realizations of Δ symmetrically. Therefore, in the cross-section I do not expect synthetically leveraged funds to significantly outperform other funds.

As a first step, Figure 5 shows the TNA-weighted cumulative return gap for the different β^H-quintiles over time. Focusing purely on this indicator suggests that risk-taking funds tend to perform rather well: their cumulative return gap amounts to +8% over the whole sample, compared with +2.4% for hedging funds and 6.5% for funds in intermediate quintiles. However, Figure 5 also indicates that the time series for risk-taking funds is

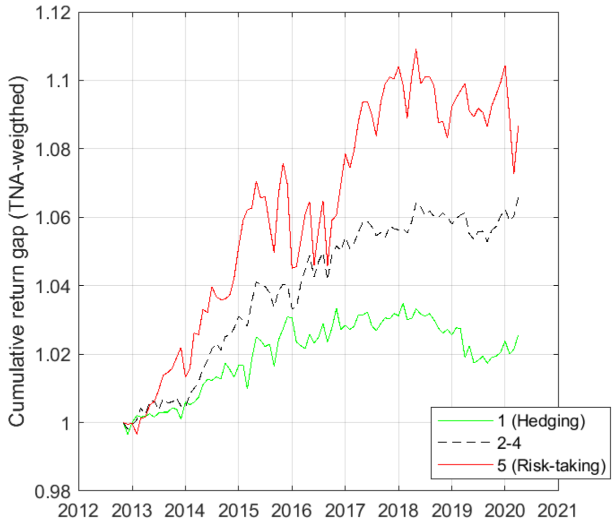

Figure 5: Cumulative return gap, Δ, over time. In a given month t, I calculate the (TNA-weighted) average Δ of funds in the different quintiles in month $t-1$.

more noisy than the other quintiles.

In line with this observation, Table 5 shows that the differences in Figure 5 are not significant and that risk-taking funds actually underperform other funds after adjusting for standard risk factors. As before, I regress the dependent variables (in this case, different performance measures) on the β^H-quintiles, where quintile 3 serves as the baseline category. I also include fund-specific control variables (fund TNA, age, and expense ratio) and time/style fixed effects (standard errors are clustered by fund and date). Following Huang et al. (2011), I show the results for both CAPM alphas and four-factor alphas over different forward horizons.[28] While risk-taking funds tend to slightly underperform based on 1-month future performance, this becomes substantially worse at longer horizons. For example, the cumulative 24-month ahead CAPM alpha of risk-taking funds is 1.8 percentage points lower compared to funds in quintile 3.[29]

[28] As has become standard practice in the literature (e.g., Evans and Fahlenbrach (2012)), these alphas are calculated by estimating the corresponding factor regressions over the previous 36 months and then using the factor loadings and the actual realizations to calculate the expected risk-adjusted net return. The 6-/12-/24-month alphas are cumulative sums of the corresponding monthly values.

[29] I should note that the underperformance of risk-taking funds cannot be fully explained by their higher expense ratios. In particular, as I show in Table 11 in the Internet Appendix, risk-taking funds continue to underperform when using gross instead of net alphas.

Dep. var.: Performance (ahead)	net alpha$^{\text{CAPM}}$ (in percent) (1-month)	(6-month)	(12-month)	(24-month)	net alpha$^{\text{4F}}$ (in percent) (1-month)	(6-month)	(12-month)	(24-month)
Quintile(β^H)								
1 (Hedging)	-0.044	-0.276	-0.813**	-1.885**	-0.023	-0.165	-0.229	-0.361
	(0.049)	(0.205)	(0.383)	(0.761)	(0.043)	(0.192)	(0.350)	(0.622)
2	0.027	0.173	-0.004	-0.466	0.019	0.082	0.130	0.239
	(0.048)	(0.175)	(0.324)	(0.545)	(0.040)	(0.144)	(0.275)	(0.492)
4	-0.040	-0.155	-0.437	-0.387	-0.064*	-0.274**	-0.411*	-0.211
	(0.037)	(0.156)	(0.265)	(0.525)	(0.033)	(0.137)	(0.234)	(0.411)
5 (Risk-taking)	-0.055	-0.170	-0.798**	-1.846***	-0.076	-0.264	-0.619**	-0.940*
	(0.060)	(0.205)	(0.333)	(0.656)	(0.057)	(0.175)	(0.291)	(0.519)
log(TNA(t-1))	0.015	0.076	0.089	0.140	-0.002	-0.007	-0.041	-0.153
	(0.011)	(0.046)	(0.086)	(0.170)	(0.010)	(0.041)	(0.078)	(0.151)
log(Age)	0.010	-0.056	-0.094	-0.231	-0.023	-0.202	-0.401	-0.848
	(0.043)	(0.162)	(0.298)	(0.595)	(0.039)	(0.138)	(0.259)	(0.522)
ExpRatio	-0.005	-0.127	-0.470	-0.825	-0.068**	-0.434***	-0.920***	-2.120***
	(0.040)	(0.177)	(0.312)	(0.589)	(0.027)	(0.122)	(0.237)	(0.475)
Constant	-0.379	-1.634	-1.642	-2.485	0.098	0.668	1.848	5.253**
	(0.260)	(0.987)	(1.666)	(2.949)	(0.236)	(0.789)	(1.402)	(2.562)
Time FEs	√	√	√	√	√	√	√	√
Style FEs	√	√	√	√	√	√	√	√
Obs.	20,500	18,896	17,068	13,689	20,500	18,896	17,068	13,689
adj.-R^2	0.116	0.106	0.113	0.131	0.144	0.132	0.152	0.181

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Performance analysis. Regression of different measures of future fund net performance on the β^H quintiles. All specifications include time and style FEs (standard errors in parentheses, clustered by fund and by date). Fund controls included lagged TNA, Age, and the expense ratio.

These results indicate that synthetically leveraged funds significantly underperform other funds. Of course, there may be other incentives for funds to use synthetic leverage. In this regard, Table 3 showed that risk-taking funds display significantly larger expense ratios than other funds. While these higher costs could potentially be justified by their more sophisticated trading strategies, the results in Table 5 raise doubts about the overall attractiveness for fund investors of paying such higher fees. In fact, even after controlling for a fund's expense ratio, the risk-adjusted performance is substantially worse.

Overall, these findings are in line with those of Huang et al. (2011), who showed that risk-shifting funds (who increased the riskiness of their asset portfolios over the prior 36 months) also showed substantial underperformance compared with other funds and significantly larger expense ratios. Similarly, Choi and Kronlund (2018) found that the larger raw returns of bond funds that reach-for-yield can be fully explained by common risk factors and that these funds actually show underperformance after adjusting for risk.

7 Synthetic Leverage and Fund Fragility

An important question is whether synthetic leverage increases fund fragility and induces more procyclical behavior of investment funds (e.g., ECB (2014); IMF (2018)). One example of such procyclical behavior would be forced asset sales due to fund investors responding more strongly to past fund performance. To date, little work has been devoted to tackling such questions in the context of synthetic leverage. Focusing on a broader definition of leverage, Molestina Vivar et al. (2020) find that leveraged corporate bond funds tend to display a stronger flow-performance sensitivity and larger flow externalities than non-leveraged funds.

7.1 Flow-Performance Relationship

To motivate the following analysis, I start out with an illustration based on the COVID-19-induced market stress period in March 2020. Specifically, I investigate fund flows and returns as a function of synthetic leverage over this period. I classify funds based on their pre-crisis β^H-quintiles in December 2019 and then calculate the aggregate cumulative flows and returns of the different quintiles for the period December 2019 up until May 2020. Note that I drop ETFs from the following analyses, since ETFs do not allow investors to redeem their fund shares like open-end funds and thus differ in terms of their externality potential (e.g., Goldstein et al. (2017)).

The results are shown in Figure 6, where the (TNA-weighted) cumulative returns for the different quintiles are indexed relative to the end of January 2020. The first major equity price drop occurred on February 24th and there was a marked stabilization following the ECB's announcement of its Pandemic Emergency Purchase Programme on March 18th. If anything, in terms of their raw returns, risk-taking funds tended to perform slightly better compared to other funds.[30] At the same time, however, risk-taking funds

[30] This finding is opposite to Kaniel and Wang (2020), who find that hedging funds tended to perform better. I confirm that risk-taking funds also tend to perform better in my sample after adjusting for standard risk-factors.

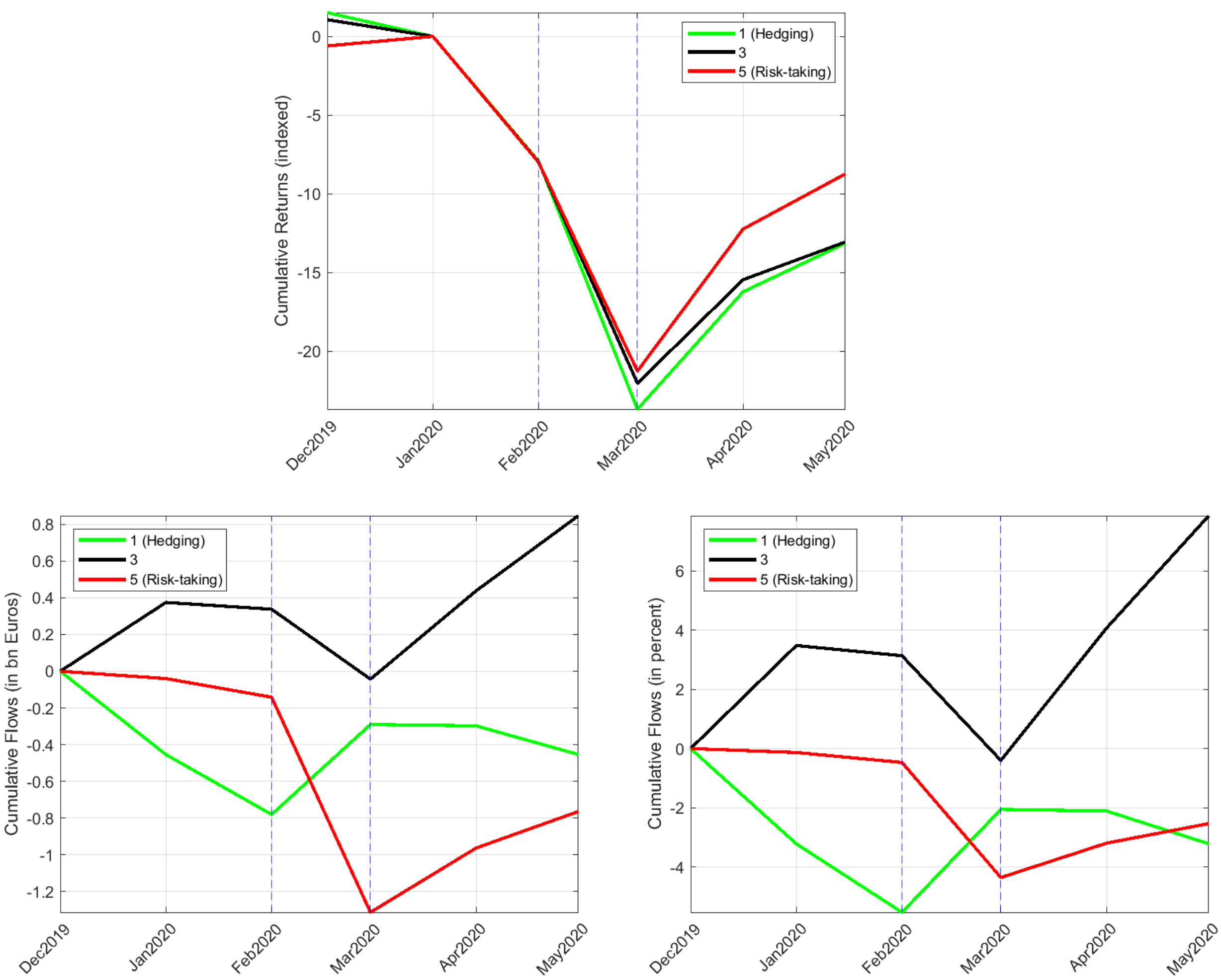

Figure 6: Cumulative raw returns (top) and cumulative flows (bottom left: in Euro billions; bottom right: as a percentage of pre-crisis TNA) around the COVID-19-induced stress episode in March 2020. Note: ETFs are excluded from this analysis.

showed substantial outflows on the order of 1 billion Euros in March, whereas hedging funds showed inflows of around 0.5 billion Euros. At the same time, however, funds in quintile 3 also showed outflows of roughly the same magnitude as risk-taking funds. Overall, it is therefore not clear whether investors in risk-taking funds indeed responded more strongly to negative fund returns during this episode.

Moving beyond this COVID19-subsample, I wish to assess whether there are systematic differences in the flow-performance relationship across the different quintiles. I investigate the following regression:

$$\begin{aligned} \text{Flows}_{t,f} =& \gamma \times \text{Perf}_{t-1,f} + \sum_{j \neq 3} \gamma_j \times \text{Perf}_{t-1,f} \times I(\text{Quintile}(\beta^H_{t,f}) = j) \\ &+ \sum_{j \neq 3} c_j \times I(\text{Quintile}(\beta^H_{t,f}) = j) + b \times X_{t,f} + \epsilon_{t,f}, \end{aligned} \tag{9}$$

where the parameter γ measures how strongly investors in funds from quintile 3 respond to lagged fund performance (Perf). The key question is whether γ is significantly larger for risk-taking funds, for which the sensitivity parameter is $\gamma + \gamma_5$. My estimation approach closely follows that of Goldstein et al. (2017), and the set of controls (X) includes lagged flows, age, lagged TNA, a load fee indicator, and the expense ratio. I also include lagged financial leverage, a fund's rolling standard deviation of realized returns over the prior 36 months, and time and style FEs. Standard errors are clustered by date and by fund.

Regarding fund performance measures, I again show the results for both CAPM and four-factor alphas, which are defined here as the intercept of the corresponding factor regression estimated over the prior 36 months. For both performance measures, I show results using all observations, and separate results based on (a) negative lagged fund performances only and (b) for high VIX periods, where the VIX is above its full sample median value.

Table 6 shows the results: funds with higher values of synthetic leverage tend to show a *weaker* flow-performance sensitivity compared to funds in quintile 3. However, while the interaction terms are generally negative, the differences are not statistically significant

Dep. var.:	Alpha CAPM (36-month, in percent)			Alpha 4F (36-month, in percent)		
Flows(t)	All	< 0	High VIX	All	< 0	High VIX
Perf(t-1)	1.260***	0.888**	1.245***	1.599***	1.211***	1.314***
	(0.353)	(0.403)	(0.418)	(0.320)	(0.394)	(0.404)
Quintile(β^H)						
1 (Hedging)	0.000	0.003	-0.000	-0.001	0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
2	-0.000	0.000	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
4	-0.002*	-0.001	-0.003**	-0.003**	-0.003	-0.004**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
5 (Risk-taking)	0.001	0.004*	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Interactions						
1 × Perf(t-1)	0.266	0.990*	0.144	-0.229	0.565	-0.232
	(0.433)	(0.547)	(0.531)	(0.389)	(0.503)	(0.496)
2 × Perf(t-1)	0.046	0.175	0.074	-0.202	-0.164	-0.119
	(0.365)	(0.500)	(0.475)	(0.391)	(0.491)	(0.536)
4 × Perf(t-1)	-0.405	-0.129	-0.355	-0.854**	-0.814	-0.857**
	(0.350)	(0.479)	(0.432)	(0.361)	(0.493)	(0.415)
5 × Perf(t-1)	-0.259	0.276	-0.186	-0.216	-0.258	0.089
	(0.382)	(0.530)	(0.453)	(0.536)	(0.520)	(0.538)
log(Age(t))	-0.005***	-0.004***	-0.005***	-0.005***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Expense Ratio	-0.000	0.000	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Flows(t-1)	0.118***	0.119***	0.110***	0.118***	0.117***	0.111***
	(0.022)	(0.028)	(0.026)	(0.023)	(0.027)	(0.027)
Leverage(t-1)	0.149*	0.163*	0.189*	0.153*	0.147*	0.189*
	(0.081)	(0.084)	(0.101)	(0.080)	(0.085)	(0.101)
I(Load)	-0.001	-0.002*	-0.001	-0.001	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sd($R_{t-36:t}$)	-0.033	-0.085	0.004	-0.093	-0.154**	-0.073
	(0.068)	(0.068)	(0.083)	(0.065)	(0.065)	(0.076)
log(TNA(t-1))	0.002***	0.001***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.164**	-0.176**	-0.208**	-0.170**	-0.161*	-0.211**
	(0.081)	(0.085)	(0.101)	(0.081)	(0.086)	(0.101)
Time FEs	√	√	√	√	√	√
Style FEs	√	√	√	√	√	√
Obs.	17,345	13,037	8,577	17,345	13,950	8,577
adj.-R^2	0.054	0.046	0.053	0.055	0.047	0.051

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Flow-performance relationship and synthetic leverage. All specifications include time and style fixed effects. Standard errors (in parentheses) clustered by fund and by date. The different alphas are the intercepts of the corresponding factor model, estimated over the previous 36 months. I show results separately for all observations, for negative performance, and for high values of the VIX (months when the VIX is in the top quintile over the full sample). Note: ETFs are excluded from this analysis.

for funds in quintile 5. I find that these results are robust to using shorter performance windows (e.g., 12 or 18 months), to using rank-adjusted performance measures, and to comparing risk-taking funds with all other funds. Overall, investors in risk-taking funds do not appear to react more strongly to fund performance. This is broadly in line with the results in Figure 6, where funds in quintile 3 showed similar returns/flows during the COVID19-episode in March 2020.

7.2 Flow Externalities

Having established that the flow-performance sensitivity of synthetically leveraged funds does not differ systematically from other funds, it could still be that large outflows of such funds may be particularly damaging in terms of (future) fund performance. For example, this could be the case if these funds were mainly trading relatively illiquid assets to satisfy investor redemptions. To tackle this question, I follow Chen et al. (2010) and estimate the following relationship:

$$\begin{aligned} \text{Perf}_{t,f} =& \theta \times \text{Outflow}_{t-1,f} + \sum_{j \neq 3} \theta_j \times \text{Outflow}_{t-1,f} \times I(\text{Quintile}(\beta^H_{t,f}) = j) \\ &+ \sum_{j \neq 3} c_j \times I(\text{Quintile}(\beta^H_{t,f}) = j) + b \times X_{t,f} + \epsilon_{t,f}, \end{aligned} \tag{10}$$

where Outflow equals one if a fund's lagged monthly flows are below -5% and zero otherwise. The set of controls includes four lags of fund performance, lagged fund TNA, and the expense ratio. As noted by Chen et al. (2010), because past performance is included in the regression, a significant $\theta < 0$ would show that large outflows affect a fund's future performance beyond what is predicted by past performance. I include date and style FEs and cluster standard errors by date and by fund. ETFs are excluded from this analysis.

Dep. var.:	Raw Return (monthly)			Alpha CAPM (monthly)			Alpha 4F (monthly)		
Perf(t)	All	Low VIX	High VIX	All	Low VIX	High VIX	All	Low VIX	High VIX
Outflow(t-1)	0.167	0.287	0.018	0.173	0.247*	0.101	0.152	0.256**	0.035
	(0.138)	(0.174)	(0.289)	(0.115)	(0.131)	(0.183)	(0.110)	(0.130)	(0.172)
Quintile(β^H)									
1 (Hedging)	-0.056	0.022	-0.120*	-0.020	0.083	-0.109*	0.019	0.080*	-0.027
	(0.044)	(0.061)	(0.068)	(0.039)	(0.052)	(0.059)	(0.039)	(0.048)	(0.065)
2	-0.031	0.036	-0.097	0.003	0.065	-0.057	0.019	0.022	0.017
	(0.045)	(0.057)	(0.069)	(0.039)	(0.050)	(0.064)	(0.039)	(0.050)	(0.060)
4	-0.040	0.018	-0.096*	-0.050	-0.019	-0.088*	-0.046	-0.030	-0.063
	(0.037)	(0.050)	(0.057)	(0.032)	(0.044)	(0.052)	(0.030)	(0.040)	(0.047)
5 (Risk-taking)	0.069*	0.104**	0.015	-0.018	-0.074*	0.028	-0.039	-0.102**	0.034
	(0.038)	(0.047)	(0.062)	(0.034)	(0.042)	(0.052)	(0.033)	(0.041)	(0.049)
Interactions									
1 × Outflow(t-1)	-0.531**	-0.650***	-0.316	-0.453*	-0.544**	-0.325	-0.424**	-0.531**	-0.310
	(0.261)	(0.235)	(0.459)	(0.231)	(0.233)	(0.351)	(0.202)	(0.244)	(0.304)
2 × Outflow(t-1)	-0.177	-0.060	-0.222	-0.286	-0.332	-0.293	-0.178	-0.414	0.045
	(0.224)	(0.249)	(0.385)	(0.212)	(0.268)	(0.305)	(0.198)	(0.294)	(0.281)
4 × Outflow(t-1)	-0.389*	-0.866***	0.158	-0.286*	-0.464**	-0.064	-0.238	-0.517***	0.059
	(0.228)	(0.273)	(0.342)	(0.168)	(0.183)	(0.292)	(0.153)	(0.182)	(0.252)
5 × Outflow(t-1)	-0.631***	-0.385	-0.707*	-0.591***	-0.303	-0.799***	-0.425**	-0.199	-0.592**
	(0.228)	(0.258)	(0.378)	(0.198)	(0.193)	(0.305)	(0.193)	(0.201)	(0.286)
Perf(t-1)	-0.033***	0.001	-0.056***	-0.007	0.008	-0.017	-0.046***	0.015	-0.095***
	(0.009)	(0.011)	(0.014)	(0.011)	(0.013)	(0.015)	(0.011)	(0.012)	(0.015)
Perf(t-2)	0.001	-0.042***	0.022	0.050***	-0.053***	0.126***	0.011	-0.045***	0.052***
	(0.009)	(0.012)	(0.015)	(0.011)	(0.014)	(0.015)	(0.009)	(0.013)	(0.011)
Perf(t-3)	0.005	0.044***	-0.049***	0.038***	0.019	0.046***	0.006	0.024**	-0.017
	(0.009)	(0.011)	(0.015)	(0.009)	(0.012)	(0.014)	(0.010)	(0.011)	(0.015)
Perf(t-4)	-0.002	-0.019*	-0.001	-0.002	-0.016	0.005	-0.024***	-0.027**	-0.022*
	(0.008)	(0.010)	(0.014)	(0.008)	(0.012)	(0.013)	(0.009)	(0.012)	(0.013)
log(TNA(t-1))	0.045***	0.058***	0.035**	0.033***	0.027***	0.038***	0.004	-0.001	0.011
	(0.008)	(0.011)	(0.014)	(0.008)	(0.009)	(0.012)	(0.007)	(0.008)	(0.010)
ExpRatio	0.021	0.057	-0.008	0.009	0.034	-0.017	-0.051*	-0.002	-0.102***
	(0.029)	(0.040)	(0.043)	(0.029)	(0.039)	(0.035)	(0.027)	(0.036)	(0.036)
Constant	-0.202	0.620***	-1.134***	-0.713***	-0.654***	-0.757***	-0.140	-0.116	-0.211
	(0.165)	(0.211)	(0.278)	(0.165)	(0.191)	(0.237)	(0.139)	(0.165)	(0.192)
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Style FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	16,566	8,479	8,087	16,566	8,479	8,087	16,566	8,479	8,087
adj.-R^2	0.838	0.591	0.874	0.148	0.182	0.141	0.173	0.189	0.174

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Externality regressions as in Chen et al. (2010). All specifications include time and style fixed effects. Standard errors (in parentheses) clustered by fund and by date. I use monthly fund performance measures as described in Evans and Fahlenbrach (2012). I show results separately for all observations, and for periods with low and high VIX (months when the VIX is above its full sample median value), respectively. Note: ETFs are excluded from this analysis.

Similar to Molestina Vivar et al. (2020), Table 7 suggests that highly synthetically leveraged funds display larger flow externalities: while θ is hardly negatively significant for funds in quintile 3, the interaction term for risk-taking funds is negatively significant in most specifications. Interestingly, this appears to be driven by periods with above-median VIX levels, since the interaction term is insignificant (albeit also negative) in the low VIX specifications. Hence, risk-taking funds display larger flow externalities, particuarly during volatile market periods. Clearly these periods are likely to correspond with potentially large margin calls. As a robustness check, Table 12 in the Internet Appendix shows an enhanced specification with different Outflow indicators. The larger externalities of risk-taking funds are present only during large Outflows, not during weak/moderate ones.

To get a better understanding of these results, Table 8 follows the approach of Coval and Stafford (2007) and illustrates how funds in the different β^H-quintiles deal with (large) outflows. I show the average portfolio adjustments between month $t-1$ and month t as a function of the observed outflows in month $t-1$. Here I define weak outflows as fund-month observations with lagged outflows (i.e., $\text{Flows}_{t-1,f} < 0$) of less than 1%. Moderate outflows lie between 1% and 5% and large outflows are above 5% as in Table 7. The first column of Table 8 shows that the average flows are comparable across the different quintiles for the three scenarios (around -0.4%, -2%, and -10%, respectively). I also show the average cash holdings in $t-1$ and in t (for the sake of comparability, both relative to the lagged fund TNA), and the number of portfolio holdings that were newly initiated, expanded, kept constant, reduced, and expanded in month t, relative to the number of holdings in $t-1$.

					Share of positions $t-1 \to t$ (in %)				
Outflows	Quintile(β^H)	Flows(t) (in %)	$\frac{\text{Cash(t-1)}}{\text{TNA(t-1)}}$	$\frac{\text{Cash(t)}}{\text{TNA(t-1)}}$	New	Expanded	Constant	Reduced	Eliminated
Weak	1 (Hedging)	-0.40	3.51	3.56	6.45	13.99	61.55	24.46	6.40
	2	-0.39	3.09	3.09	5.49	14.60	61.59	23.81	5.18
	3	-0.41	3.50	3.47	4.86	13.97	63.90	22.14	4.71
	4	-0.41	3.47	3.56	5.82	13.21	66.03	20.77	5.93
	5 (Risk-taking)	-0.38	4.78	4.82	5.36	11.46	68.55	19.99	4.94
Moderate	1 (Hedging)	-2.01	2.70	2.89	6.66	14.00	58.44	27.56	6.33
	2	-2.05	2.55	2.95	5.71	14.24	56.99	28.77	5.51
	3	-2.08	2.92	3.15	5.72	13.60	59.63	26.76	5.82
	4	-2.02	2.91	3.17	5.81	12.95	61.21	25.84	5.69
	5 (Risk-taking)	-1.95	3.61	3.77	5.31	11.32	66.48	22.20	5.31
Large	1 (Hedging)	-9.85	4.87	5.78	8.39	14.66	53.37	31.97	9.30
	2	-9.86	2.92	2.58	5.84	16.47	45.71	37.82	6.28
	3	-9.62	2.60	2.49	6.10	19.40	47.32	33.28	6.28
	4	-9.76	2.91	3.70	6.80	20.26	49.24	30.51	7.75
	5 (Risk-taking)	-9.62	4.72	4.03	7.92	22.05	52.08	25.87	7.36

All months

Table 8: Average asset-level portfolio adjustments as a function of funds' net flows à la Coval and Stafford (2007). Results are shown separately for different β^H-quintiles. I define *weak* outflows as fund-month observations with outflows of less than 1%. *Moderate* outflows are between 1% and 5% and *large* outflows are larger than 5%. Note: ETFs are excluded from this analysis.

Low VIX

		Flows(t-1)	Cash(t-1)	Cash(t)	Share of positions $t-1 \rightarrow t$ (in %)				
Outflows	Quintile(β^H)	(in %)	TNA(t-1)	TNA(t-1)	New	Expanded	Constant	Reduced	Eliminated
Weak	1 (Hedging)	-0.42	3.63	3.56	6.61	13.25	63.15	23.61	6.40
	2	-0.39	2.95	2.97	5.66	14.06	62.89	23.05	5.14
	3	-0.41	3.14	3.23	4.72	13.65	64.04	22.30	4.41
	4	-0.40	3.27	3.37	5.64	12.87	67.36	19.76	5.80
	5 (Risk-taking)	-0.38	4.78	4.82	5.05	11.02	70.01	18.97	4.46
Moderate	1 (Hedging)	-1.99	2.58	2.56	6.28	13.97	59.18	26.86	5.94
	2	-2.08	2.41	2.81	5.76	14.65	57.89	27.45	5.19
	3	-2.05	2.67	3.00	6.91	13.07	59.20	27.73	6.59
	4	-1.92	2.87	3.19	5.22	12.33	64.10	23.57	5.26
	5 (Risk-taking)	-1.85	3.46	3.67	5.58	10.10	68.73	21.17	5.47
Large	1 (Hedging)	-9.24	4.24	6.45	9.65	16.59	55.76	27.65	8.47
	2	-9.08	2.25	2.11	3.55	15.00	49.91	35.09	3.64
	3	-9.56	2.30	1.83	6.91	17.28	48.34	34.38	7.10
	4	-9.34	2.84	3.56	7.90	19.11	50.10	30.79	8.35
	5 (Risk-taking)	-9.69	3.56	3.60	7.24	18.26	59.95	21.79	6.40

High VIX

		Flows(t-1)	Cash(t-1)	Cash(t)	Share of positions $t-1 \rightarrow t$ (in %)				
Outflows	Quintile(β^H)	(in %)	TNA(t-1)	TNA(t-1)	New	Expanded	Constant	Reduced	Eliminated
Weak	1 (Hedging)	-0.39	3.40	3.56	6.30	14.71	60.02	25.27	6.40
	2	-0.39	3.23	3.23	5.31	15.17	60.24	24.59	5.22
	3	-0.41	3.91	3.74	5.02	14.33	63.73	21.94	5.05
	4	-0.41	3.68	3.77	6.01	13.57	64.56	21.86	6.09
	5 (Risk-taking)	-0.38	4.78	4.82	5.71	11.95	66.91	21.14	5.47
Moderate	1 (Hedging)	-2.03	2.82	3.23	7.06	14.04	57.67	28.29	6.73
	2	-2.02	2.70	3.10	5.67	13.82	56.06	30.12	5.84
	3	-2.12	3.19	3.31	4.46	14.17	60.09	25.74	5.00
	4	-2.12	2.95	3.16	6.38	13.55	58.40	28.05	6.10
	5 (Risk-taking)	-2.06	3.77	3.88	5.03	12.62	64.08	23.29	5.13
Large	1 (Hedging)	-10.29	5.32	5.29	7.48	13.27	51.66	35.07	9.90
	2	-10.74	3.72	3.14	8.41	18.12	40.99	40.89	9.26
	3	-9.68	2.91	3.18	5.22	21.72	46.20	32.08	5.39
	4	-10.26	3.00	3.86	5.56	21.56	48.26	30.18	7.08
	5 (Risk-taking)	-9.56	5.57	4.35	8.44	24.94	46.08	28.98	8.09

Table 9: Low versus high VIX subsample (months with below/above median VIX). Average asset-level portfolio adjustments as a function of funds' net flows à la Coval and Stafford (2007). Results are shown separately for different β^H-quintiles. I define *weak* outflows as fund-month observations with outflows of less than 1%. *Moderate* outflows are between 1% and 5% and *large* outflows are larger than 5%. Note: ETFs are excluded from this analysis.

The results suggest that risk-taking funds tend to keep relatively more positions untouched across all three outflow scenarios (69%, 66%, and 52% of the positions) relative to funds in quintile 3 (64%, 60%, and 47%). On the other hand, faced with large outflows risk-taking funds eliminate a larger number of positions relative to funds in quintile 3 (7.4% versus 6.3%). Given that risk-taking funds tend to show larger SMB loadings (cf. Table 3), their trading activity is likely to occur in less liquid stocks. Remarkably, risk-taking funds do not appear to make use of their cash buffers in the case of weak and moderate outflows (where the average cash ratio actually tends to increase), but draw upon their relatively large cash holdings (cf. Table 3) particularly during times of large investor redemptions.

Further evidence along these lines is provided in Table 9, where I present separate results for high-/low-VIX subsamples (below/above median, as in Table 7). Comparing the case of large outflows between these two market states shows that risk-taking funds generally display substantially larger cash ratios during high VIX periods, where large margin calls are also more likely. While funds across all quintiles generally tend to trade more actively during high VIX periods compared to low VIX periods, risk-taking funds tend to reduce and eliminate a larger number of positions compared with funds in quintile 3. In line with the results in Table 7, this is not the case during low VIX periods. Table 13 in Internet Appendix C shows that these results also hold in a regression framework.

8 Conclusions

In this paper, I propose a novel measure of synthetic leverage that does not require information on funds' derivatives trading/securities lending activities. In my application for German equity funds during the period September 2009 to May 2020, I show that synthetic leverage varies strongly both in the cross-section and over time. In particular, I find that risk-taking via synthetic leverage increases from 2015 onwards, suggesting an intricate relationship with the macro-financial environment. Returns of synthetically leveraged funds tend to be negative on a risk-adjusted basis. Lastly, I show that these funds tend to display larger flow externalities. Taken together, these results suggest that synthetic leverage should be closely monitored in the future.

From a methodological perspective, it is important to note that my proposed synthetic leverage measure treats positive and negative fund returns symmetrically. Future work could contrast this approach with asymmetric measures that specifically focus on the lower tail of the fund's return distribution (e.g., estimating β^H based on quantile regressions). Moreover, while this paper focused on the subset of equity funds, my methodology can be applied to other fund types as well, most importantly (corporate) bond funds. It would be interesting to see whether my main findings carry over to these other fund types. In particular, it would be interesting to investigate whether there is a causal relationship between fund risk-taking via synthetic leverage and the stance of monetary policy (e.g. Choi and Kronlund (2018)). Lastly, based on more granular derivatives/SFT data one could explore how synthetically leveraged funds position themselves in these markets and, crucially, who their counterparties are. Such analyses are important to further assess the systemic implications of synthetic leverage.

References

Agarwal, V., G. D. Gay, and L. Ling (2011). Window dressing in mutual funds. *Review of Financial Studies 27(11)*, 3133–3170.

Agarwal, V., S. Ruenzi, and F. Weigert (2017). Tail risk in hedge funds: A unique view from portfolio holdings. *Journal of Financial Economics 125(3)*, 610–636.

Almazan, A., K. Brown, M. Carlson, and D. Chapman (2004). Why constrain your mutual fund manager? *Journal of Financial Economics 73(2)*, 289–321.

Aragon, G. O., L. Li, and J. Qian (2017). The use of credit default swaps by bond mutual funds: Liquidity provision and counterparty risk. *Journal of Financial Economics (forthcoming)*.

Bai, J., T. G. Bali, and Q. Wen (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics 131*, 619–642.

Banegas, A., G. Montes-Rojas, and L. Siga (2016). Mutual fund flows, monetary policy and financial stability. *Federal Reserve, Finance and Economics Discussion Series (FEDS)*.

Barbu, A., C. Fricke, and E. Moench (2020). Procyclical asset management and bond risk premia. *Deutsche Bundesbank Discussion Paper*.

Blocher, J. and R. E. Whaley (2014). Passive investing: The role of securities lending. *Working Paper*.

Boguth, O. and M. Simutin (2018). Leverage constraints and asset prices: Insights from mutual fund risk taking. *Journal of Financial Economics 127*(2), 325–341.

Bollen, N. and J. Busse (2006). Tick size and institutional trading costs: Evidence from mutual funds. *Journal of Financial and Quantitative Analysis 41*, 915–937.

Breuer, P. (2002). Measuring off-balance-sheet leverage. *Journal of Banking & Finance 26*, 223–242.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*, 57–82.

Chen, H., L. Cohen, and U. Gurun (2021). Don't take their word for it: The misclassification of bond mutual funds. *Journal of Finance (forthcoming)*.

Chen, Q., I. Goldstein, and H. Jiang (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics 97*, 239–262.

Chevalier, J. and G. Ellison (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy 105*(6), 1167–1200.

Chevalier, J. and G. Ellison (1999). Career concerns of mutual fund managers. *Quarterly Journal of Economics 114*(2), 389–432.

Chodorow-Reich, G. (2014). Effects of unconventional monetary policy on financial institutions. *Brookings Papers on Economic Activity (Spring*, 155–204.

Choi, J. and M. Kronlund (2018). Reaching for yield in corporate bond mutual funds. *Review of Financial Studies 31*(5), 1930–1965.

Committee of European Securities Regulators (2010). Guidelines on risk measurement and the calculation of global exposure and counterparty risk for ucits. Technical report.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*, 479–512.

Daniel, K., L. Garlappi, and K. Xiao (2021). Monetary policy and reaching for income. *Journal of Finance (forthcoming)*.

Duarte, F. and T. Eisenbach (2020). Fire-sale spillovers and systemic risk. *Journal of Finance (forthcoming)*.

European Central Bank (2014). Structural and systemic risk features of Euro Area investment funds. Financial Stability Review.

Evans, R., M. A. Ferreira, and M. P. Prado (2017). Fund performance and equity lending: Why lend what you can sell? *Review of Finance*, 1093–1121.

Evans, R. B. and R. Fahlenbrach (2012). Institutional investors and mutual fund governance: Evidence from retail-institutional fund twins. *Review of Financial Studies 25*, 3530–3571.

Feroli, M., A. K. Kashyap, K. Schoenholtz, and H. S. Shin (2014). Market tantrums and monetary policy. Report for the 2014 US monetary policy forum.

Fricke, D. and H. Wilke (2020). Connected funds. *Deutsche Bundesbank Discussion Paper 48/2020*.

Goldstein, I., H. Jiang, and D. Ng (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics 126*(3), 592–613.

Greppmair, S., S. Jank, P. A. C. Saffi, and J. Sturgess (2020). Securities lending and information acquisition. *Mimeo (Deutsche Bundesbank)*.

Grinblatt, M. and S. Titman (1993). Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of Business 66*, 47–68.

Huang, J., C. Sialm, and H. Zhang (2011). Risk shifting and mutual fund performance. *Review of Financial Studies 24*, 2575–2616.

International Monetary Fund (2018). Global financial stability review. Technical report.

International Organization of Securities Commissions (1999). Securities lending transactions: Market development and implications. Technical report.

Jiang, W., J. Ou, and Z. Zhu (2019). Mutual fund holdings of credit default swaps: Liquidity, yield, and risk. Technical report.

Joseph, A. (2019). A framework for statistical inference on machine learning models. Working Paper, Bank of England.

Kacperczyk, M., C. Sialm, and L. Zheng (2008). Unobserved actions of mutual funds. *Review of Financial Studies 21*, 2379–2416.

Kaniel, R. and P. Wang (2020). Unmasking mutual fund derivative use during the covid-19 crisis. *SSRN Working Paper*.

Kaplan, S. N., T. J. Moskowitz, and B. A. Sensoy (2013). The effects of stock lending on security prices: An experiment. *Journal of Finance 68*, 1891–1936.

Koski, J. and J. Pontiff (1999). How are derivatives used? evidence from the mutual fund industry. *Journal of Finance 54*, 791–816.

Meier, I. and E. Schaumburg (2006). Do funds window dress? evidence for u.s. domestic equity mutual funds. Technical report.

Molestina Vivar, L., M. Wedow, and C. Weistroffer (2020). Burned by leverage? flows and fragility in bond mutual funds. *ECB Working Paper No. 2413*.

Pastor, L., R. F. Stambaugh, and L. A. Taylor (2015). Scale and skill in active management. *Journal of Financial Economics 116*(1), 23–45.

Pastor, L., R. F. Stambaugh, and L. A. Taylor (2020). Fund tradeoffs. *Journal of Financial Economics 138*(3), 614–634.

Shapley, L. (1954). A value for n-person games. *Contributions to the Theory of Games*, 307–317.

Stulz, R. M. (2010). Credit default swaps and the credit crisis. *Journal of Economic Perspectives 24*, 73–92.

Internet Appendix

Synthetic Leverage and Fund Risk-Taking

A Regulatory Background: Global Derivatives Exposures in the EU

The UCITS Directive 2010/43/EU and the Guidelines on Risk Measurement and the Calculation of Global Exposure and Counterparty Risk (CESR (2010)) regulate the use of leverage of UCITS funds domiciled in the EU.[31] The UCITS Directive specifies that funds may borrow up to 10% of its TNA for purposes other than investment. Moreover, the Directive contains specific guidelines on the calculation of global exposures from the use of derivatives, which must be calculated at least on a daily basis and must be complied with on an ongoing basis. With regard to the calculation of global exposures, UCITS management companies can choose between two broad approaches:

- The **commitment approach** is applicable to funds with basic investment strategies that take directional risk by means of derivatives instruments. Effectively, the approach converts derivatives exposures into equivalent positions in the underlying instruments (market value). In addition to derivatives positions, this approach takes into account techniques and non-derivative instruments that may create leverage (such as repurchase agreements or securities lending transtions[32]). Moreover, the commitment approach allows fund managers to reduce their global exposure via netting/hedging arrangements, which must satisfy a number of strict criteria. The UCITS Directive specifies that a fund's global exposure should not exceed its TNA.

- For more sophisticated investment strategies that take non-directional risk (e.g., volatility risk, gamma risk, or basis risk), fund managers can use one of two **Value-at-Risk** (VaR) approaches:

[31] Alternative Investment Funds in the EU are regulated under the Alternative Investment Fund Managers Directive (AIFMD). Under the AIFMD, asset managers have to report different leverage measures compared to the UCITS Directive. Also, whereas the UCITS Directive limits the use of leverage, the AIFMD does not impose hard limits.

[32] The CESR (2010) explains that a repo transaction will almost always give rise to leverage for the selling counterparty, since the cash collateral received must be reinvested at a yield greater than the financing costs incurred in order to make a return. Similarly, for securities lending transactions the securities lender may reinvest the cash collateral received, which also creates leverage, i.e., global exposure.

1. The **relative VaR** compares a fund's return VaR with the VaR of the fund's *unleveraged benchmark* portfolio. The relative VaR should not exceed twice the benchmark VaR, which means that the fund is allowed to double the risk of an extreme loss. Specifically, the benchmark portfolio ...

   - should be unleveraged and should not include any derivatives instruments (except for UCITS engaging in long/short strategies).
   - should be consistent with the investment objectives, policies and limits of the UCITS portfolio. In other words, the reference portfolio should have a risk profile that is very close, if not identical, to the UCITS' unleveraged securities portfolio.
   - used by the UCITS should not change frequently, otherwise the relative VaR should not be used.

2. The **absolute VaR** approach requires that a fund's VaR may not exceed 20% of its TNA. This approach would be particularly relevant for UCITS that invest in several asset classes (e.g., mixed funds) without a specific benchmark target. A number of calculation standards are specified for the absolute VaR. For example, fund managers should use ...

   - a one-tailed confidence interval of 99%,
   - a holding period equivalent to 1 month (20 business days),
   - input data of at least one year (except for volatile market periods),
   - at least daily VaR calculations.

Note that neither VaR approach explicitly incorporates the use of derivatives and/or securities financing transactions. In fact, as discussed by **?**, the absolute VaR approach generally allows a greater usage of derivatives than the two alternative approaches. Whereas both the committment approach and the relative VaR approach aim to curtail the gearing effect of leverage (whichever its source), the absolute VaR approach does not limit leverage per se, but rather the maximum potential return loss under normal market conditions.

Relation to Δ-based Framework. I should note that the relative VaR approach is related to my methodology in the following sense: here, I use R^H as the unleveraged benchmark portfolio return, since it satisfies most of the criteria laid out above. For the relative VaR,

$$\kappa^{\text{rel}} = \frac{\text{VaR}(R)}{\text{VaR}(R^H)} < 2 \tag{11}$$

would then be an alternative measure of synthetic leverage.

Under the absolute VaR, a synthetic leverage measure would be

$$\kappa^{\text{abs}} = \text{VaR}(R) - 0.2. \tag{12}$$

In principle, I could estimate these two VaR measures. One important issue, however, is that the UCITS Directive requires, among other things, the use of daily information. Here, I only have monthly information on the two fund return series (including the reported asset portfolios).

B Shapley Value Regressions

The concept of Shapley values comes from coalitional game theory (Shapley (1954); Joseph (2019)). One can think of a regression as the game, where each explanatory variable is a player and the quality of the fit is the payoff. By cooperating, players can receive a certain payoff. The relative importance of a player, its Shapley value, thus depends on its contribution to the total payoff. Intuitively, for each of the K factors, we check how much R^2 changes on average when adding the factor to a given model, across all possible model specifications. More formally, let $X(k,q)$ be the q-membered subset of X in which factor k appears, and $R^2(k,q)$ be the corresponding R^2 from the regression $y = b_0 + b_q \cdot X(k,q) + \epsilon$. Also, let $X(l,r)$ be the r-membered subset of X in which factor k does not appear, with corresponding $R^2(l,r)$. The relative importance (Shapley value, S_k) of factor k is equal to

$$S_k = \frac{1}{K} \sum_{q=1}^{K} \left[\sum_{c=1}^{C} (R^2(k,q) - R^2(l,q-1))_c \right] / C, \tag{13}$$

where C is the number of evaluations that were carried out.

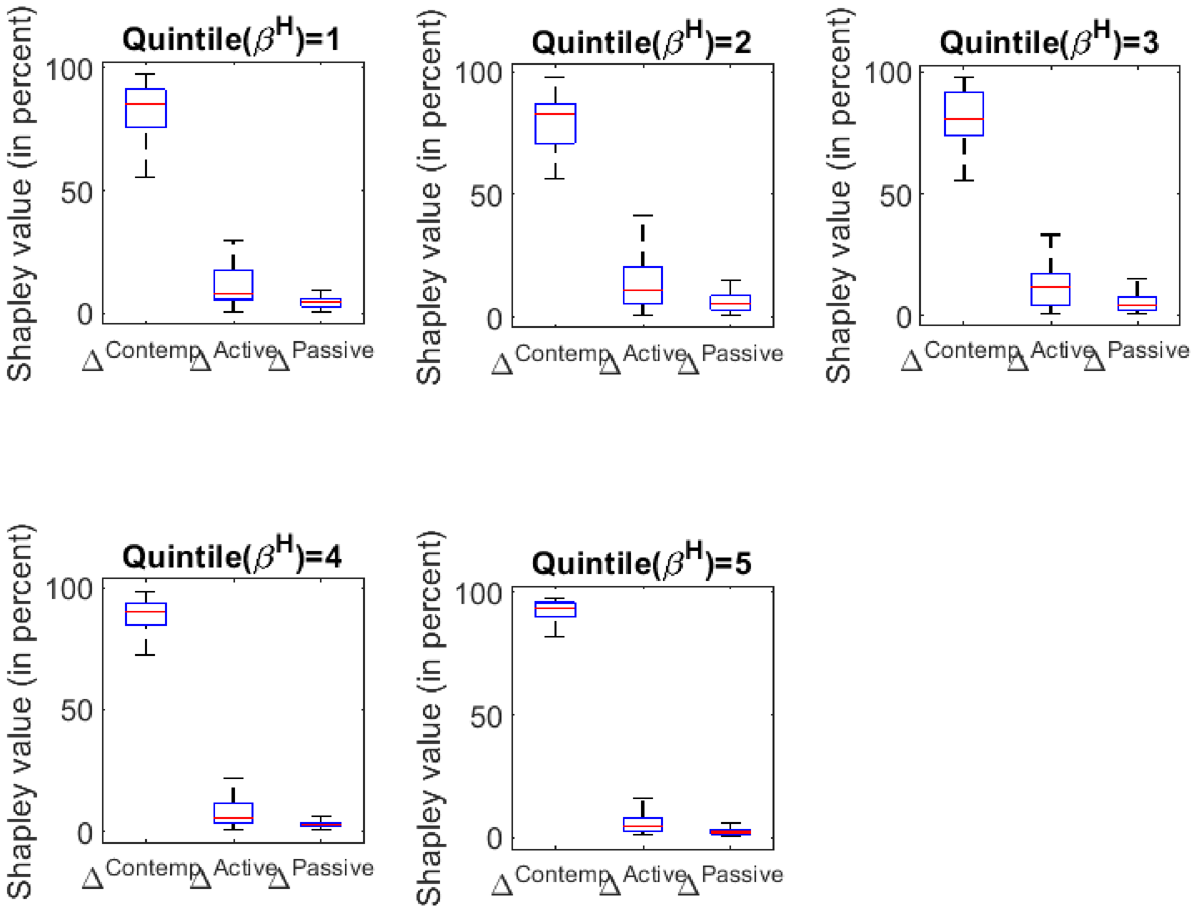

Figure 7: Illustration of the cross-sectional distribution of the relative contribution for the three components of Δ (as measured by the Shapley value). For each fund f with at least 36 monthly observations, I estimate the corresponding Shapley values over the full sample. I show the results for funds from different β^H quintiles (using the fund-specific full sample average value of β^H).

C Robustness Analyses

To move beyond the univariate approach in Table 10, I also estimate a multinominal logistic regression with the basic structure

$$\text{Prob}(\text{Quintile}(\beta^H_{t,f}) = j) = \frac{\exp(\beta'_j \times x_{t,j})}{\sum_k^J \exp(\beta'_k \times x_{t,k})} \text{ for } j = 1, \ldots, 5. \quad (14)$$

As before, I define quintile 3 as the baseline category, such that all parameters are estimated relative to this category.[33] Parameters are estimated using Maximum Likelihood (standard errors clustered at the fund level).

The results are shown in Table 10, where I drop some of the characteristics from Table 3 due to potential collinearity issues. The left-hand specification shows the results for the full sample, excluding the derivatives and securities lending indicators. The right-hand specification shows the results for the reduced sample period including these indicators. While the results are broadly consistent with those from the univariate analysis in Table 3, some results turn out to be insignificant after adjusting for a number of characteristics at the same time. For example, in the multivariate comparison, both the turnover ratio and the expense ratio of risk-taking funds turn out to be indistinguishable from those of funds in quintile 3. With regard to the validation, however, even after controlling for other fund characteristics, risk-taking funds are significantly more likely to make use of derivatives, while there is no significant effect of securities lending.

[33] A more parsimonious approach would be to use the ordered logistic regression. The key difference is that the ordered logistic regression restricts the marginal effects to be the same for each outcome. In contrast, the multinomial logistic regression permits full parameters flexibility. Given that my sample is reasonably large, the benefits of the multinomial logit make it the preferred specification.

Multinomial Logit

Prob(Quintile(β^H_{t+1})=j)	Full sample				Reduced sample: 2014/12-2020/05			
	1 (Hedging)	2	4	5 (Risk-taking)	1 (Hedging)	2	4	5 (Risk-taking)
$R_{t-35:t}$	-21.823	-16.797	75.650***	176.017***	-18.887	-34.149*	98.941***	178.324***
	(23.153)	(17.533)	(20.862)	(23.298)	(26.134)	(17.937)	(25.653)	(29.191)
$Sd(R_{t-35:t})$	-37.890*	-12.099	-4.426	32.689	-6.598	23.171	-38.793	54.854
	(19.366)	(16.271)	(16.428)	(22.053)	(27.993)	(21.213)	(28.764)	(36.560)
$DownsideRisk(R_{t-35:t})$	-0.161	2.277	23.921***	39.533***	-15.243	-14.774	41.690***	37.628**
	(9.421)	(7.072)	(8.038)	(9.125)	(12.019)	(9.009)	(12.933)	(14.766)
$Flows_{t-35:t}$	-15.758	3.561	-4.769	19.034	-18.797	-3.685	-13.043	4.240
	(11.608)	(8.531)	(9.731)	(13.408)	(12.909)	(8.770)	(11.508)	(13.001)
$Sd(Flows_{t-35:t})$	3.385	1.673	1.464	0.304	4.799	2.110	8.700	8.976
	(5.088)	(3.910)	(4.714)	(6.977)	(6.598)	(4.529)	(5.611)	(7.175)
$Turnover_{t-35:t}$	2.856	1.261	1.880	-1.681	6.876**	3.297	3.549	1.042
	(2.447)	(1.715)	(1.827)	(3.599)	(2.947)	(2.276)	(2.179)	(4.051)
log(Age)	-0.010	-0.057	0.084	0.176	-0.063	-0.265	0.014	0.030
	(0.228)	(0.155)	(0.183)	(0.278)	(0.238)	(0.164)	(0.192)	(0.314)
$CashRatio_{t-35:t}$	-3.507	-3.931*	5.199**	13.078***	-3.562	-1.880	6.798**	14.104***
	(2.945)	(2.278)	(2.468)	(2.862)	(3.496)	(2.662)	(2.762)	(3.322)
ExpenseRatio	0.158	0.196	0.024	-0.184	0.230	0.224	0.125	0.005
	(0.255)	(0.198)	(0.216)	(0.302)	(0.306)	(0.228)	(0.229)	(0.346)
I(ETF/Index fund)	0.452	0.731**	-1.038**	-2.299***	0.431	0.175	-1.017**	-2.151***
	(0.531)	(0.334)	(0.461)	(0.731)	(0.619)	(0.393)	(0.511)	(0.818)
$log(HHI_t)$	0.683***	0.279**	-0.420***	-0.661***	0.714***	0.216*	-0.187	-0.376
	(0.197)	(0.119)	(0.143)	(0.256)	(0.220)	(0.129)	(0.154)	(0.281)
$Leverage_{t-35:t}$	-54.074	-52.475	-29.126	38.362	-72.702	-36.441	-65.395*	-28.986
	(47.001)	(37.815)	(41.283)	(48.269)	(45.479)	(29.716)	(34.651)	(40.598)
$log(TNA_t)$	0.011	0.015	0.005	-0.055	-0.003	0.079	-0.024	-0.159
	(0.097)	(0.059)	(0.064)	(0.103)	(0.110)	(0.070)	(0.075)	(0.115)
$log(TNA^{Family})$	-0.119	-0.124**	0.019	-0.008	-0.014	-0.006	0.045	0.064
	(0.083)	(0.052)	(0.059)	(0.081)	(0.104)	(0.056)	(0.063)	(0.093)
Morningstar Rating	-0.217*	0.051	0.045	-0.092	-0.250*	0.003	0.022	-0.083
	(0.111)	(0.081)	(0.095)	(0.151)	(0.131)	(0.093)	(0.103)	(0.153)
Minimum Investment Amount	0.040	-0.018	-0.016	-0.056	0.036	-0.028	-0.033	-0.062
	(0.029)	(0.020)	(0.028)	(0.035)	(0.033)	(0.023)	(0.030)	(0.039)
$I(Derivatives_t)$					0.197	-0.128	0.115	0.836***
					(0.275)	(0.200)	(0.184)	(0.266)
$I(SecLending_t)$					-0.103	-0.225	0.134	0.512
					(0.270)	(0.179)	(0.196)	(0.324)
Constant	60.891	56.205	24.494	-45.069	77.075*	36.650	61.490*	22.317
	(47.203)	(38.045)	(41.555)	(48.359)	(45.508)	(29.710)	(34.867)	(40.710)
Obs.	15,787				11,537			
pseudo-R^2	0.099				0.109			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Multivariate analysis of the characteristics of risk-taking (and hedging) funds based on a multinominal logistic regression. Standard errors (in parentheses) clustered at the fund level. Quintile 3 serves as the baseline category. The left-hand columns show results for the full sample and the right-hand columns for the reduced sample, including indicators for securities lending and derivatives usage.

Dep. var.: Performance (ahead)	gross alpha$^{\text{CAPM}}$ (in percent) (1-month)	(6-month)	(12-month)	(24-month)	gross alpha$^{\text{4F}}$ (in percent) (1-month)	(6-month)	(12-month)	(24-month)
Quintile(β^H)								
1 (Hedging)	-0.044	-0.277	-0.818**	-1.899**	-0.023	-0.166	-0.234	-0.375
	(0.049)	(0.204)	(0.383)	(0.765)	(0.043)	(0.192)	(0.350)	(0.619)
2	0.027	0.174	-0.007	-0.481	0.020	0.084	0.127	0.224
	(0.048)	(0.176)	(0.325)	(0.544)	(0.040)	(0.144)	(0.275)	(0.488)
4	-0.040	-0.155	-0.435	-0.387	-0.064*	-0.274**	-0.408*	-0.211
	(0.037)	(0.156)	(0.265)	(0.527)	(0.033)	(0.138)	(0.234)	(0.413)
5 (Risk-taking)	-0.055	-0.167	-0.789**	-1.833***	-0.076	-0.261	-0.610**	-0.927*
	(0.060)	(0.205)	(0.333)	(0.656)	(0.057)	(0.175)	(0.291)	(0.518)
log(TNA(t-1))	0.015	0.073	0.081	0.119	-0.002	-0.010	-0.049	-0.174
	(0.011)	(0.046)	(0.086)	(0.169)	(0.010)	(0.041)	(0.078)	(0.151)
log(Age)	0.010	-0.048	-0.074	-0.158	-0.023	-0.194	-0.381	-0.775
	(0.043)	(0.162)	(0.298)	(0.591)	(0.039)	(0.137)	(0.259)	(0.517)
ExpRatio	0.078*	0.358**	0.476	0.983*	0.015	0.051	0.026	-0.312
	(0.040)	(0.177)	(0.312)	(0.588)	(0.027)	(0.122)	(0.235)	(0.469)
Constant	-0.377	-1.585	-1.473	-2.022	0.100	0.717	2.018	5.717**
	(0.260)	(0.990)	(1.669)	(2.938)	(0.237)	(0.789)	(1.398)	(2.557)
Time FEs	√	√	√	√	√	√	√	√
Style FEs	√	√	√	√	√	√	√	√
Obs.	20,500	18,896	17,068	13,689	20,500	18,896	17,068	13,689
adj.-R^2	0.116	0.102	0.101	0.112	0.142	0.120	0.127	0.127

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Performance analysis. Regression of different measures of future fund gross performance on the β^H quintiles. All specifications include time and style FEs (standard errors in parentheses, clustered by fund and by date). Fund controls included lagged TNA, Age, and the expense ratio.

Dep. var.:	Raw Return			Alpha CAPM (monthly)			Alpha 4F (monthly)		
Perf(t)	All	Low VIX	High VIX	All	Low VIX	High VIX	All	Low VIX	High VIX
$Outflow^{weak}$(t-1)	-0.068	-0.146*	0.018	-0.082	-0.198***	0.065	-0.015	-0.124*	0.098
	(0.069)	(0.081)	(0.108)	(0.060)	(0.075)	(0.092)	(0.053)	(0.070)	(0.078)
$Outflow^{moderate}$(t-1)	0.051	-0.046	0.111	-0.033	-0.131	0.087	0.062	-0.031	0.159
	(0.090)	(0.091)	(0.140)	(0.071)	(0.091)	(0.117)	(0.065)	(0.077)	(0.101)
$Outflow^{large}$(t-1)	0.145	0.209	0.044	0.130	0.128	0.143	0.155	0.190	0.104
	(0.146)	(0.177)	(0.297)	(0.117)	(0.141)	(0.186)	(0.116)	(0.137)	(0.176)
Quintile(β^H)									
1 (Hedging)	-0.113	-0.141	-0.086	-0.047	-0.029	-0.040	0.033	0.026	0.051
	(0.076)	(0.103)	(0.114)	(0.065)	(0.082)	(0.094)	(0.060)	(0.076)	(0.091)
2	-0.074	-0.165*	0.017	-0.042	-0.049	-0.014	0.004	-0.064	0.072
	(0.073)	(0.086)	(0.109)	(0.066)	(0.084)	(0.102)	(0.058)	(0.077)	(0.095)
4	-0.071	-0.107	-0.028	-0.100	-0.143*	-0.049	-0.042	-0.081	-0.015
	(0.074)	(0.087)	(0.108)	(0.065)	(0.079)	(0.094)	(0.055)	(0.071)	(0.083)
5 (Risk-taking)	0.061	0.003	0.086	-0.028	-0.173**	0.124	0.003	-0.141**	0.150*
	(0.064)	(0.076)	(0.098)	(0.061)	(0.073)	(0.089)	(0.055)	(0.068)	(0.079)
Interactions									
1 × $Outflow^{weak}$(t-1)	0.138	0.309**	-0.008	0.079	0.215**	-0.093	0.005	0.126	-0.121
	(0.101)	(0.130)	(0.160)	(0.089)	(0.103)	(0.136)	(0.088)	(0.105)	(0.137)
2 × $Outflow^{weak}$(t-1)	0.160*	0.353***	-0.063	0.092	0.198*	-0.066	0.042	0.171	-0.102
	(0.092)	(0.112)	(0.147)	(0.083)	(0.108)	(0.124)	(0.080)	(0.106)	(0.123)
4 × $Outflow^{weak}$(t-1)	0.048	0.212*	-0.132	0.073	0.209**	-0.108	0.031	0.129	-0.061
	(0.095)	(0.114)	(0.143)	(0.082)	(0.100)	(0.119)	(0.068)	(0.090)	(0.105)
5 × $Outflow^{weak}$(t-1)	0.065	0.195*	-0.072	0.045	0.204**	-0.157	-0.016	0.120	-0.152
	(0.093)	(0.109)	(0.137)	(0.079)	(0.098)	(0.121)	(0.073)	(0.091)	(0.108)
1 × $Outflow^{moderate}$(t-1)	-0.019	0.131	-0.166	-0.036	0.067	-0.161	-0.087	-0.027	-0.150
	(0.121)	(0.153)	(0.193)	(0.100)	(0.141)	(0.158)	(0.101)	(0.135)	(0.157)
2 × $Outflow^{moderate}$(t-1)	-0.163	0.170	-0.493**	0.023	0.114	-0.089	-0.024	0.027	-0.064
	(0.151)	(0.144)	(0.245)	(0.129)	(0.136)	(0.214)	(0.115)	(0.132)	(0.180)
4 × $Outflow^{moderate}$(t-1)	0.045	0.144	-0.060	0.093	0.140	0.024	-0.091	-0.041	-0.130
	(0.114)	(0.128)	(0.179)	(0.101)	(0.126)	(0.160)	(0.093)	(0.112)	(0.146)
5 × $Outflow^{moderate}$(t-1)	-0.118	0.059	-0.237	-0.066	0.005	-0.185	-0.201**	-0.108	-0.306**
	(0.103)	(0.125)	(0.170)	(0.096)	(0.120)	(0.158)	(0.099)	(0.113)	(0.144)
1 × $Outflow^{large}$(t-1)	-0.474*	-0.485**	-0.350	-0.425*	-0.430*	-0.394	-0.438**	-0.476*	-0.387
	(0.263)	(0.241)	(0.464)	(0.235)	(0.237)	(0.352)	(0.210)	(0.248)	(0.305)
2 × $Outflow^{large}$(t-1)	-0.134	0.139	-0.336	-0.239	-0.216	-0.337	-0.162	-0.326	-0.010
	(0.231)	(0.245)	(0.400)	(0.218)	(0.276)	(0.310)	(0.205)	(0.300)	(0.295)
4 × $Outflow^{large}$(t-1)	-0.358	-0.741***	0.091	-0.235	-0.340*	-0.104	-0.240	-0.464**	0.011
	(0.238)	(0.282)	(0.349)	(0.174)	(0.204)	(0.301)	(0.159)	(0.199)	(0.256)
5 × $Outflow^{large}$(t-1)	-0.622***	-0.283	-0.776**	-0.580***	-0.202	-0.892***	-0.465**	-0.157	-0.708**
	(0.235)	(0.262)	(0.388)	(0.204)	(0.205)	(0.319)	(0.200)	(0.212)	(0.294)
Fund controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Style FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	16,566	8,479	8,087	16,566	8,479	8,087	16,566	8,479	8,087
adj.-R^2	0.838	0.592	0.874	0.148	0.182	0.141	0.173	0.189	0.174

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Externality regressions as in Table 7, but with different Outflow indicators. All specifications include time and style fixed effects. Standard errors (in parentheses) clustered by fund and by date. I use monthly fund performance measures as described in Evans and Fahlenbrach (2012). I show results separately for all observations, and for periods with low and high VIX (months when the VIX is above its full sample median value), respectively. Note: ETFs are excluded from this analysis.

Dep. var.: Share of	Small Outflows			Moderate Outflows			Large Outflows		
positions ...	... Constant	... Reduced	... Eliminated	... Constant	... Reduced	... Eliminated	... Constant	... Reduced	... Eliminated
Quintile(β^H)=1	-4.028***	2.204***	-0.142	-3.663**	-0.679	-2.043***	-1.943	-0.217	0.490
	(0.445)	(0.237)	(0.204)	(1.260)	(1.204)	(0.299)	(3.143)	(2.356)	(0.752)
Quintile(β^H)=2	-2.976***	1.410***	0.008	-4.152**	1.910	-0.766**	-4.512**	1.781	-1.662***
	(0.521)	(0.294)	(0.210)	(1.378)	(1.036)	(0.264)	(1.174)	(2.685)	(0.281)
Quintile(β^H)=4	-1.251**	-0.199	0.110	2.867**	-2.531**	-1.757*	2.744	-0.957	1.731
	(0.290)	(0.175)	(0.084)	(0.746)	(0.891)	(0.645)	(3.091)	(1.588)	(1.534)
Quintile(β^H)=5	-2.213	1.536**	-0.018	-1.123	-0.051	-0.937	13.046**	-12.876**	-1.591
	(1.104)	(0.459)	(0.188)	(1.036)	(1.120)	(0.512)	(3.244)	(3.524)	(1.397)
Quintile(β^H)=1 × High VIX	2.315**	-0.259	0.139	2.643**	0.986	1.817**	3.166	7.281***	2.751**
	(0.611)	(0.374)	(0.265)	(0.914)	(0.570)	(0.462)	(4.456)	(1.456)	(0.818)
Quintile(β^H)=2 × High VIX	2.331**	-0.331	-0.387	1.887	1.032	2.211***	6.663	3.514	0.844
	(0.643)	(0.340)	(0.196)	(1.294)	(0.873)	(0.369)	(5.324)	(3.014)	(0.532)
Quintile(β^H)=4 × High VIX	0.920	0.830**	0.084	-4.988***	5.246***	3.003***	2.652	-4.167	-0.842
	(0.532)	(0.274)	(0.147)	(0.737)	(0.565)	(0.524)	(4.162)	(2.711)	(1.867)
Quintile(β^H)=5 × High VIX	-0.318	1.005**	-0.068	0.712	0.297	0.853	-9.885**	6.565**	3.848*
	(0.515)	(0.274)	(0.130)	(1.039)	(0.936)	(0.488)	(3.232)	(1.726)	(1.526)
log(Number Pos(t-1))	0.508	-2.748	0.711	3.979	-6.872**	1.289**	12.591	-6.787	3.776
	(4.400)	(2.817)	(0.851)	(3.099)	(1.526)	(0.284)	(6.033)	(4.847)	(2.828)
High VIX	-3.087***	1.046**	0.469**	-1.831	0.220	-1.416**	-5.544	0.269	-0.240
	(0.421)	(0.325)	(0.117)	(0.876)	(0.734)	(0.326)	(3.513)	(2.099)	(0.995)
Constant	65.538**	32.145*	2.133	45.956**	54.562***	1.364	-2.925	61.668**	-8.630
	(19.130)	(12.136)	(3.727)	(12.748)	(5.727)	(1.004)	(24.202)	(19.073)	(11.080)
Fund FEs	√	√	√	√	√	√	√	√	√
adj.-R^2	0.584	0.424	0.249	0.525	0.356	0.245	0.510	0.297	0.258
Obs.	7,112	7,112	7,112	2,970	2,970	2970	498	498	498

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Regression of asset-level portfolio adjustments as a function of funds' net flows à la Coval and Stafford (2007). As in Tables 8-9, I define *weak* outflows as fund-month observations with outflows of less than 1%. *Moderate* outflows are between 1% and 5% and *large* outflows are larger than 5%. All regressions include fund FEs, standard errors are clustered by date and quintile. Note: ETFs are excluded from this analysis.