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The Effect of Regulatory Constraints on Fund Performance: New Evidence from UCITS Hedge Funds*

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Abstract

This article examines the effect of regulatory constraints on fund performance and risk by comparing conventional and UCITS hedge funds. Using a matching estimator approach, we estimate the indirect cost of UCITS regulation to be between 1.06% and 4.05% per annum in terms of risk-adjusted returns. These performance differences are likely to stem from UCITS constraints such as those governing eligible assets, diversification, and short selling, and cannot be explained by differences in redemption terms or level of leverage. We confirm that our performance results are not driven by management company characteristics, fund manager characteristics, or unobserved confounder bias.

JEL classification: G11, G12, G23

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1. Introduction

The aim of this article is to examine the effect of regulatory constraints on the performance and risk of alternative investment funds. Regulatory constraints imposed on investment funds vary significantly in terms of diversification and liquidity requirements, risk limits, and eligible assets and instruments. Since regulatory constraints directly affect the investment opportunity set of a hedge fund manager as well as potentially constraining that manager's efficient portfolio management techniques, it is almost certain that constraints impact fund performance and risk. To better understand the implications of regulatory constraints, we compare UCITS[1] hedge funds to conventional hedge funds managed under the Dodd Frank Act or the AIFM Directive.[2] Since the UCITS Directive is not as restrictive as the Investment Company Act of 1940, it provides us with a novel setting to examine the effects of regulatory constraints. Even though the origin of UCITS regulation is Europe, UCITS funds are recognized—and can be marketed—in at least seventy-five countries worldwide.[3] Our study sample likely contains almost the entire UCITS hedge fund population. As Table I reports, the current size of the UCITS hedge fund universe is around $420 billion, which is around one-fifth of the $2.4 trillion hedge fund assets reported to seven commercial databases. The UCITS hedge fund universe, therefore, constitutes an economically important yet unexamined part of the asset management industry. Building on UCITS regulatory restrictions, to our knowledge, this article is the first to contribute to the delegated portfolio management literature by using a careful matching estimator approach to quantify the effect of regulatory constraints.

To identify the effect of regulatory constraints associated with UCITS hedge funds when compared to conventional hedge funds, we employ Rubin's (1974) potential outcome framework that defines the causal effect as the difference between an observed outcome and its counterfactual. Since we do not observe the same hedge funds both with and without the UCITS regulatory constraint, we estimate the average treatment effects using the Abadie and Imbens (2006, 2011) matching estimator approach. This approach is particularly well suited for our research setting since it allows us to approximate the randomized experiment in a way that is economically motivated and consistent with institutional details. Management firms set the legal structure of a hedge fund at inception so that it (along with other chosen variables) maximizes the present value of lifetime expected compensation. Since the fund's UCITS structure typically does not change over the life of the fund, it is natural to utilize equivalent conventional hedge funds in estimating the effect of regulatory constraints. Estimators for treatment effects based on matching have several advantages over regression-based estimators. Matching greatly reduces the dependency on functional form and allows for greater transparency in the modeling process. Compared to instrumental variables estimation, we do not need to worry about exclusion restrictions and related distributional assumptions that may not be valid.

1 The acronym UCITS stands for Undertakings for Collective Investment in Transferable Securities, which is the European harmonized and regulated fund product. It can be sold on a cross-border basis within the EU based solely on its authorization in a single EU member state.

2 The objective of the Alternative Investment Fund Manager (AIFM) Directive is to create a comprehensive and secure framework for the supervision and prudential oversight of such managers in the EU.

3 Carne Group, "UCITS Guide for Alternative Managers," June 30, 2012.

Table I. Summary statistics

Panel A reports the aggregate AUM of UCITS hedge funds and conventional hedge funds. "*N*" is the number of funds in given year. "Total AUM" provides aggregate AUM that is measured in billions of US dollars for hedge funds that report to the commercial databases (BarclayHedge, Eurekahedge, eVestment, HFR, Lipper TASS, Morningstar, and Preqin). "Attrition rate" is the percentage of funds that became inactive during the year. For both unmatched and matched samples, Panel B presents the mean difference tests for UCITS and conventional hedge funds. "Initial (Maximum) size" denotes the fund's initial (maximum) size in millions of US dollars. "Management fee" shows the average management fee within a specific category. "Incentive fee" denotes the performance-based fee that fund charges. "High-water mark" indicates whether a fund imposes a high-water mark provision. "Restriction period" is the sum of redemption and notice periods. "Lockup period" denotes the length of time when investors are restricted from withdrawing their initial investment. "Leverage level" is the amount of average leverage. "Inception date" denotes when the fund started to report returns.

Panel A: Number of funds and total AUM

	UCITS			Conventional		
Year	*N*	Total AUM	Attrition	*N*	Total AUM	Attrition
2003	201	9.39	0.00	5,661	665.73	8.58
2004	250	16.82	0.00	6,412	947.28	8.36
2005	312	31.56	0.00	7,174	1098.40	10.01
2006	402	58.68	0.64	7,868	1496.61	10.64
2007	506	81.60	0.50	8,370	1911.79	12.04
2008	622	50.90	1.38	8,240	1375.43	17.97
2009	814	96.45	1.45	8,310	1381.71	14.13
2010	1,037	163.19	3.56	8,411	1604.33	13.01
2011	1,189	200.24	6.65	8,456	1527.26	13.30
2012	1,219	267.27	11.35	8,319	1696.95	14.76
2013	1,243	374.07	11.57	8,224	1851.86	14.00
2014	1,259	427.81	9.57	7,920	1912.28	14.58
2015	1,258	458.00	10.48	7,168	2025.50	15.82
2016	1,161	433.50	13.83	6,137	1963.11	18.53

Panel B: Summary statistics of fund characteristics

		Unmatched			Matched		
Variable	UCITS	Unmatched	Diff	*t*-statistic	Conventional	Diff	*t*-statistic
Maximum size (M USD)	530.95	396.57	134.38	3.91	411.28	119.67	2.73
Initial size (M USD)	111.01	141.27	−30.26	−2.71	80.54	30.46	2.52
Log of initial size	3.37	2.94	0.43	6.56	3.26	0.11	1.38
Restriction period (in weeks)	0.48	11.69	−11.22	−90.05	0.50	−0.02	−17.25
Lockup period (in weeks)	0.00	13.64	−0.26	−44.20	0.00	0.00	−1.77
Leverage level	51.39	57.81	−6.42	−1.72	44.84	6.54	1.38
Inception date	2009.8	2006.3	3.5	24.65	2009.6	0.1	0.83
Reporting start date	2011.3	2009.5	1.8	21.24	2011.3	0.0	−0.21
Management fee (%)	1.285	1.287	−0.002	−13.61	1.286	−0.001	−3.565
Incentive fee (%)	12.515	12.569	−0.054	−17.85	12.510	0.005	1.131
High-water mark (%)	65.51	65.71	−0.20	−11.49	65.49	0.01	0.61

Our matching approach is well suited to overcome endogeneity biases that can arise from more simplistic methodologies such as those comparing conventional and UCITS hedge funds without matching estimators. Some management companies may launch UCITS funds with specific characteristics such as being, for example, higher liquidity. Our methodology explicitly addresses such endogeneity concerns by matching on observable UCITS regulatory constraints such as redemption terms and leverage. Our results can, therefore, be interpreted as a comparison of UCITS and conventional hedge funds' performance that takes into account performance differences arising from observable fund characteristics. There are however some aspects of UCITS regulation that affect funds in a way that we cannot measure and distinguish separately. The hedge fund data vendors that we rely on do not provide accurate position level information that would allow us to examine the effect of other UCITS regulatory constraints, such as those pertaining to eligible assets, diversification rules, and limitations to a fund's ability to physically sell short.

Using the Abadie and Imbens (2006, 2011) matching estimator approach, we test hypotheses regarding performance and risk. Consistent with the view that UCITS rules constrain the investment opportunity set, we document that UCITS hedge funds deliver lower risk-adjusted performance than conventional hedge funds. Given that hedge fund managers can invest globally in a wide range of asset classes and in illiquid securities, it is not straightforward to assess their risk. Therefore, as a baseline benchmark model, we use a global seven-factor model and its stepwise and smoothing-adjusted versions (details are presented in Section 3.2). Since UCITS regulatory constraints are related to different aspects of liquidity, our benchmark model contains two factors designed to adjust for covariation with market liquidity risk (Pastor and Stambaugh, 2003) and funding liquidity risk (Frazzini and Pedersen, 2014). The underperformance of UCITS hedge funds does not result from potential differences in compensation structures since we find very similar results using both net-of-fee and gross-of-fee risk-adjusted returns. We estimate that UCITS restrictions have an economically and statistically significant effect on the risk-adjusted performance of between 1.06% and 4.05% per annum depending on the benchmark model.[4] The matching estimator methodology allows us to conclude that these performance differences are likely to stem from UCITS constraints such as those governing eligible assets, diversification, and short selling, and cannot be explained by differences in redemption terms or level of leverage.

As our risk hypothesis posits, we find that UCITS hedge funds tend to have lower risk levels than conventional funds. The standard deviations are between 1.24% and 1.53% per annum lower for UCITS funds than for matched conventional funds. To better understand the implications of UCITS regulation, we decompose the total risk into systematic and fund-specific risk components. Consistent with the view that the matching captures differences in systematic risk loadings, we do not find any statistically significant difference in systematic risk between UCITS and conventional hedge funds. Fund-specific risk drives the differences in total risk, suggesting that conventional hedge funds are taking more idiosyncratic bets than UCITS funds. To generate alpha, fund managers need to accept idiosyncratic risk by definition. We find that Sharpe ratios and alpha *t*-statistics are higher for conventional funds than for UCITS hedge funds. This implies that conventional hedge funds are rewarded for the idiosyncratic risk that they take. Overall, UCITS regulation seems to work as intended in the sense that it limits the riskiness of UCITS hedge funds

4 This range is obtained from Table X that summarizes the results based on a large set of benchmark models.

while the idiosyncratic risk taken by matched conventional hedge funds seems to be beneficial for their investors since it leads to relatively superior risk-adjusted performance.

To confirm that our performance difference results are robust, we run a large battery of sensitivity tests. By matching conventional and UCITS funds having the same fund manager or within the same fund management company, we ensure the underperformance of UCITS hedge funds is not associated with management company or fund manager characteristics. This analysis suggests that our matching estimator analysis is not contaminated by unobserved management company-level or fund manager-level confounders related to both treatment assignment and outcome. Because we match on the same fund manager, it is unlikely that performance differences are due to differences in manager talent between UCITS and conventional funds.[5] We cannot however rule out the hypothetical possibility that fund family-level favoritism behavior drives differences in performance. A management company could in theory give its best ideas to conventional hedge funds because of their higher fees and more performance-sensitive clientele. However, such behavior is unlikely and would violate the fiduciary duty of the management company to its investors in different funds.[6]

To ensure that UCITS constraints related to observable fund characteristics do not drive our conclusions, we exactly match the redemption terms and level of leverage between conventional and UCITS hedge funds. Several papers (e.g., Aragon, 2007) document that hedge funds with tight share restrictions outperform; we confirm that even after exact redemption term matching UCITS funds deliver lower risk-adjusted returns than the conventional funds. We also verify that the performance differences hold when we exactly match leverage levels between UCITS and conventional hedge funds. Thus, the performance differences do not seem to be driven by inaccurate liquidity term or leverage matching.

We perform further tests to confirm that our results are robust to the design of the matching methodology. Using the Rosenbaum (2002) bounds, we confirm that our results are not sensitive to the presence of a hidden confounder. Although we carefully match UCITS and conventional funds using observed characteristics, there may exist unobserved characteristics that are not correlated with observed characteristics but are related to outcome variables. This does not seem to be the case based on our analysis which reveals that hidden bias due to an unobserved confounder that can reverse our conclusions is very unlikely. Finally, we employ sophisticated techniques to achieve the optimal balance of fund characteristics between treated and control groups. After applying standard propensity score matching, the genetic matching algorithm developed by Diamond and Sekhon (2013), and the entropy balancing approach of Hainmueller (2012), our results still strongly indicate that UCITS hedge funds underperform conventional hedge funds.

An important follow-up question arises: Why do UCITS hedge funds exist in equilibrium if they underperform conventional hedge funds even after a careful matching estimator analysis? To address this issue, we investigate the motives of hedge fund investors and

5 This is supported by Deuskar *et al.* (2011) who document that mutual funds are able to retain managers with good performance in the face of competition from a growing hedge fund industry.

6 Nohel, Wang, and Zheng (2010) show that side-by-side mutual fund managers deliver higher performance than their peer mutual funds, while side-by-side hedge fund managers provide similar performance as their style category peers. Their article supports the idea that there is no conflict of interest that undermines mutual fund investors. However, Cici, Gibson, and Moussawi (2010) cannot rule out the possibility that side-by-side mutual fund investors are adversely affected by favoritism in an economically meaningful way.

the behavior of management companies. Since the financial crisis, there has been strong demand for more regulated and transparent hedge fund-type investment vehicles. To benefit from changed investor preferences, management companies may strategically launch UCITS hedge funds instead of conventional hedge funds. However, although management companies might be able to gather more assets by launching UCITS funds, they would be better-off by launching conventional funds since these generate higher fee revenues. Consequently, to maximize the present value of expected future compensation, if a management company is able to attract capital to conventional hedge funds, it should launch them instead of UCITS hedge funds.

Our findings support the view that UCITS regulation protects investors, and, therefore, some investors may prefer UCITS funds to better performing conventional hedge funds. We document that management firms that have had relatively low past performance and experienced outflows are more likely to launch UCITS hedge funds. By doing so, these companies are able to gather more capital flows because of investors' high demand for more regulated and transparent products. However, we find that for some management companies (typically those that have had relatively good performance and not experienced outflows), it is optimal to run conventional funds since they are more profitable. Overall, our findings are consistent with an equilibrium in which management firms that experienced lower (higher) performance and flow maximize expected fees by launching and running UCITS (conventional) hedge funds.

The article proceeds as follows: Section 2 derives testable hypotheses and links our article to the existing literature; Section 3 describes the data and provides details regarding the benchmark model and matching estimation approach; Section 4 reports the main results; Section 5 reports the equilibrium analysis results; Section 6 describes the robustness checks undertaken; and Section 7 concludes.

2. Testable Hypotheses and Related Literature

2.1 UCITS Restrictions and Testable Hypotheses

The EU implemented the UCITS Directive in 1985. The directive was extended in 2003 to permit the use of derivatives not only for hedging but also for speculative purposes. This extension made the creation of UCITS hedge funds possible.

Several UCITS rules constrain the investment opportunity set and possible portfolio weights by restricting eligible assets and short selling. Broadly speaking, transferable and liquid assets such as exchange-traded assets are considered eligible, but there are some exceptions. The use of derivatives is subject to stringent requirements to protect the investor from excess leverage and counterparty risk. Derivatives under the UCITS regime may only be entered into where the underlying of the derivative would otherwise be an eligible asset under the so-called "look through rule." The UCITS Directive prohibits the physical (or uncovered) short selling of securities. However, it is possible to obtain synthetic short exposure by using derivatives, most commonly via swaps or by using contracts for differences.

The UCITS diversification rule also may affect the investment opportunity set by protecting investors from excessive exposure to the idiosyncratic risk posed by any single issuer. The foundation of diversification rules within the framework of UCITS is the so-called 5/10/40 rule. The rule states, for instance, that a UCITS fund cannot invest more than 10% of its net asset value in securities issued by a single corporate issuer. Furthermore, the sum of all exposures greater than 5% should not exceed 40% of the fund's net asset valuation. Conventional hedge funds are not restricted by diversification rules.

The UCITS hedge funds must have a separate risk management function and are subject to leverage limits and value-at-risk limits that do not explicitly apply to equivalent conventional hedge funds. The UCITS Directive restricts the use of leverage to protect investors from excessive borrowing and has provisions that address the maximum amount of leverage funds can incur and how to ensure that funds have adequate coverage. In addition, UCITS funds must carefully monitor and manage liquidity risk when investing in any financial assets. UCITS hedge funds must also provide biweekly liquidity for investors, while conventional hedge funds do not typically have restrictions regarding notice, redemption, or lockup periods, and they can even introduce "gates" and "side pockets" for illiquid, hard-to-value assets (Aiken, Clifford, and Ellis, 2015).

The UCITS format aims to protect investors by requiring funds to report net asset valuations that are both timely and accurate. The latest market closing prices must be used when valuing publicly traded securities; when those are not available, the "fair market value" should be used. Rules require that UCITS funds must establish valuation procedures for derivatives that are of an appropriate level of complexity and must disclose those procedures to investors. An outside firm may be appointed to undertake these valuations, but if they are performed internally then the process must be independent of portfolio management *per se* in order to avoid conflicts of interest.

Differences between the regulations governing UCITS hedge funds and conventional hedge funds lead to two testable hypotheses:

Hypothesis 1. *UCITS hedge funds deliver lower performance than conventional hedge funds due to regulatory constraints and a resulting constrained investment opportunity set.*

Hypothesis 2. *Due to tighter regulation, UCITS hedge funds' risk level is lower than the risk level of conventional hedge funds.*

2.2 Related Literature and Contribution

This article is related to several streams of the delegated portfolio management literature. A number of studies examine the drivers of hedge fund risk-adjusted returns using fund characteristics such as share restrictions (Aragon, 2007), manager option deltas (Agarwal, Daniel, and Naik, 2009), past fund performance (Kosowski, Naik, and Teo, 2007; Jagannathan, Malakhov, and Novikov, 2010), fund age (Aggarwal and Jorion, 2010), fund R^2 with respect to common factors (Titman and Tiu, 2011), usage of derivatives and options (Chen, 2011; Aragon and Martin, 2012), and strategy distinctiveness (Sun, Wang, and Zheng, 2012). Closest to us is Almazan *et al.* (2004) who document that various mutual fund investment constraints that, for instance, limit managers' opportunity to employ derivative securities or short sell, are not related to risk-adjusted returns. We contribute to this literature by showing that UCITS regulatory constraints have a significant effect on hedge fund risk-adjusted returns and risk.

Our article is related to the emerging literature on the performance drivers of alternative mutual funds, liquid hedge funds, and hedge funds that report to separate account platforms.[7] Agarwal, Boyson, and Naik (2009) document that alternative mutual funds (which

7 There are earlier studies of UCITS hedge funds (Stefanini *et al.*, 2010; Tuchschmid, Wallerstein, and Zanolin, 2010; Darolles, 2014). These studies use smaller samples of UCITS hedge funds

are governed by the US Investment Company Act of 1940) outperform traditional mutual funds while underperforming conventional hedge funds mainly due to differences in incentives. In contrast to that article, we focus on UCITS hedge funds and compare their performance to conventional hedge funds instead of mutual funds. This is justified because UCITS rules are less stringent than those followed by US alternative mutual funds that are required to provide daily liquidity and are not allowed to charge asymmetric performance-based fees. Closest to us is Cao *et al.* (2017) who examine the costs of removing share restrictions using hedge fund data from a separate account platform. Our article contributes to this literature by exploiting a matching estimator approach which allows us to control explicitly for the role of fund characteristics that might explain fund performance differences. After careful matching, we can conclude that not only previously documented fund characteristics such as share restrictions, but also other UCITS regulatory constraints such as eligible assets, diversification rules, and limitations to sell short, drive hedge fund performance. Indeed, our matching estimator framework is particularly well suited to identifying the indirect cost of regulation on fund performance that is unrelated to share restrictions and other known drivers of hedge fund performance.

Our article is also related to literature that studies the strategic behavior of investment management firms. Pioneering mutual fund papers (Massa, 2003; Nanda, Wang, and Zheng, 2004) examine the degree of product differentiation and positive spillover effects. More recent papers (Cici, Gibson, and Moussawi, 2010; Nohel, Wang, and Zheng, 2010; Deuskar *et al.*, 2011) investigate the performance implications and agency problems when mutual funds and hedge funds are managed side-by-side. Closest to us are papers that examine hedge fund firms' growth strategies. Kolokolova (2011) documents that hedge fund firms with high past returns are more likely to launch new funds in order to attract flows and thereby fee revenues. Fung *et al.* (2020) focus on the performance of the firms' first fund since its superior performance allows the firm to grow from a single-product firm to a multiproduct firm that is able to gather more fee revenues. Relative to that literature we deepen the understanding of firm strategic behavior by documenting that poorly performing hedge fund firms are more likely to launch UCITS hedge funds, while better-performing firms launch conventional hedge funds since running them leads to higher fee revenues.

3. Data and Methodology

3.1 Data

We evaluate the effects of regulatory constraints on hedge fund performance using monthly returns and assets under management (AUM) data of live and dead hedge funds reported to BarclayHedge, Eurekahedge, eVestment, Hedge Fund Research (HFR), Lipper TASS, Morningstar, and Preqin databases. For each hedge fund, along with the UCITS indicator variable[8] we collect the fund variables related to compensation structure, share restrictions, leverage, database listing date, inception date, and investment strategy. Like Barth *et al.*

and do not analyze the effect of UCITS restrictions on fund performance, risk, and net asset valuations.

8 UCITS indicator gets a value of one when the fund is identified as a UCITS hedge fund, and otherwise zero. We determine UCITS funds by using vendors' classifications and by parsing from fund names and strategy descriptions.

(2020), we classify hedge funds into eight Form PF investment strategies: Credit, Equity, Event-driven, Macro, Managed futures, Multistrategy, Relative value, and Other. Although the survivorship bias-free hedge fund data starts from January 1994, we focus on the period starting from January 2003. This is motivated by the 2003 change in EU regulation that allowed management firms to launch UCITS funds with a possibility to employ various derivatives not only to hedging but also for efficient portfolio management purposes. While we download hedge fund data in mid-2017, we mitigate the impact of strategic delays in reporting by hedge funds by dropping the last few months of returns (Aragon and Nanda, 2017) thereby ending our study period at December 2016.

To merge the commercial databases, we apply the aggregation procedure developed by Joenväärä *et al.* (2019). This yields a total of 23,002 funds, of which 2,005 are UCITS hedge funds and 20,997 are conventional hedge funds. At the end of sample period, 7,298 (31.7%) of funds are still reporting to databases, comprising 1,161 (57.9%) UCITS funds and 6,137 (29.2%) conventional funds. Out of all UCITS funds, 21 (1.1%) report to all seven commercial databases, while 945 (47.1%) report to only one. The largest number of such vendor unique UCITS funds is found in Eurekahedge (387), HFR (191), and BarclayHedge (174) databases. Together, these three databases comprise 1,793 (89.4%) of our sample UCITS funds, but only 15,232 (72.5%) of conventional funds. Table I reports the total AUM in billions of US dollars for both UCITS and conventional hedge funds. As of December 2016, UCITS funds managed around one-fifth of the total hedge fund universe that was reported to commercial databases. The use of seven databases guarantees that our sample is as comprehensive as possible and likely contains an almost complete UCITS hedge fund population, thereby creating a unique setting to study the effect of regulatory constraints.

Because hedge fund firms report voluntarily to data vendors, data potentially suffers from many biases (Liang, 2000; Fung and Hsieh, 2000, 2009). To mitigate data biases and to correct obvious data errors, we follow the procedures outlined in Joenväärä *et al.* (2019). As Table I shows, data vendors started to collect information on the delisting of UCITS funds around 2007; the attrition rates for the UCITS funds are very close to zero before 2007. To mitigate the effect of potential survivorship bias, we restrict our sample period to start from January 2007.[9] This choice is also supported by the low number of UCITS hedge funds before that date. Another concern is the timing of when data vendors started to collect information on a fund's UCITS status. To control for potential look-ahead bias, as a robustness test reported in Section 6, we utilize multiple database snapshots starting in 2007 and redo our main tests.

To address backfill bias, like Joenväärä *et al.* (2019), we utilize all available database-level information on a fund's listing dates to produce a fund-level listing date and remove all return observations prior to that date as backfilled. If available, we select the earliest reported listing date as the fund-level listing date. Otherwise, we use the algorithm of Jorion and Schwarz (2019) to impute the listing dates, and again select the earliest date. This approach minimizes the backfill bias and maximizes the amount of return observations. We find that the average number of backfilled return observations is 6.4 months higher for UCITS funds (25.9 months) compared to the conventional funds (19.5 months). This indicates that listing data method provides a fairer way than arbitrary cuts such as 12 or 24 months.

9 Our results are virtually identical when we start our sample from January 2003.

3.2 Performance Benchmarking

Since hedge fund managers have the freedom to allocate globally across different asset classes, invest in illiquid instruments, and employ leverage as well as derivatives, it is challenging to evaluate their risk. Therefore, throughout this article, we use several ways to model the risk of hedge funds. As a baseline model, we employ the global seven-factor model.[10] The factors of the model are the excess return on global equity market, size factor, and value factor of Fama and French (2012); global cross-sectional momentum of Asness, Moskowitz, and Pedersen (2013); global time-series momentum of Moskowitz, Ooi, and Pedersen (2012); global betting-against-beta of Frazzini and Pedersen (2014); and liquidity risk of Pastor and Stambaugh (2003). Recent literature has shown that this model has considerable explanatory power on aggregate hedge fund returns (see Joenväärä *et al.*, 2019; Barth *et al.*, 2020).

Several UCITS regulatory constraints are related to different aspects of liquidity. Our baseline model contains two factors that are designed to adjust for covariation with the market liquidity risk (Pastor and Stambaugh, 2003) and the funding liquidity risk (Frazzini and Pedersen, 2014).[11] Literature has documented that both aspects are important, even for liquid hedge funds that grant favorable redemption terms to investors. For instance, according to Teo (2011), there exists a substantial variation in the liquidity risk of these liquid hedge funds, and some of the liquid funds are suffering from an asset–liability mismatch. Literature has also documented that hedge fund returns exhibit positive serial correlation, which is consistent with the return smoothing (e.g., Asness, Krail, and Liew, 2001). Without adjustment, smoothing implies that typical performance measures will be biased upward (Getmansky, Lo, and Makarov, 2004). To address issues related to the level of liquidity, we build our regression models using both standard OLS and maximum likelihood methods that allow us to control for return smoothing.

Our baseline global seven-factor model is described below:

$$R_t - r_{f,t} = \alpha + \sum_{k=1}^{7} \beta_k f_{k,t} + \epsilon_t, \tag{1}$$

where $R_t - r_{f,t}$ is the excess returns of the fund at time t, and $f_{k,t}$ represents the returns of risk factors. The challenge associated with estimating Equation (1) is that we observe potentially smoothed returns R_t which leads to upward biased skill (α) and downward biased risk (β_k) estimates. We address this problem, like Getmansky, Lo, and Makarov (2004), by assuming that the observed returns of the hedge fund, R_t^0, are smoothed, following the MA(2) process:

$$\begin{aligned} R_t^0 &= \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}, \\ &\theta_0 + \theta_1 + \theta_2 = 1. \end{aligned} \tag{2}$$

where R_t is the true, unsmoothed, and unobserved returns. Combining Equation (1) with Equation (2) yields an equation that describes the relation between the factors and the observed smoothed returns:

10 Our results are quantitatively similar when we use the Fung-Hsieh (2004) seven- or eight-factor models, or stepwise model containing a large set of risk factors.

11 Sadka (2010), Teo (2011), and Cao *et al.* (2013) examine liquidity risk and liquidity timing in hedge fund space.

$$
\begin{aligned}
R_t^0 - r_{f,t} &= \alpha + \sum_{k=1}^{7} \left(\theta_0 \beta_k f_{k,t} + \theta_1 \beta_k f_{k,t-1} + \theta_2 \beta_k f_{k,t-2}\right) + u_t, \\
u_t &= \theta_0 \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}, \\
\theta_0 &+ \theta_1 + \theta_2 = 1.
\end{aligned} \tag{3}
$$

We estimate this regression model with MA(2) process presented by Equation (3) using the maximum likelihood approach as described in Getmansky, Lo, and Makarov (2004). As a main performance measure, we use the intercept of the regression (α) which is denoted throughout the article as a global alpha. To control for the effects of leverage on fund performance, we use the *t*-statistic of global alpha as an alternative measure. As well as being invariant for leverage, the *t*-statistic of alpha also corrects for outliers by normalizing the estimate in terms of its estimated precision (Kosowski *et al.*, 2006).

Like all other HFR that uses factor models, identification of the factors is problematic. Since some of our regressions are estimated with relatively few monthly observations, the problem can arise because of a substantial number of factors and only a limited number of degrees of freedom. For example, when we use 24 monthly return observations along with the seven global factors, the global alpha is estimated with only sixteen degrees of freedom. To ensure that our regression models are parsimonious, as an alternative for our baseline seven-factor model, we use stepwise regressions to identify the factors from the set of global factors.[12] Since several studies (e.g., Bollen and Whaley, 2009; Patton and Ramadorai, 2013) document that the equity market factor is most commonly included in the regression model, we always keep it in our models. In addition to market factor, we add two factors sequentially based on their Schwarz's Bayesian information criterion. This allows the data to select the set of factors for each fund that best explains that fund's returns.

To summarize, throughout this article, we measure risk-adjusted performance in three ways:

- Global alpha and its *t*-statistic
- Stepwise alpha and its *t*-statistic
- Smoothing-adjusted stepwise alpha and its *t*-statistic.

These measures are estimated for each fund having at least twenty-four return observations. To estimate our performance measures, we use both net-of-fee and gross-of-fee returns to confirm that potential compensation structure differences between UCITS and conventional funds are not driving our results.

3.3 Matching Estimator Approach

To estimate the effect of UCITS constraints on hedge fund performance, we rely on Rubin's potential outcome framework (e.g., Rubin, 1974), in which the causal effect is defined as the difference between an observed outcome and its counterfactual. If the treatment assignment is randomized, causal inference is straightforward since the two groups are drawn from the same population by construction, and the assignment of treatment is independent from outcome variable and covariates. However, in an observational framework, covariates are rarely balanced (i.e., the treatment and control groups have the same joint distribution of observed covariates) across treatment and control groups. Hence, the average

12 In our robustness tests reported in Section, we find that our results are robust when we use the augmented set of factor.

treatment effect for the treated cannot be directly estimated since the potential outcome is not observed for the treated. To identify average treatment effects, following Rosenbaum and Rubin (1983), we assume that the treatment assignment is strongly ignorable. This means that the treatment assignment is unconfounded (i.e., treatment assignment and the observed covariates are conditionally independent) and there is a positive probability of receiving each treatment for all values of covariates (i.e., overlap property). To ensure that these properties are satisfied, we use matching estimators for average treatment effects. In practice, we match each UCITS fund to one or several conventional funds with similar values of matching variables. Thereafter, we estimate the difference between UCITS and the corresponding conventional funds by averaging the performance differences between each UCITS fund and the corresponding matched conventional funds. However, the matching is challenging when done on several regulatory constraints as well as other fund variables. It is also rarely the case that there are exact matches for all variables, leading to potential bias arising from these differences. To overcome these issues, we employ the bias-adjusted matching estimator developed by Abadie and Imbens (2006, 2011) which is designed to address such estimation problems.

The choice of matching variables is motivated by UCITS regulatory constraints and by fund characteristics' ability to explain hedge fund performance. As baseline matching variables, we use the fund's investment strategy,[13] initial size, restriction period, lockup period, the average level of leverage, inception date, and first return reporting date. Both investment strategy (Brown and Goetzmann, 2003) and fund size (Berk and Green, 2004) are significant drivers of the cross-sectional variability in fund performance. The restriction period, defined as a sum of redemption period and advance notice period, as well as the lockup period are important regulatory constraints that have been documented to explain hedge fund performance (Aragon, 2007; Agarwal, Daniel, and Naik, 2009). In fact, Barth and Monin (2020) show that share restrictions explain 55% of hedge fund alpha, while portfolio illiquidity explains 27% of it. As a third regulation-motivated matching variable, we use the level of leverage. According to Barth, Hammond, and Monin (2020), the level of leverage is related to the riskiness of a hedge fund's portfolio.[14] Since the Abadie and Imbens (2006, 2011) matching estimator approach uses cross-sectional data, in our application of their methodology, we are careful to use both the fund inception date and the reporting date of the first nonbackfilled return observation. The fund's inception date is used because a fund's launch conditions are associated with the quality of the fund (Sun, Sun, and Zheng, 2020), whereas the matching of the return reporting period ensures that we adjust for backfilling bias and account for macroeconomic conditions and time-varying hedge fund performance (Avramov *et al.*, 2011; Avramov, Barras, and Kosowski, 2013).

Panel B of Table I reports the covariate balance for both the unmatched sample and the matched sample that is achieved based on Mahalanobis distance matching. Panel B reveals that there are significant differences in the means of fund characteristics for the unmatched samples. However, when each UCITS fund is matched to the closest possible conventional

13 Although Abadie and Imbens (2006, 2011) assume that covariates have continuous distributions, it is possible to use discrete covariates by estimating average treatment effects within subsamples defined by their values.

14 They show that the association between leverage and risk is nuanced, and that leverage is in part used to scale the payoffs of low-beta, high-alpha securities, resulting in an essentially flat relationship between leverage and portfolio risk.

fund, the characteristics of funds are very close to each other. Out of six matching variables, we only find statistically significant mean difference between UCITS and conventional funds the restriction period characteristic. Fortunately, the difference is only 0.2 weeks and therefore in economic terms very low. Nevertheless, to confirm that the covariate imbalance does not drive our results, in Section 4.3, we exactly match the restriction period between UCITS and conventional funds before we estimate the effects of regulatory constraints.

Panel B also reports the differences in compensation variables that are not used for matching because they are related to outcome variables. We find that although the average management fee is statistically higher for conventional funds, economically speaking the differences are not meaningful. In our empirical analysis, we use both net-of-fee and gross-of-fee returns that allow us to control for effects of potential differences in compensation structure.

4. Empirical Results

In this section, we test the hypotheses developed in Section 2.1 using the matching estimator approach presented in Section 3.3.

4.1 Baseline Matching Estimator Results

Table II reports the average performance of all UCITS and conventional funds and the estimated performance difference between them using the bias-adjusted matching estimator approach of Abadie and Imbens (2006, 2011) with heteroskedasticity-consistent statistical tests.[15] The results are shown when we match each UCITS fund to one, three, or five conventional funds characterized by the lowest Mahalanobis distance based on the matching variables defined in Section 3. The results show that UCITS hedge funds deliver lower performance than the conventional hedge funds. These results are not sensitive to the number of matched conventional funds or to the choice of benchmark model.

We find that the net-of-fee (gross-of-fee) mean returns excess to risk-free are −0.03% (2.27%) per year for UCITS hedge funds. The corresponding mean estimates for the matched conventional hedge funds are from 1.24% to 1.44% (from 3.52% to 4.00%) per year. The bias-adjusted coefficients for matching estimator range from −1.27% to −1.48% for net-of-fee returns and from −1.25% to −1.73% for gross-of-fee returns with *t*-statistics ranging from −2.35 to −3.62 and −2.10 to −3.43, respectively. This suggests that the treated UCITS hedge funds deliver both statistically and economically lower mean excess returns than those of matched conventional funds.

Table II shows that the risk level of matched conventional hedge funds is higher than UCITS hedge funds. For example, the net-of-fees annualized standard deviation for UCITS funds is 13.70% per year, while the corresponding values for the matched conventional funds range from 14.93% to 15.23% per year.[16] The bias-adjusted coefficients for the matching estimators range from −1.24% to −1.53% per year with *t*-statistics ranging from −2.24 to −3.43. This suggests that the treated UCITS funds pose lower risk. However, the corresponding net-of-fee Sharpe ratio differences based on the matching estimators range

15 Our results hold when we do not adjust standard errors for heteroskedasticity.

16 Our results are very similar when we use the expected shortfall or value-at-risk instead of standard deviation.

Table II. Baseline matching estimator results

This table presents the matching estimator results for performance difference between UCITS hedge funds and matched conventional hedge funds. "UCITS" ("Conventional") denotes the mean of the specific measure for the UCITS (Conventional) group. "Coefficient" is the bias-adjusted coefficient of the Abadie and Imbens (2006, 2011) matching estimator. A positive sign indicates that the value of the measure is higher for UCITS hedge funds. "*t*-statistic" refers to the heteroskedasticity-adjusted *t*-statistic of the matching estimator. Matched funds are defined by matching UCITS hedge funds based on the Mahalanobis distance between the fund's investment strategy, initial size, inception date, restriction period, lockup period, and level of leverage. For each UCITS hedge fund, we match one, three, or five corresponding funds characterized by the lowest distance. "Mean" denotes the fund's annualized average return. "Standard deviation" denotes the fund's return standard deviation. "Sharpe ratio" denotes the annualized Sharpe ratio. "Global alpha" is the annualized intercept of the seven-factor model consisting of global equity market excess return, size factor, and value factor of Fama and French (2012); global cross-sectional momentum of Asness, Moskowitz, and Pedersen (2013); global time-series momentum of Moskowitz, Ooi, and Pedersen (2012); global betting-against-beta of Frazzini and Pedersen (2014); and liquidity risk of Pastor and Stambaugh (2003). "Systematic risk" is defined as the difference of return standard deviation and idiosyncratic risk. "Idiosyncratic risk" denotes the residual risk that is obtained from the global seven-factor model. "Stepwise alpha" is based on three factors that are chosen optimally using the Bayesian information criterion. "Smoothing-adj. alpha" is adjusted using the Getmanksy, Lo, and Makarov (2004) approach. All measures are estimated for each fund having at least twenty-four return observations. The study period is from January 2007 through December 2016.

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
Mean (% pa)	One match	−0.03	1.24	−1.27	−2.35	2.27	3.52	−1.25	−2.10
	Three matches	−0.03	1.41	−1.45	−3.30	2.27	4.00	−1.73	−3.41
	Five matches	−0.03	1.44	−1.48	−3.62	2.27	3.91	−1.64	−3.43
Standard deviation (% pa)	One match	13.70	14.93	−1.24	−2.24	13.89	15.01	−1.12	−1.73
	Three matches	13.70	15.01	−1.31	−2.66	13.89	15.66	−1.77	−3.25
	Five matches	13.70	15.23	−1.53	−3.43	13.89	15.78	−1.89	−3.63
Sharpe ratio (pa)	One match	−0.04	0.17	−0.21	−4.68	0.12	0.34	−0.22	−4.52
	Three matches	−0.04	0.15	−0.19	−5.28	0.12	0.35	−0.23	−5.31
	Five matches	−0.04	0.14	−0.19	−5.26	0.12	0.32	−0.21	−5.05
Global alpha (% pa)	One match	−8.90	−5.62	−3.29	−4.25	−7.26	−3.21	−4.05	−4.87

(continued)

Table II. Continued

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	t-statistic	UCITS	Conventional	Coefficient	t-statistic
	Three matches	−8.90	−5.36	−3.55	−5.94	−7.26	−3.01	−4.25	−5.94
	Five matches	−8.90	−5.36	−3.54	−6.38	−7.26	−3.26	−4.00	−5.78
t-statistic of alpha	One match	−1.57	−0.63	−0.93	−9.12	−1.16	−0.28	−0.88	−8.20
	Three matches	−1.57	−0.69	−0.88	−9.94	−1.16	−0.27	−0.89	−8.99
	Five matches	−1.57	−0.69	−0.88	−10.28	−1.16	−0.34	−0.82	−8.74
Systematic risk (% pa)	One match	5.57	5.41	0.16	0.59	5.67	5.48	0.19	0.59
	Three matches	5.57	5.31	0.26	1.19	5.67	5.54	0.14	0.55
	Five matches	5.57	5.40	0.17	0.86	5.67	5.59	0.08	0.38
Idiosyncratic risk (% pa)	One match	8.11	9.51	−1.40	−3.37	8.21	9.51	−1.30	−2.73
	Three matches	8.11	9.68	−1.57	−4.21	8.21	10.09	−1.87	−4.60
	Five matches	8.11	9.81	−1.70	−5.01	8.21	10.14	−1.93	−4.87
Stepwise alpha (% pa)	One match	−7.16	−3.81	−3.35	−5.49	−5.38	−1.74	−3.64	−5.67
	Three matches	−7.16	−3.63	−3.53	−7.04	−5.38	−1.40	−3.98	−6.37
	Five matches	−7.16	−3.55	−3.60	−7.57	−5.38	−1.44	−3.95	−6.54
t-statistic of alpha	One match	−1.55	−0.51	−1.05	−9.26	−1.06	−0.10	−0.96	−7.73
	Three matches	−1.55	−0.56	−0.99	−10.23	−1.06	−0.07	−0.98	−8.41
	Five matches	−1.55	−0.54	−1.01	−10.49	−1.06	−0.12	−0.93	−8.52
Smoothing-adj. alpha (% pa)	One match	−6.57	−3.47	−3.10	−5.60	−4.68	−1.36	−3.33	−5.45
	Three matches	−6.57	−3.33	−3.23	−6.67	−4.68	−1.24	−3.44	−5.71
	Five matches	−6.57	−3.30	−3.26	−6.95	−4.68	−1.39	−3.29	−5.52
t-statistic of alpha	One match	−1.48	−0.47	−1.01	−7.53	−0.95	0.00	−0.94	−6.01
	Three matches	−1.48	−0.52	−0.96	−7.40	−0.95	0.16	−1.11	−6.37
	Five matches	−1.48	−0.49	−0.99	−7.18	−0.95	0.09	−1.04	−5.67

from −0.19 to −0.21 with *t*-statistics ranging from −4.68 to −5.28. Although matched conventional hedge funds take more risk than UCITS funds, they also deliver higher rewards relative to the risk taken. These results support the idea that UCITS hedge fund managers may be less willing to take risks—or that their risk-taking is limited by the regulation.

Next we compare results from the baseline global seven-factor model to the stepwise and smoothing-adjusted versions of the benchmark model. Across all model variants, we find that the UCITS hedge funds consistently deliver lower alphas than matched conventional funds. The annualized net-of-fee alphas range from −8.90% to −6.57% per year for the UCITS funds and from −3.30 to −5.62 per year for the matched conventional funds. The gross-of-fee alphas are higher, but they remain negative for both UCITS funds and conventional funds. This is slightly surprising, but as we discuss in Section 4.4 the magnitude of conventional fund alphas based on standard portfolio sorts is comparable to recent studies.

The statistically highly significant matching estimator coefficients for alpha differences range from −3.10% to −3.60% per year. Thus, treated UCITS hedge funds deliver lower alphas than the group of matched conventional funds. The inference remains consistent when we conduct our matching estimator using the leverage invariant alpha *t*-statistics. In fact, we find that the statistical significance of performance difference between UCITS and conventional funds is even higher when it is measured using alpha *t*-statistics. In our Appendix Table A1, we show that these performance differences between UCITS and conventional funds hold across investment styles.

The factor model approach allows us to break up each individual hedge fund's total risk into systematic and fund-specific or idiosyncratic risk components. We find that the systemic risk between UCITS hedge funds and matched conventional funds is statistically indistinguishable. This suggests both that the systematic risk levels are similar between UCITS and matched conventional funds. In addition, the matching seems to be well balanced since we do not observe significant differences in systematic risk that are associated with fund performance (Bali, Brown, and Caglayan, 2012).[17] The idiosyncratic risk is lower for the UCITS funds than for the matched conventional hedge funds. The matching estimator coefficient for idiosyncratic risk difference ranges from −1.40% to −1.70% per year. The results suggest that conventional funds take on more idiosyncratic risk and that this is beneficial in so far as they deliver higher performance than UCITS funds, as evidenced by the alpha *t*-statistics that are invariant to idiosyncratic risk. One potential explanation for the performance difference between UCITS funds and conventional funds documented earlier is that UCITS regulatory constraints prevent UCITS funds from taking as high levels of idiosyncratic risk as matched conventional funds, the reason being that alpha cannot be achieved without taking idiosyncratic risk.

4.2 Company-Level and Fund Manager-Level Matching

So far, using the fund-level matching approach, we have established that UCITS funds underperform matched conventional funds. However, hedge fund management companies or fund manager-specific characteristics may play an important role in determining the performance differences between UCITS and conventional funds. The unobserved

17 The results are unchanged when match funds using estimated betas instead of baseline fund characteristics.

heterogeneity related to the management company or fund manager may cause a hidden bias in the estimation of treatment effects. For example, the management companies that run mainly UCITS funds may not have access to sophisticated information-gathering techniques, or the fund managers that run UCITS funds may be fundamentally different from the fund managers that run conventional hedge funds.

To control for the possibility that unobserved confounders related to management company or fund manager are driving the performance differences between UCITS and conventional funds, we conduct three within-pair comparisons in which we match each UCITS fund to the closest possible conventional fund both within management company and within fund manager. First, for each UCITS fund, we identify the closest possible conventional fund within the same management company. We identify 287 such companies that fulfill these conditions. Next, we match each UCITS fund to the closest possible conventional fund so that both funds are run by the same manager. We find 247 within-fund manager pairs. Finally, we require that a fund manager runs funds within the same management company. We identify 201 such fund pairs.

The results reported in Table III show that UCITS hedge funds deliver lower global alphas than their matched pairs even if we control for firms and managers. Our findings hold for all three variants of our benchmark model. As expected, the performance differences are slightly wider when we match funds only by management company. However, the performance differences remain economically large and statistically highly significant even when we use the tightest match (which requires that both management company and fund manager are the same). According to Table III, under this scenario the net-of-fees alpha differences range from −3.30% to −4.92% per year. These results are robust to potential differences in leverage, since the respective differences in alpha *t*-statistics range from −0.62 to −0.87 and are also highly statistically significant.

Collectively, the robustness of our findings suggests that our matching estimator analysis is not contaminated by unobserved management company-level or fund manager-level confounders related to treatment assignment and outcome.

4.3 Exact Regulatory Constraints Matching

We next estimate the effect of UCITS regulation constraints on fund performance when the redemption terms as well as leverage are exactly matched between UCITS and conventional funds. Exact matching is important since we aim to compare as equivalent funds as possible to ensure the liquidity and leverage differences do not drive our findings.

We start this analysis by matching UCITS and conventional funds by requiring that conventional funds provide at least biweekly liquidity for their investors and do not impose a lockup period for the initial investments. Panel A of Table IV shows that after controlling for liquidity differences in this way, performance differences between UCITS and conventional funds are slightly smaller than the baseline case reported in Table II. Nevertheless, alpha and its *t*-statistic differences are still economically substantial and statistically highly significant across the three benchmark model variants.[18] For example, the net-of-fee alpha differences range from −3.07% to −3.26% per year suggesting that regulatory constraints other than redemption terms play an important role in determining the performance

18 We show results for three matches. The results for one or five matches are quantitatively similar.

Table III. Matching within a hedge fund company and fund manager

This table presents the matching estimator results for performance difference between UCITS and matched conventional hedge funds that are managed by the same firm ("Firm"), the same manager ("Manager"), or manager that belongs to the same firm ("Both"). "UCITS" ("Conventional") denotes the mean alpha for the UCITS (Conventional) group. "Coefficient" is the bias-adjusted coefficient of the Abadie and Imbens (2006, 2011) matching estimator. A positive sign indicates that the value of the alpha is higher for UCITS hedge funds. "*t*-statistic" refers to the heteroskedasticity-adjusted *t*-statistic of the matching estimator. Matched conventional funds are defined by matching UCITS hedge funds within a hedge fund firm, manager, or both based on the Mahalanobis distance between the fund's investment strategy, initial size, inception date, restriction period, lockup period, and level of leverage. For each UCITS hedge fund, we match only one corresponding fund characterized by the lowest distance. "Global alpha," "Stepwise alpha," and "Smoothing-adjusted alpha" are defined as in Table II. All measures are estimated for each fund having at least twenty-four return observations. The study period is from January 2007 through December 2016.

Variable	Matched within	Net-of-fees returns				Gross-of-fees returns			
		UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
Global alpha (% pa)	Firm	−6.61	−2.53	−4.07	−11.09	−4.67	−0.38	−4.29	−10.10
t-statistic of alpha	Firm	−1.25	−0.62	−0.63	−10.93	−0.78	−0.24	−0.54	−8.87
Stepwise alpha (% pa)	Firm	−5.77	−1.07	−4.70	−14.46	−3.53	1.63	−5.16	−14.24
t-statistic of alpha	Firm	−1.32	−0.50	−0.82	−13.64	−0.71	0.07	−0.78	−12.10
Smoothing-adj. alpha (% pa)	Firm	−5.42	−0.25	−5.18	−16.23	−3.02	2.26	−5.28	−15.29
t-statistic of alpha	Firm	−1.17	−0.46	−0.71	−10.39	−0.59	0.10	−0.69	−8.46
Global alpha (% pa)	Manager	−7.15	−3.68	−3.47	−11.55	−4.79	−1.64	−3.15	−8.51
t-statistic of alpha	Manager	−1.27	−0.64	−0.63	−12.95	−0.79	−0.28	−0.51	−9.88
Stepwise alpha (% pa)	Manager	−6.22	−1.81	−4.41	−16.69	−3.88	1.43	−5.30	−16.91
t-statistic of alpha	Manager	−1.34	−0.50	−0.84	−15.94	−0.76	0.14	−0.90	−16.08
Smoothing-adj. alpha (% pa)	Manager	−5.97	−1.12	−4.85	−18.02	−3.26	1.84	−5.10	−16.35
t-statistic of alpha	Manager	−1.23	−0.54	−0.69	−8.81	−0.65	0.05	−0.70	−8.77
Global alpha (% pa)	Both	−7.14	−3.84	−3.30	−11.57	−4.84	−1.75	−3.09	−8.67
t-statistic of alpha	Both	−1.31	−0.70	−0.62	−13.46	−0.83	−0.33	−0.50	−9.91
Stepwise alpha (% pa)	Both	−6.20	−1.71	−4.49	−17.93	−3.80	1.60	−5.40	−18.02
t-statistic of alpha	Both	−1.37	−0.51	−0.87	−16.98	−0.77	0.14	−0.91	−16.59
Smoothing-adj. alpha (% pa)	Both	−5.92	−1.00	−4.92	−19.13	−3.16	2.09	−5.25	−17.44
t-statistic of alpha	Both	−1.23	−0.56	−0.66	−8.71	−0.63	0.01	−0.64	−8.15

Table IV. Exact regulatory constraint matching

Panel A presents the matching estimator results for performance difference between UCITS and conventional hedge funds when the matched conventional funds are defined by matching UCITS hedge funds based on requiring that the fund's restriction period cannot exceed 14 days (restriction period is longer than its median) and the distance between the fund's investment strategy, initial size, inception date, lockup period, and level of leverage. Panel B presents the respective results when the conventional hedge fund's restriction period is longer than a median fund's restriction period. Panel C presents the respective results when the conventional hedge fund's leverage is matched exactly. Panel D presents the respective results when the conventional hedge fund's leverage is higher than a median fund's median leverage. "UCITS" ("Conventional") denotes the mean alpha for the UCITS (Conventional) group. "Coefficient" is the bias-adjusted coefficient of the Abadie and Imbens (2006, 2011) matching estimator. A positive sign indicates that the value of the alpha is higher for UCITS hedge funds. "*t*-statistic" refers to the heteroskedasticity-adjusted *t*-statistic of the matching estimator. For each UCITS hedge fund, we match three corresponding funds characterized by the lowest distance. "Global alpha," "Stepwise alpha," and "Smoothing-adj. alpha" are defined as in Table II. All measures are estimated for each fund having at least twenty-four return observations. The study period is from January 2007 through December 2016.

Panel A: Exact liquidity matching between UCITS and conventional funds

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	t-statistic	UCITS	Conventional	Coefficient	t-statistic
Global alpha (% pa)	Three matches	−8.90	−5.70	−3.20	−4.14	−7.26	−2.75	−4.51	−5.02
t-statistic of alpha	Three matches	−1.57	−0.74	−0.83	−7.56	−1.16	−0.25	−0.91	−7.65
Stepwise alpha (% pa)	Three matches	−7.16	−3.90	−3.26	−4.65	−5.38	−1.46	−3.92	−5.35
t-statistic of alpha	Three matches	−1.55	−0.60	−0.95	−7.53	−1.06	−0.08	−0.98	−7.17
Smoothing-adj. alpha (% pa)	Three matches	−6.57	−3.50	−3.07	−4.48	−4.68	−1.12	−3.56	−4.54
t-statistic of alpha	Three matches	−1.48	−0.55	−0.93	−5.23	−0.95	0.18	−1.13	−4.28

Panel B: UCITS versus only conventional funds with above-median redemption term

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
Global alpha (% pa)	Three matches	−8.90	−0.79	−8.11	−14.17	−7.26	1.48	−8.74	−11.28
t-statistic of alpha	Three matches	−1.57	0.29	−1.86	−18.80	−1.16	0.78	−1.94	−15.01
Stepwise alpha (% pa)	Three matches	−7.16	−0.25	−6.91	−13.70	−5.38	2.32	−7.70	−11.75

(continued)

Table IV. Continued

Panel B: UCITS versus only conventional funds with above-median redemption term

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
t-statistic of alpha	Three matches	−1.55	0.47	−2.02	−17.29	−1.06	1.14	−2.20	−14.00
Smoothing-adj. alpha (% pa)	Three matches	−6.57	−0.11	−6.46	−12.92	−4.68	2.32	−7.00	−10.87
t-statistic of alpha	Three matches	−1.48	0.69	−2.17	−13.93	−0.95	1.51	−2.46	−10.02

Panel C: Exact leverage matching between UCITS and conventional funds

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
Global alpha (% pa)	Three matches	−8.90	−5.11	−3.79	−7.19	−7.26	−2.85	−4.41	−6.72
t-statistic of alpha	Three matches	−1.57	−0.68	−0.89	−10.07	−1.16	−0.27	−0.89	−9.19
Stepwise alpha (% pa)	Three matches	−7.16	−3.40	−3.76	−8.37	−5.38	−1.34	−4.04	−7.09
t-statistic of alpha	Three matches	−1.55	−0.53	−1.02	−10.24	−1.06	−0.06	−1.00	−8.64
Smoothing-adj. alpha (% pa)	Three matches	−6.57	−3.27	−3.30	−7.50	−4.68	−1.06	−3.62	−6.47
t-statistic of alpha	Three matches	−1.48	−0.45	−1.03	−8.02	−0.95	0.22	−1.17	−6.85

Panel D: UCITS versus only conventional funds with above-median leverage

		Net-of-fees returns				Gross-of-fees returns			
Variable	Matched	UCITS	Conventional	Coefficient	*t*-statistic	UCITS	Conventional	Coefficient	*t*-statistic
Global alpha (% pa)	Three matches	−8.90	−4.39	−4.51	−4.78	−7.26	−2.24	−5.02	−5.13
t-statistic of alpha	Three matches	−1.57	−0.56	−1.01	−8.32	−1.16	−0.11	−1.05	−7.01
Stepwise alpha (% pa)	Three matches	−7.16	−2.74	−4.42	−5.17	−5.38	−0.26	−5.12	−6.42
t-statistic of alpha	Three matches	−1.55	−0.40	−1.15	−7.78	−1.06	0.20	−1.26	−7.33
Smoothing-adj. alpha (% pa)	Three matches	−6.57	−2.59	−3.98	−4.69	−4.68	−1.13	−3.55	−4.33
t-statistic of alpha	Three matches	−1.48	−0.22	−1.26	−6.74	−0.95	0.40	−1.35	−4.82

differences between UCITS and conventional hedge funds. Examples of such potential regulatory constraints are constraints regarding eligible assets or higher compliance costs associated with UCITS regulation.

Next, we focus on the case when the hedge funds allow onerous liquidity terms to their investors. In matching, we keep everything else equal but require that the restriction period is longer than its median across all conventional funds. Results presented in Panel B of Table IV show that these illiquid conventional hedge funds deliver net-of-fee (gross-of-fee) alphas that range from −0.11% to −0.79% (from 1.48% to 2.32%) per year. The alphas of illiquid conventional funds are strikingly large compared to those of UCITS funds. For instance, the matching estimator coefficient for net-of-fee alpha differences ranges from −8.11% to −6.46% per year. These findings are in a line with Aragon (2007) and Agarwal, Daniel, and Naik (2009). The magnitude of these estimates suggests that some investors are willing to pay a large premium by investing in hedge funds that are managed under the UCITS Directive.

Panel C of Table IV reports the results for when we estimate the effect of UCITS regulation constraints on fund performance by exactly matching the leverage between UCITS and conventional funds. The results show that even after matching leverage exactly, alphas and (leverage invariant) alpha *t*-statistic differences between UCITS and conventional funds are both statistically and economically significant. Panel D of Table IV reports the results when we keep everything else the same but impose large leverage differences between UCITS and conventional funds. The results suggest that UCITS funds underperform conventional hedge funds. However, consistent with Barth, Hammond, and Monin (2020), the alpha differences between UCITS and conventional funds seem to be unrelated to level of leverage.

Overall, our matching estimator analysis indicates that even after exact redemption term and leverage matching UCITS funds underperform conventional funds, suggesting that UCITS constraints unrelated to these factors are also important determinants of performance differences between funds.

4.4 Portfolio Sorts and Persistence Tests

In this section, we conduct a set of portfolio sorts without and with matching. One advantage of the portfolio sort approach is that it allows us to relate our results to the extant literature that uses them to evaluate hedge fund performance. More importantly from a methodological point of view, portfolio sorts are designed to match calendar time perfectly. This is important because the quality of the matches in the previous analyses may worsen for periods that are far away from the time of matching.

The value-weighted (VW) performance of the UCITS fund portfolio is compared to three different VW portfolios of conventional funds over the period from January 2007 to December 2016.[19] The first portfolio of conventional funds contains all conventional funds. The second portfolio contains a set of matched funds that are characterized by the lowest distance based on the predefined matching variables, while the third portfolio contains a set of exactly liquidity-matched conventional funds. To keep the same calendar time and number of funds in portfolios, for every month we match each UCITS fund to one conventional fund characterized by the lowest distance.

19 The results are similar when we use equal-weighting instead of value-weighting. We opt for value-weighting as a baseline because it better describes how the whole UCITS hedge fund industry performs against conventional hedge funds.

The results from Table V confirm that performance differences between UCITS hedge funds and conventional hedge funds remain economically and statistically significant when performance is evaluated using standard portfolio sorts. As expected, the spread between UCITS funds and conventional funds is widest when the benchmark model contains all conventional funds (Panel A). The net-of-fee (gross-of-fee) alphas of the spread are −6.63% (−6.92%) per year with a *t*-statistic of −3.63(−3.75). For the baseline matched portfolios (Panel B), the respective alpha spreads are slightly lower but still statistically and economically significant at −4.29% (−4.73%) per year with a *t*-statistic of −4.12 (−3.84). When we match the liquidity terms between UCITS and conventional funds exactly (Panel C), the respective alpha spreads are only slightly lower than in a baseline case. The adjusted R^2 with respect to the global seven-factor model are very similar for both UCITS and conventional funds. In addition, Table V shows that UCITS hedge funds underperform conventional hedge funds in terms of benchmark-free mean returns and Sharpe ratios.

The magnitude of the conventional fund alphas reported in Table V is comparable to alphas reported by existing studies (e.g., Edelman, Fung, and Hsieh, 2013; Jorion and Schwarz, 2019). For example, by using a comprehensive database and a careful data bias adjustment, Joenväärä *et al.* (2019) document that the hedge fund industry delivers net-of-fee alpha that is indistinguishable from zero, whereas gross-of-fee alpha is positive and statistically significant. For commodity trading advisors that tend to be liquid, Bhardwaj, Gorton, and Rouwenhorst (2014) show that net-of-fee excess returns are insignificantly different from zero and aggregate alpha is insignificant relative to a set of basic futures strategies (value, momentum, carry) that are in the public domain.

So far, we have analyzed the performance of the UCITS hedge fund industry as a whole and ignored the fact that some of the best performing funds may deliver alpha to their investors. To further investigate this possibility, we conduct a set of performance persistence tests in which we compare the performance persistence between UCITS funds and matched conventional funds. We focus on fund portfolios of the top twenty-five and top fifty funds. The reason for this is two-fold. First, twenty-five to fifty is typically the number of funds held by hedge fund investors. Second, fund short sales are very rare which means that the performance spread between top and bottom funds is less informative than the performance of the portfolio of top funds.[20]

In the spirit of Carhart (1997), we sort the top twenty-five and top fifty funds into portfolios based on their past global alpha *t*-statistics that are estimated from the prior 2 years' data. We use portfolio rebalancing periods ranging from a month to a year, and we calculate out-of-sample VW returns for both the top twenty-five and top fifty fund portfolios across these rebalancing horizons. Finally, we estimate the alpha top twenty-five and top fifty spreads between UCITS and conventional fund portfolios.

Figure 1 plots the top twenty-five and top fifty portfolio global alphas across the rebalancing horizons for both UCITS and conventional funds. Across rebalancing horizons, top twenty-five and top fifty fund performances are significantly higher for conventional funds.[21] For the most realistic annual rebalancing horizons, the global net-of-fee alpha spread between top twenty-five (top fifty) UCITS and conventional fund portfolios is

20 See Joenväärä, Kosowski, and Tolonen (2019) who examine the effects of investment constraints on hedge fund returns.

21 Appendix Tables A2 and A3 report the statistical tests for top twenty-five and top fifty portfolio comparisons.

Table V. Calendar time-matched performance of UCITS hedge funds and conventional hedge funds

This table presents the VW portfolio sort results when the performance of UCITS hedge fund portfolios is compared to portfolios based on either all conventional funds (Panel A), baseline matched conventional funds (Panel B), or exactly liquidity matched conventional hedge funds (Panel C). "Mean" is the annualized mean excess return for respective VW portfolio. "Sharpe" is the annualized Sharpe ratio defined as the mean excess returns divided by the standard deviation of portfolio returns. "Global alpha" is the annualized intercept of the global seven-factor model for respective VW portfolio. "Alpha t-statistic" is the t-statistic of the global alpha. "Adj. R^2" refers to the adjusted R^2 of the model. Statistical inference is based on Newey and West (1987) standard errors. The study period is from January 2007 through December 2016.

Panel A: All conventional funds versus UCITS hedge funds

	Net-of-fee returns					Gross-of-fee returns				
Portfolio	Mean (% pa)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)	Mean (% pa)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)
UCITS	−0.585	−0.041	−6.583	−2.994	87.5	2.092	0.146	−3.706	−1.709	86.7
Conventional	3.704	0.644	0.048	0.054	81.6	6.963	1.198	3.212	3.207	79.2
Spread	−4.289	−0.685	−6.631			−4.871	−1.052	−6.918		
t-statistic	−1.079	−3.999	−3.628			−1.248	−5.337	−3.750		

Panel B: Baseline matched conventional funds versus UCITS hedge funds

	Net-of-fee returns					Gross-of-fee returns				
Portfolio	Mean (% pa)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)	Mean (pa %)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)
UCITS	−0.585	−0.041	−6.583	−2.994	87.5	2.092	0.146	−3.706	−1.709	86.7
Conventional	2.705	0.220	−2.293	−1.162	87.5	5.795	0.467	1.023	0.472	84.6

(continued)

Table V. Continued

Panel B: Baseline matched conventional funds versus UCITS hedge funds

Portfolio	Net-of-fee returns					Gross-of-fee returns				
	Mean (% pa)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)	Mean (pa %)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)
Spread	−3.290	−0.261	−4.291			−3.703	−0.321	−4.729		
t-statistic	−2.052	−3.107	−4.115			−2.096	−3.267	−3.841		

Panel C: Exactly liquidity matched conventional funds versus UCITS hedge funds

Portfolio	Net-of-fee returns					Gross-of-fee returns				
	Mean (pa %)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)	Mean (pa %)	Sharpe (pa)	Global alpha (% pa)	Alpha t-statistic	Adj. R^2 (%)
UCITS	−0.585	−0.041	−6.583	−2.994	87.5	2.092	0.146	−3.706	−1.709	86.7
Conventional	2.976	0.212	−2.413	−1.179	87.8	5.976	0.418	0.378	0.160	85.2
Spread	−3.561	−0.253	−4.170			−3.884	−0.272	−4.082		
t-statistic	−2.436	−2.877	−3.221			−2.494	−2.763	−3.104		

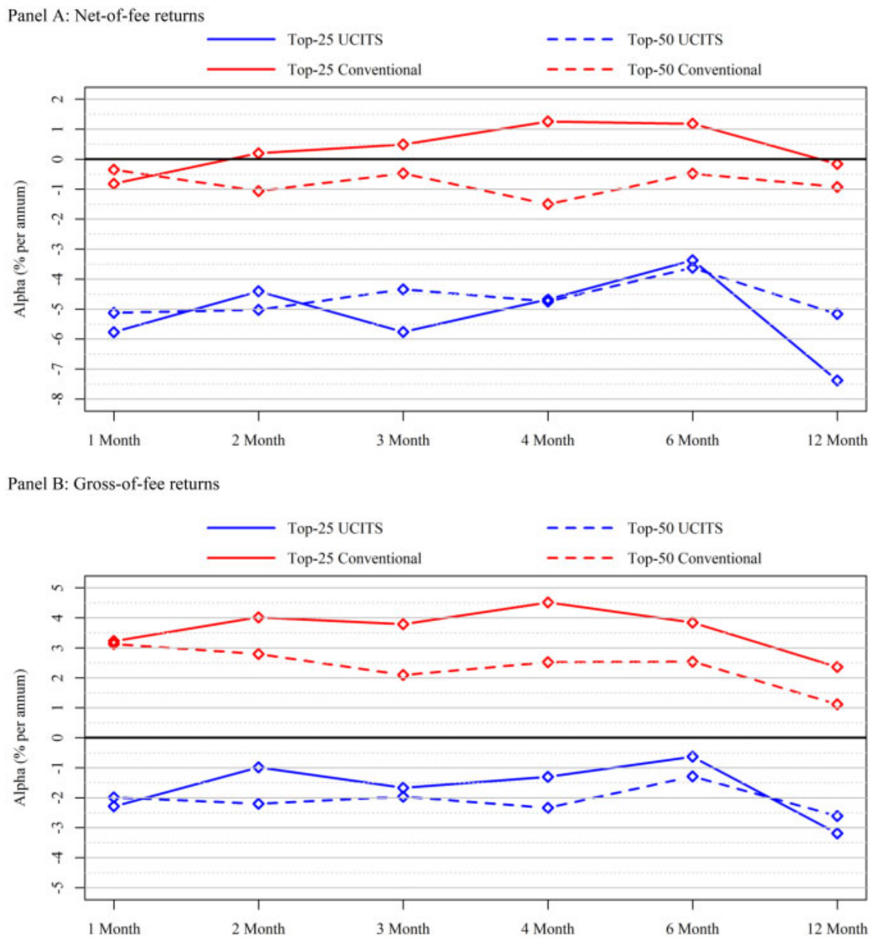

Figure 1. Performance persistence differences between UCITS and conventional hedge funds. This figure plots the (annualized) global alphas for UCITS hedge funds and matched conventional hedge funds. It displays the top twenty-five and top fifty fund portfolios' VW global alphas across rebalancing frequencies. Using *t*-statistics of the global alpha, funds are sorted into top twenty-five and top fifty fund portfolios that are rebalanced at 1, 2, 3, 4, 6, and 12 month frequencies. The *t*-statistics are estimated using the twenty-four most recent return observations. The out-of-the sample period is from January 2007 through December 2016. (**A**) Net-of-fee returns. (**B**) Gross-of-fee returns

−7.22% (−4.24%) per annum with a *t*-statistic of −2.61 (−1.83). Given their biweekly investor-level liquidity, the top UCITS fund portfolios are investable for UCITS fund investors, even at the monthly rebalancing frequency. Therefore, we examine the performance persistence of the top fund portfolios in further detail. Figure 1 shows that the top UCITS fund portfolios deliver alphas that are negative across all rebalancing horizons no matter whether they measured net-of-fees or gross-of-fees. This implies that performance chasing by UCITS investors would result in significant negative risk-adjusted returns. The conclusions are different when we examine the top twenty-five and top fifty conventional hedge funds. Their net-of-fee alphas are close to zero, whereas their gross-of-fee alphas are positive. This suggests that managers that run conventional top funds extract all the economic rents.

To make sure that redemption restrictions are matched exactly between UCITS and conventional funds, we run the top fund portfolio tests using only conventional funds that provide biweekly liquidity to their investors. Figure 2 shows that the conclusions are very similar to those based on the baseline matched funds in Figure 1. Across rebalancing horizons, the liquid conventional funds deliver higher top twenty-five and top fifty fund portfolio alphas than UCITS funds. We find that the global net-of-fee alpha spread between top twenty-five (top fifty) UCITS funds and conventional liquid fund portfolios are −6.74% (−3.88%) per annum with a *t*-statistic of −2.14 (−1.56). Hence, the differences in redemption terms are not driving the top fund performance persistence differences.

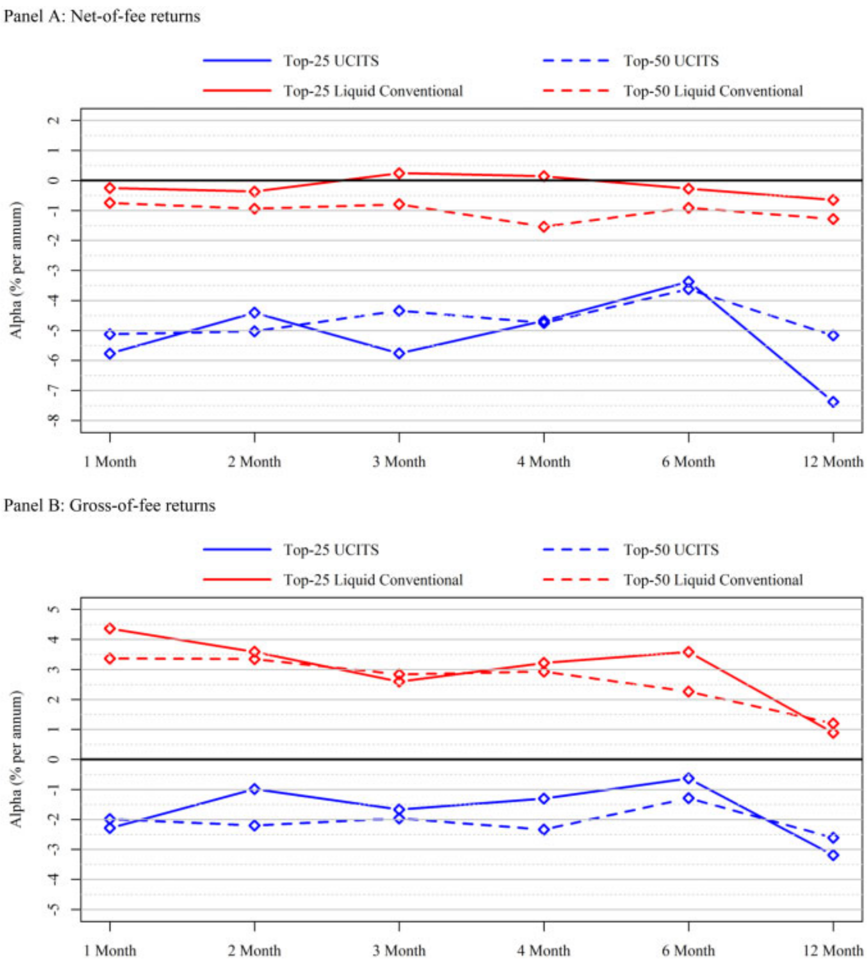

Figure 2. Feasibility and performance persistence. This figure plots the (annualized) global alphas for the UCITS hedge funds and matched liquid conventional hedge funds. It displays the top twenty-five and top fifty fund portfolios' VW global alphas across rebalancing frequencies. Using *t*-statistics of the global alpha, funds are sorted into top twenty-five and top fifty fund portfolios that are rebalanced at 1, 2, 3, 4, 6, and 12 month frequencies. The *t*-statistics are estimated using the twenty-four most recent return observations. The out-of-the sample period is from January 2007 through December 2016. (**A**) Net-of-fee returns. (**B**) Gross-of-fee returns.

Overall, we conclude that UCITS hedge funds underperform conventional hedge funds in an economically and statistically significant way. The conclusion is consistent when it is drawn from the matching estimator analysis, matched portfolio sorts, or matched performance persistence tests.

5. Equilibrium Analysis

Why do UCITS hedge funds exist in equilibrium if they underperform conventional hedge funds? To better understand the motives of investors and management companies, we explore the decision to launch a hedge fund. To maximize the present value of lifetime expected fee streams generated by the fund, management companies should choose the fund's legal structure as well as other variables such as compensation structure and redemption terms optimally at the fund's inception. On the one hand, it might be optimal for management companies to launch more tightly regulated UCITS hedge funds in order to satisfy high investor demand for investment vehicles with high levels of transparency and regulatory oversight. On the other hand, some management companies may extract higher fee revenues by launching and managing conventional hedge funds.

We start by analyzing the management company-level determinants of UCITS fund and conventional fund launches. For that purpose, we conduct the following conditional Probit analysis:

$$\begin{aligned} Prob.\ (FundLaunch)_{i,t} = {} & \gamma_0 + \gamma_1 FirmAlpha_{i,t-1} + \gamma_2 FirmFlow_{i,t-1} + \gamma_3 FirmAge_{i,t-1} \\ & + \gamma_4 FirmSize_{i,t-1} + \gamma_5 Restriction_i + \gamma_6 HighWaterMark_i \\ & + \gamma_7 ManagementFee_i + \gamma_8 IncentiveFee_i \\ & + \gamma_9 \log\left(1 + UCITS\ \ Funds_{i,t-1}\right) \\ & + \gamma_{10} \log\left(1 + Conventional\ \ Funds_{i,t-1}\right) + \varepsilon, \end{aligned}$$

where *FundLaunch* gets a value of one when a firm *i* launches a UCITS hedge fund and a value of zero if the management company *i* launches a conventional fund during the quarter *t*. Time-varying variables include *FirmAlpha* (firm-level global alpha estimated using a 24 month window), *FirmFlow* (firm-level flow estimated using a 24 month window), and *FirmAge* (*FirmSize*). The time-invariant variables include firm-level redemption restriction period (*Restriction*) and compensation structure variables (*HighWaterMark*, *ManagementFee*, and *IncentiveFee*). All these firm-level variables are obtained by value-weighting the respective fund-level values. To control for the firm's tendency to launch a particular type of fund, we include $Log(1 + UCITS\ Funds)$ and $Log(1 + Conventional\ Funds)$, where *UCITS Funds* (*Conventional Funds*) are defined as the number of UCITS (conventional) funds the management company runs. Throughout the Probit specifications, we impose time-fixed effects and employ robust standard errors that are double clustered by quarter and management firm.

The results from Table VI support the view that firm-level past alpha and flows are associated with the type of hedge fund launched. The coefficients for past firm-level alphas and flows suggest that management companies that experienced low performance and flows are more likely to launch UCITS funds, while management companies with high past performance and flows have a higher likelihood of launching conventional funds. The marginal effects imply that a one standard deviation decrease (increase) in firm-level alpha results in a 1.95% increase (decrease) in the probability of launching a UCITS (conventional) hedge fund. Respectively, a similar one standard deviation decrease (increase) in firm-level flows

Table VI. Probability of UCITS fund and conventional fund launches

This table presents conditional Probit analysis results, in which the fund launching decision of a management company is explained by hedge fund firm-level variables. "Fund Launch" is assigned a value of one when a management firm launches a UCITS hedge fund during the quarter and a value of zero if the management company launches a conventional fund during the quarter. "N_UCITS" refers to the number of UCITS hedge funds the firm manages during the previous quarter. "N_Conventional" refers to the number of conventional hedge funds that the company managed during the previous quarter. "Firm alpha" is the firm's previous quarter global alpha estimated from the past 24 month returns (VW fund-level alpha). "Firm flow" is the firm's previous 24 month flows (VW fund-level flow). "Firm size" ("Firm age") is the firm's previous quarter size (age) computed using value-weighting across the firm's funds. The time-invariant firm characteristics variables are computed using the value-weighting across the firm's funds. In all Probit models, only firm quarters with a fund launch are included. Regressions include quarterly fixed effects. Standard errors are double clustered by quarter and firm (associated *t*-statistics are presented in parentheses). The study period is from January 2007 through December 2016.

Variable	Probability (fund launch)	
Log (1 + N_UCITS)	0.6965	0.7687
	(6.52)	(3.24)
Log (1 + N_Conventional)	−0.4016	−0.3473
	(−7.50)	(−3.66)
Log (1 + N_UCITS) × Log (1 + N_Conventional)		−0.0472
		(−0.54)
Firm alpha (% per annum)	−0.0062	−0.0060
	(−2.18)	(−2.13)
Firm flow (% per annum)	−0.0008	−0.0008
	(−2.98)	(−2.88)
Log (Firm size)	0.0269	0.0240
	(1.17)	(1.00)
Firm age (in years)	0.0161	0.0160
	(4.42)	(4.74)
Firm restriction (in weeks)	−0.0193	−0.0191
	(−2.36)	(−2.20)
Firm high-water mark	0.1865	0.1936
	(1.92)	(2.00)
Firm management fee (% per annum)	−0.3956	−0.3967
	(−4.36)	(−4.37)
Firm incentive fee (% per annum)	−0.0069	−0.0072
	(−0.92)	(−0.99)
N	3,678	3,678

generates a 4.75% increase (decrease) in the probability of launching a UCITS (conventional) hedge fund. These effects are economically meaningful, since the unconditional probability that a firm opens a UCITS (conventional) fund in any given quarter is 1.15% (3.28%).

The results in Table VI show that the signs and significance of fund-type variables are consistent with the equilibrium outcome prediction that certain types of management companies are more likely to launch UCITS while others may prefer to launch conventional funds. The management companies that tend to provide more onerous redemption fees and charge lower fees are more likely to launch UCITS funds, while companies with funds having tight redemptions and relatively high fees are more likely to open conventional funds. This is supported by the fact that the number of UCITS (conventional) funds is positively associated with the likelihood to open a UCITS (conventional) fund. After controlling for the role of these variables, we still find that the past firm-level alphas and flows are important determinants of fund launching decisions.

Having established that management company characteristics are related to fund launches, we next turn to the determinants of firm-level capital flows. This allows us to examine the idea that the management companies receive more flows by running UCITS funds than conventional funds, even after controlling for the role of past performance and other firm-level characteristics. The rationale for relatively high flows to UCITS hedge funds is the substantial demand for hedge fund investments that are less opaque and more tightly regulated than conventional funds. To test for this conjecture, we run the following multivariate regression on firm flow:

$$\begin{aligned} FirmFlow_{i,t} = {} & \lambda_0 + \lambda_1 \log\left(1 + UCITS\ \ Funds_{i,t-1}\right) + \lambda_2 \log\left(1 + Conventional\ \ Funds_{i,t-1}\right) \\ & + \lambda_3 FirmPermPercentile_{i,t-1} + \lambda_4 FirmAge_{i,t-1} + \lambda_5 FirmSize_{i,t-1} \\ & + \lambda_6 Restriction_i + \lambda_7 HighWaterMark_i + \lambda_8 ManagementFee_i \\ & + \lambda_9 IncentiveFee_i + \nu, \end{aligned}$$

where the dependent variable, $FirmFlow_{i,t}$, is the quarterly firm-level flow. All the other explanatory variables are the same as the previous Probit analysis, except for the *FirmPermPercentile*, which is defined as the performance percentile based on the previous quarter firm-level value-weighted raw returns.[22] The regressions include quarter fixed effects and employ robust standard errors that are double clustered by quarter and management firm.

The results reported in Table VII indicate that firm-level flows respond to the number of UCITS funds, but not to the respective number of conventional funds. After controlling for the role of past performance and other firm characteristics, the coefficient estimates for number of UCITS funds are positive and highly significant, while insignificant for the number of conventional funds. The coefficient estimates for the number of UCITS funds translate into meaningful economic effects. One standard deviation increase in the number of managed UCITS funds is associated with 1.59 times higher firm-level quarterly flows, whereas running one additional UCITS fund results in a 1.16 times increase in respective flows.

To confirm that the higher flows are not driven just by fund redemption terms that are related to fund flows (Aragon, Liang, and Park, 2014; Getmansky *et al.*, 2019), we decompose the $Log(1 + Conventional\ \ Funds)$ variable into the number of liquid hedge funds (i.e., those that provide at least biweekly liquidity as UCITS are required to do) and the rest of the conventional hedge funds. We observe from Table VII that the coefficient for the number of liquid hedge funds is indistinguishable from zero suggesting that management companies do not get more flows by managing a higher number of liquid conventional hedge

22 Our conclusions are not sensitive to change when run flow regressions with performance rank derived from CAPM alpha and Fung-Hsieh alpha. As per Agarwal, Green, and Ren (2018), investors may respond more to fund alpha than return.

Table VII. Fund launches and firm-level capital flows

This table reports the results for the flow-performance panel regressions, in which firm-level quarterly flow is explained by the number of UCITS hedge funds that a firm manages and a set of control variables. "N_UCITS" refers to the number of UCITS hedge funds that the firm managed during the past quarter. "N_Conventional" refers to the number of conventional hedge funds that the firm managed during the past quarter. "N_Liquid_Conventional" refers to the number of liquid conventional hedge funds that the firm managed during the past quarter. "N_Illiquid_Conventional" refers to the number of illiquid conventional hedge funds that the firm managed during the past quarter. "Firm performance percentile" is the firm's previous quarter performance percentile based on raw returns. The other variables are defined in Table VII. Regressions include quarterly fixed effects. Standard errors are estimated using double clustering by quarter and firm (associated *t*-statistics are presented in parentheses). The study period is from January 2007 through December 2016.

Variable	Quarterly firm-level flow (% per quarter)					
Log (1 + N_UCITS)	1.9510		1.9542			1.9045
	(5.10)		(5.18)			(5.08)
Log (1 + N_Conventional)		−0.3613	0.0112			
		(−1.25)	(0.04)			
Log (1 + N_Liquid_Conventional)				0.4308		0.4018
				(0.95)		(0.93)
Log (1 + N_Illiquid_Conventional)					−0.6259	−0.2723
					(−2.05)	(−0.97)
Firm performance percentile	0.0980	0.0974	0.0980	0.0975	0.0974	0.0980
	(15.36)	(15.36)	(15.34)	(15.39)	(15.36)	(15.36)
Log (Firm size)	−0.6674	−0.5753	−0.6681	−0.5959	−0.5646	−0.6554
	(−6.31)	(−5.48)	(−6.30)	(−5.66)	(−5.53)	(−6.30)
Firm age (in years)	−0.2694	−0.2647	−0.2696	−0.2723	−0.2624	−0.2677
	(−10.62)	(−9.83)	(−10.41)	(−10.38)	(−9.71)	(−10.45)
Firm restriction (in weeks)	−0.0172	−0.0311	−0.0171	−0.0269	−0.0264	−0.0122
	(−1.41)	(−2.53)	(−1.42)	(−2.25)	(−2.17)	(−1.03)
Firm high-water mark	0.5852	0.5706	0.5858	0.6483	0.6800	0.6799
	(1.79)	(1.74)	(1.79)	(1.89)	(2.02)	(1.96)
Firm management fee (% per annum)	0.0521	−0.0236	0.0519	−0.0425	−0.0191	0.0508
	(0.24)	(−0.11)	(0.23)	(−0.19)	(−0.09)	(0.23)
Firm incentive fee (% per annum)	−0.0400	−0.0530	−0.0400	−0.0536	−0.0507	−0.0378
	(−1.65)	(−2.17)	(−1.65)	(−2.19)	(−2.08)	(−1.56)
Adj. R^2 (%)	2.71	2.65	2.71	2.65	2.66	2.71
N	104,306	104,306	104,306	104,306	104,306	104,306

funds. Hence, our results support the view that during our study period investors directed more capital to UCITS funds, not to conventional hedge funds.

Although by managing a high number of UCITS funds management companies can gather more assets in equilibrium, conventional funds can be more profitable for management companies. Indeed, conventional hedge funds may generate more profits for their management companies because of higher returns and fees compared to those of UCITS hedge funds. To explore how management companies benefit from different types of funds, we run the following multivariate regressions on realized fees and dollar profits:

$$
\begin{aligned}
RealizedFees_{i,t} \text{ or } DollarProfits_{\ i,t} = {} & \delta_0 + \delta_1 \log\left(1{+}UCITS\ Funds_{i,t-1}\right) \\
& + \delta_2 \log\left(1 + Conventional\ Funds_{\mathrm{i},t-1}\right) \\
& + \delta_3 FirmPerfPercentile_{i,t-1} + \delta_4 FirmAge_{i,t-1} \\
& + \delta_5 FirmSize_{i,t-1} + \delta_6 Restriction_i \\
& + \delta_7 HighWaterMark_i + \delta_8 ManagementFee_i \\
& + \delta_9 IncentiveFee_i + \upsilon,
\end{aligned}
$$

where $RealizedFees_{i,t}$ are the firm-level realized gross-of-fees minus the respective net-of-fees (measured as a fraction of firm AUM in percentile terms), and $DollarProfits_{\ i,t}$ are defined by multiplying the realized fees by the size of the firm (measured as millions of US dollars). The rest of the specification is as per previous regressions on flows.

Consistent with our equilibrium argument, Table VIII reports that coefficients for realized fees are positive and significant for both number of UCITS funds and conventional funds. The magnitude of these coefficients is very similar, suggesting that both types of funds are equally profitable in equilibrium. However, when we decompose the number of conventional funds into liquid funds and rest of the funds, we find that the coefficient for the number of liquid funds is indistinguishable from zero, while the coefficient for the number of illiquid hedge funds is positive and highly significant. The results are very similar when we measure benefits using dollar profits instead of realized fees. Hence, the number of UCITS funds and the number of illiquid conventional funds are positively associated with profits generated by the management companies.

To further explore the equilibrium mechanisms of how management companies generate their profits, we employ the matching estimator approach within a management company and a fund manager. By comparing UCITS and conventional hedge funds within the same management company and fund manager, we can fix company characteristics and fund manager talent. This allows us to achieve more equivalent comparisons that are robust to unobserved management company-level or fund manager-level confounders. The matching estimator procedure is similar to the performance analysis presented in Section 4, but here we use as outcome variables firm-level flows, realized fees, and dollar profits instead of fund-level performance measures. Using within firm and manager matched pairs, Table IX reports that UCITS funds have higher flows than conventional funds. In contrast, as our equilibrium interpretation suggests, within matched firm pairs and manager pairs, both realized fees and profits are higher for conventional funds compared to the respective estimates for UCITS funds. These differences are also economically large and statistically highly significant. To highlight, when both the management company and the fund manager are matched, we find that the average UCITS fund generates 5.62% higher flows per annum than a matched conventional fund, while the average conventional fund generates \$3.32 million more profits per year than a UCITS fund.

Collectively, our results show that management companies that launch UCITS hedge funds can gather more flows from investors that prefer more regulated funds. However, since UCITS hedge funds have, on average, lower returns than conventional hedge funds, management companies make more profits by managing conventional funds than UCITS funds. Hence, management companies with better performing conventional funds are better-off by managing a higher number of conventional funds than UCITS funds.

Table VIII. Profits generated by UCITS funds and conventional funds

This table reports the results for the panel regressions, in which firm-level realized fees and dollar profits are explained by the number of UCITS hedge funds that the company manages and a set of control variables. "Realized fees" are defined as the firm's realized gross-of-fees returns minus net-of-fees returns as a fraction of AUM. "Dollar profits" are calculated by multiplying realized fees by the size of the firm. The other variables are defined in Tables VII and VIII. Regressions include quarterly fixed effects. Standard errors are double clustered by quarter and firm (associated *t*-statistics are presented in parentheses). The study period is from January 2007 through December 2016.

Variable	Quarter-ahead realized fees (fraction of AUM)						Quarter-ahead dollar profit (millions of USD)					
Log (1 + N_UCITS)	0.0327		0.0483			0.0455	2.8031		3.6473			3.5412
	(1.75)		(2.56)			(2.40)	(3.35)		(4.31)			(4.26)
Log (1 + N_Conventional)		0.0451	0.0548					2.2380	2.9717			
		(2.58)	(3.08)					(4.35)	(5.57)			
Log (1 + N_Liquid_Conventional)				−0.0031		0.0184				0.5420		1.7823
				(−0.10)		(0.58)				(1.05)		(3.26)
Log (1 + N_Illiquid_Conventional)					0.0425	0.0532					2.0643	2.9688
					(2.34)	(2.88)					(4.21)	(5.47)
Firm performance percentile	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045	0.0107	0.0103	0.0115	0.0099	0.0101	0.0114
	(5.53)	(5.53)	(5.55)	(5.52)	(5.53)	(5.54)	(3.27)	(3.21)	(3.44)	(3.14)	(3.17)	(3.44)
Log (Firm size)	−0.0239	−0.0249	−0.0275	−0.0225	−0.0245	−0.0271	2.5919	2.5895	2.3968	2.7059	2.6094	2.4037
	(−5.90)	(−5.86)	(−6.47)	(−5.53)	(−5.77)	(−6.42)	(16.75)	(17.16)	(15.22)	(17.67)	(17.34)	(15.38)
Firm age (in years)	−0.0056	−0.0064	−0.0066	−0.0056	−0.0062	−0.0065	0.1165	0.0750	0.0632	0.1129	0.0840	0.0636
	(−3.58)	(−4.15)	(−4.25)	(−3.56)	(−4.00)	(−4.15)	(3.50)	(1.93)	(1.78)	(3.17)	(2.19)	(1.76)
Firm restriction (in weeks)	0.0010	0.0008	0.0012	0.0007	0.0005	0.0009	0.0314	0.0128	0.0418	0.0146	−0.0036	0.0333
	(0.67)	(0.56)	(0.80)	(0.50)	(0.33)	(0.62)	(2.04)	(0.88)	(2.69)	(0.99)	(−0.24)	(2.16)
Firm high-water mark	−0.4250	−0.4219	−0.4209	−0.4257	−0.4313	−0.4297	−1.1651	−1.0174	−0.9382	−1.0991	−1.4780	−1.3039
	(−9.84)	(−9.83)	(−9.82)	(−9.90)	(−9.93)	(−9.96)	(−3.26)	(−2.82)	(−2.67)	(−2.98)	(−4.05)	(−3.65)
Firm management fee (% per annum)	0.2528	0.2493	0.2511	0.2513	0.2498	0.2512	1.3484	1.1200	1.2599	1.2054	1.1469	1.2462
	(14.70)	(14.26)	(14.56)	(14.41)	(14.27)	(14.54)	(4.39)	(3.74)	(4.17)	(4.03)	(3.81)	(4.14)
Firm incentive fee (% per annum)	0.0370	0.0365	0.0368	0.0367	0.0364	0.0367	0.1333	0.0994	0.1240	0.1122	0.0974	0.1213
	(16.03)	(15.94)	(15.99)	(16.04)	(15.89)	(15.93)	(6.44)	(4.63)	(6.14)	(5.19)	(4.57)	(6.03)
Adj. R^2 (%)	5.43	5.44	5.45	5.43	5.44	5.45	22.35	22.30	23.08	21.88	22.26	23.09
N	88,728	88,728	88,728	88,728	88,728	88,728	88,728	88,728	88,728	88,728	88,728	88,728

Table IX. Flows, realized fees, and dollar profits within a hedge fund company and fund manager

This table presents the matching estimator results for flows, realized fees, and dollar profit differences between UCITS hedge funds and matched conventional hedge funds that are managed by the same firm ("Firm"), the same manager ("Manager"), or manager that belongs to the same firm ("Both"). "UCITS" ("Conventional") denotes the flows, realized fees, or dollar profits for the UCITS (Conventional) group. "Coefficient" is the bias-adjusted coefficient of the Abadie and Imbens (2006, 2011) matching estimator. "*t*-statistic" refers to the heteroskedasticity-adjusted *t*-statistic of the bias-adjusted Abadie and Imbens (2006, 2011) matching estimator. Matched conventional funds are defined by matching UCITS hedge funds within a hedge fund firm, manager, or both based on the distance between the fund's investment strategy, initial size, inception date, restriction period, lockup period, and level of leverage. For each UCITS hedge fund, we match only one corresponding fund characterized by the lowest distance. "Flows" are management company-level flows measured as a fraction of AUM. "Realized fees" are management company-level realized fees measured as a fraction of AUM. "Dollar profits" are management company-level dollar profits measured in millions of US dollars per annum.

Variable	Family	No. of Matched UCITS	UCITS	Conventional	Coefficient	*t*-statistic
Flows (% per annum)	Firm	267	7.01	1.33	5.68	4.85
Realized fees (% per annum)	Firm	246	2.28	2.82	−0.55	−7.76
Dollar profits (millions of US dollars per annum)	Firm	244	6.37	10.04	−3.67	−6.57
Flows (% per annum)	Manager	237	6.78	0.94	5.84	4.90
Realized fees (% per annum)	Manager	218	2.48	3.08	−0.60	−8.40
Dollar profits (millions of US dollars per annum)	Manager	217	5.93	8.11	−2.18	−3.75
Flows (% per annum)	Both	192	4.90	−0.72	5.62	4.98
Realized fees (% per annum)	Both	178	2.32	3.01	−0.69	−10.53
Dollar profits (millions of US dollars per annum)	Both	177	5.97	9.29	−3.32	−6.03

6. Robustness Checks

6.1 Matching Design Sensitivity

Our baseline matching analysis assumes that we have matched on all influential fund characteristics and that there is not an unobserved confounder that may account for the difference across the treatment and control groups.

As an alternative way to estimate the treatment effect in the conditioned sample, we use standard propensity score matching and genetic matching approaches. Since the Mahalanobis distance does not perform well when covariates have nonellipsoidal distributions, Rosenbaum and Rubin (1983) proposed that the propensity score should be used for matching. Diamond and Sekhon (2013) propose a genetic search algorithm to determine a set of weights for each covariate such that the optimal balance is achieved after matching. Their algorithm can be seen as a generalization of propensity score and Mahalanobis distance matching.

Panels A and B of Table X report average treatment effects that are estimated when the matching is performed using the genetic search algorithm and standard propensity score. We observe that all three variants of global alpha remain economically meaningful and statistically highly significant, indicating that UCITS funds underperform conventional hedge funds as our main results suggest.

Next, we employ entropy reweighting developed by Hainmueller (2012) to create a balanced sample and achieve average treatment effects. Rather than predicting treatment as accurately as possible, entropy balancing attempts to balance the distribution of covariates evenly between the treatment and control groups by reweighting data so that the covariate distributions in the reweighted data satisfy a set of specified moment conditions. In practice, we estimate weights by minimizing the entropy of the weights subject to exact moment balancing constraints for the first four moments of the matching variables results in Panel C of Table X show that UCITS funds deliver consistently lower global alphas than those of conventional funds. Our results are robust when we use a modern method that focuses on achieving accurate balance between covariates.

To assess how robust our findings are to hidden bias arising from an unobserved confounder, we apply the Rosenbaum (2002) bounds. These bounds are designed to quantify the degree to which our key identification assumption must be violated for our conclusion on performance differences between UCITS and conventional hedge funds to be reversed. From a statistical perspective, Rosenbaum (2002) emphasizes that treated and control groups may differ on an unobserved characteristic even after matching on observed characteristics. In other words, hedge funds with the same observed covariates may have different probabilities of being treated if they have different unobserved covariates. A sensitivity parameter is used to quantify the difference in the odds of exposure for two funds that have the same observed covariates but that diverge on unobserved covariates. The aim is to determine the smallest value of this so-called gamma parameter that will change the p-value of the "true" outcome-treated association to a nonsignificant level. The results displayed in Figure 3 indicate that our findings are not sensitive to possible hidden bias due to an unobserved confounder that affects the odds ratio of the UCITS dummy by a factor up to around two. For all three variants of alphas, the gamma parameter is close to two or above. The findings are very similar for our baseline matching estimator approach, genetic matching, and standard propensity score matching. Overall, it is very unlikely that hidden bias due to an unobserved confounder can reverse our conclusions regarding the performance difference between UCITS and conventional funds.

Table X. Robustness tests

This table examines the sensitivity of our main performance results in different ways of estimating treatment effects. Panel A (Panel B) presents the matching estimator results when the covariate balance is achieved using the genetic matching approach (standard propensity score). Panel C presents results when entropy reweighting developed by Hainmueller (2012) is used to create a balanced sample and achieve average treatment effects. Panel D presents the matching estimator results for a subsample that is free from potential look-ahead bias and changes in fund type (see Figure 4). In Panel E, matched funds are defined by matching UCITS hedge funds based on the distance between the fund's betas to the corresponding benchmark model. Panel F presents matching estimator results for the global eight-factor model which is the Lustig, Roussanov, and Verdelhan (2011) currency factor augmented version of the global seven-factor model; its stepwise version; its smoothing-adjusted version; the Fung–Hsieh seven- and eight-factor models; the broad stepwise model which contains global factors, Fung–Hsieh factors, and Agarwal-Naik (2004) factors. Results in Panel F are based on the baseline matching procedure presented in Table II. In all panels, each UCITS hedge fund is matched to three corresponding conventional hedge funds characterized by the lowest distance. All measures are estimated for each fund having at least twenty-four return observations.

Panel A: Genetic matching

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global seven-factor alpha (% pa)	−8.90	−5.08	−3.83	−5.29
t-statistics	−1.57	−0.62	−0.94	−9.20
Stepwise global seven-factor alpha (% pa)	−7.16	−3.36	−3.79	−5.93
t-statistics	−1.55	−0.50	−1.06	−8.52
Smoothing-adj. global seven-factor alpha (% pa)	−6.57	−3.19	−3.38	−5.41
t-statistics	−1.48	−0.41	−1.06	−6.35

Panel B: Propensity score matching

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global seven-factor alpha (% pa)	−8.90	−5.07	−3.83	−5.01
t-statistics	−1.57	−0.68	−0.88	−8.63
Stepwise global seven-factor alpha (% pa)	−7.16	−3.11	−4.05	−6.17
t-statistics	−1.55	−0.52	−1.03	−8.84
Smoothing-adj. global seven-factor alpha (% pa)	−6.57	−2.75	−3.81	−5.81
t-statistics	−1.48	−0.04	−1.44	−6.64

Panel C: Entropy balanced matching

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global seven-factor alpha (% pa)	−8.90	−6.37	−2.53	−2.59
t-statistics	−1.57	−0.69	−0.87	−8.42
Stepwise global seven-factor alpha (% pa)	−7.16	−4.35	−2.81	−2.82
t-statistics	−1.55	−0.63	−0.93	−7.68
Smoothing-adj. global seven-factor alpha (% pa)	−6.57	−3.84	−2.72	−2.71
t-statistics	−1.48	−0.49	−0.99	−6.66

(continued)

Table X. Continued

Panel D: Adjusted for potential look-ahead bias

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global seven-factor alpha (% pa)	−9.52	−6.80	−2.72	−3.11
t-statistics	−1.48	−0.79	−0.69	−5.93
Stepwise global seven-factor alpha (% pa)	−7.45	−4.09	−3.36	−4.92
t-statistics	−1.52	−0.59	−0.93	−7.17
Smoothing-adj. global seven-factor alpha (% pa)	−6.63	−3.14	−3.49	−5.41
t-statistics	−1.17	−0.22	−0.95	−3.99

Panel E: Beta matching

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global seven-factor alpha (% pa)	−8.90	−5.41	−3.50	−12.81
t-statistics	−1.57	−0.87	−0.69	−12.44
Stepwise global seven-factor alpha (% pa)	−7.16	−3.45	−3.71	−12.45
t-statistics	−1.55	−0.68	−0.87	−12.72
Smoothing-adj. global seven-factor alpha (% pa)	−6.57	−3.21	−3.36	−11.09
t-statistics	−1.48	−0.53	−0.95	−9.59

Panel F: Choice of benchmark model

Variable	UCITS	Conventional	Coefficient	*t*-statistic
Global eight-factor alpha (% pa)	−3.33	−2.23	−1.10	−1.93
t-statistics	−0.55	−0.31	−0.24	−2.97
Stepwise global eight-factor alpha (% pa)	−2.65	−1.59	−1.06	−2.21
t-statistics	−0.54	−0.21	−0.33	−3.31
Smoothing-adj. global eight-factor alpha (% pa)	−2.54	−1.37	−1.16	−2.47
t-statistics	−0.52	−0.22	−0.30	−2.33
Fung–Hsieh seven-factor alpha (% pa)	−8.40	−6.48	−1.92	−3.68
t-statistics	−1.63	−0.99	−0.64	−8.01
Fung–Hsieh eight-factor alpha (% pa)	−4.26	−3.01	−1.25	−2.77
t-statistics	−0.87	−0.48	−0.40	−5.07
Broad stepwise alpha (% pa)	−3.93	−2.51	−1.41	−2.78
t-statistics	−0.92	−0.46	−0.46	−4.33
Smoothing-adj. broad stepwise alpha (% pa)	−3.27	−2.11	−1.16	−2.43
t-statistics	−0.76	−0.35	−0.41	−3.04

6.2 Potential Look-Ahead Bias

To rule out the possibility that the look-ahead bias is driving our findings, we conduct the matching estimator tests using data snapshots that are collected from various data vendors for different vintage years of the databases. Databases generally did not collect the UCITS indicator variable in the early years of the UCITS regulation that started in 2003. Therefore, the returns of our UCITS sample may potentially have a look-ahead bias. To eliminate this concern and to show that our results are robust to potential changes in the legal structure such as the UCITS status, we gather a set of historical database vintages and remove each UCITS fund's returns prior to or up

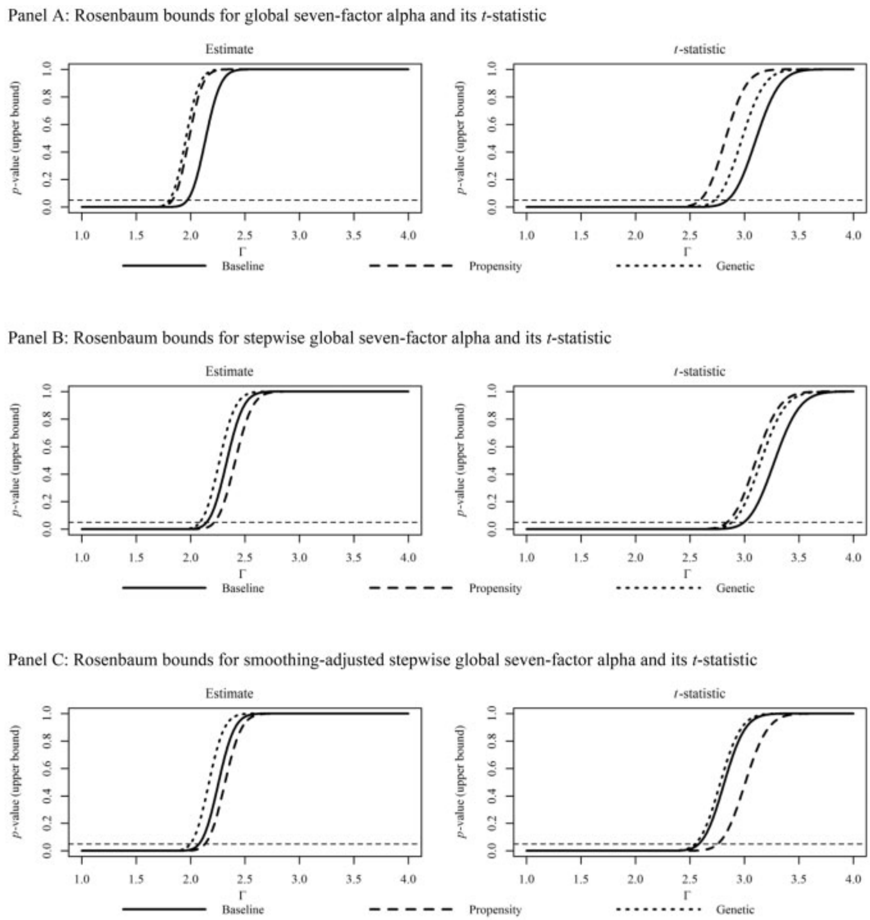

Figure 3. Sensitivity analysis for unobserved confounding. This figure presents Rosembaum (2002) sensitivity analysis which applies bounds to assess the magnitude of the increase in uncertainty of the treatment effect estimation when hidden biases exist. Rosenbaum bounds are based on the log of the coefficient for the unobserved covariate, Γ, which is a measure of the hidden bias of the treatment effects. To perform a sensitivity analysis, we select values of one to four for Γ, and thereafter we use Wilcoxon signed-rank statistic to estimate the upper bound for *p*-value considering that the treatment estimation is sensitive to hidden bias. Panels A, B, and C present the sensitivity analysis for baseline matched, propensity score, and genetic algorithm matched samples for all three alpha variants. (**A**) Rosenbaum bounds for global seven-factor alpha and its *t*-statistic. (**B**) Rosenbaum bounds for stepwise global seven-factor alpha and its *t*-statistic. (**C**) Rosenbaum bounds for smoothing-adjusted stepwise global seven-factor alpha and its *t*-statistic.

to the release date of the earliest database vintage that reports the fund as a UCITS fund.[23] Figure 4 plots the earliest date that each of our UCITS funds is detected in a database vintage. It shows that, for example, in November 2013 we can identify the UCITS variable in around 50%

23 Our set of historical snapshots consists of six HFR snapshots (from November 2007, June 2009, April 2011, April 2012, November 2013, and June 2015), three BarclayHedge snapshots (from November 2010, November 2013, and May 2015), and six EurekaHedge snapshots (from December 2007, February 2008, December 2009, December 2010, November 2013, and Jun 2015).

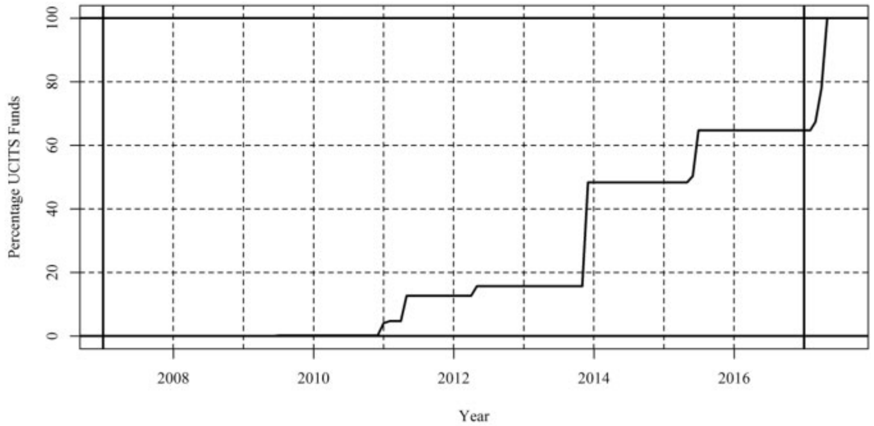

Figure 4. Earliest date for the UCITS fund status. This figure plots the earliest date that each UCITS fund was detected in database snapshot data. A set of historical database snapshots is gathered. Then we remove each UCITS fund's returns prior or up to the release date of the earliest snapshot that reports the fund as a UCITS fund. Our set of historical snapshots consists of six HFR snapshots (from November 2007, June 2009, April 2011, April 2012, November 2013, and June 2015), three BarclayHedge snapshots (from November 2010, November 2013, and May 2015), and six Eurekahedge snapshots (from December 2007, February 2008, December 2009, December 2010, November 2013, and June 2015).

of funds. This implies that data vendors have not backfilled these funds' UCITS indicator variable, and therefore from that date funds cannot suffer from look-ahead bias. Overall, from snapshot data, we detect 499 UCITS funds with at least 24 month return history that do not suffer from potential look-ahead bias. Results presented in Panel D of Table X show that UCITS funds underperform conventional hedge funds when we use only UCITS funds that cannot suffer from look-ahead bias, indicating that it does not drive our results.

6.3 Beta Matching

Our baseline matching estimator results rely on variables such as redemption terms and level of leverage which are motivated by UCITS regulation. However, although we use investment strategy as a matching variable, our matching cannot guarantee that the systematic risk loading differences between UCITS and conventional funds are not driving the performance results. In addition, the strategy classification can be challenging for some funds that follow, for example, unconventional or niche strategies. Therefore, to ensure that the matching balance is not poor because of strategy misclassification, we implement various ways to match UCITS funds to conventional funds using the estimated risk loadings or factor betas. Such an approach is common in studies that compare socially responsible mutual funds to conventional mutual funds (see, e.g., Bollen, 2007; Gil-Bazo, Ruiz-Verdú, and Santos, 2010). To address this issue, we match UCITS funds to the closest possible conventional funds using the estimated betas obtained from each of the three variants of our benchmark model. Results in Panel E of Table X indicate that beta-matched estimators deliver very similar results to our baseline matching.

6.4 Benchmark Model Choice

Although we believe that the global seven-factor model is particularly well-suited to measuring performance differences between UCITS and conventional funds, we ensure that differences are not driven by the choice of benchmark model. We first augment the global seven-factor model by the Lustig, Roussanov, and Verdelhan (2011) currency risk factor.

Then, we present our results using both standard Fung–Hsieh (2004) seven- and eight-factor models. Even these models may omit some risk factors that drive performance differences. Therefore, following Titman and Tiu (2011), we employ a large set of risk factors in a stepwise regression model to estimate alphas and risk loadings. The global factors, Fung and Hsieh (2004) factors, and two Agarwal and Naik (2004) option factors are used in the broad stepwise regression model. Panel F of Table X shows that UCITS funds underperform conventional hedge funds independent of whether we use the global eight-factor model, the Fung–Hsieh seven- or eight-factor models, or the broad stepwise models. Our results are therefore robust to the choice of benchmark model.

7. Conclusions

In this article, we examine the effect of regulatory constraints on fund performance, risk, and net asset valuations. Using a matching estimator approach that allows a causal interpretation of our results, we test two hypotheses and document several novel insights related to regulatory constraints. First, we show that UCITS hedge funds deliver lower performance than matched conventional hedge funds. Using a wide range of benchmark model specifications, we estimate the indirect cost of UCITS regulation to be between 1.06% and 4.05% per annum. The matching estimator approach allows us to conclude that performance differences are due to UCITS constraints governing eligible assets, diversification, and short selling, but not due to redemption terms, leverage, and other fund characteristics that we use in matching. Second, consistent with tight risk limits required by UCITS rules, we find that UCITS hedge funds' risk levels are lower than those of matched conventional funds. Our results also reveal that the idiosyncratic risk is higher for matched conventional funds, while the systematic risk levels of UCITS funds are on a par with conventional funds. Conventional funds' greater risk-taking does not harm their investors as evidenced by reward-to-risk-type measures such as Sharpe ratios which are higher for conventional funds than UCITS funds.

Since UCITS hedge funds underperform conventional funds, we analyze why UCITS hedge funds exist in equilibrium. Our analysis reveals that for hedge fund firms that have experienced poor returns and outflows, it is easier to launch and attract capital to UCITS funds. In fact, anecdotal evidence suggests that in the aftermath of the financial crisis, there has been a higher demand for tightly regulated and transparent vehicles such as UCITS hedge funds than for more opaque conventional hedge funds. On the contrary, we find that better-performing hedge fund firms, which have not experienced outflows, can still attract assets into conventional hedge funds which tend to generate more fee revenues. Overall, although we caution against a causal interpretation of our analysis of fund launches, the empirical evidence is consistent with an equilibrium in which hedge fund firms attract more assets by managing UCITS funds, but higher fee revenues by running conventional funds.

The recent implementation of the AIFM Directive may provide new avenues for future research. The directive has already allowed national supervisors, the European Securities and Markets Authority and the European Systemic Risk Board to gather the information required for monitoring the financial system and protecting investors. However, in contrast to the USA, where the confidential Form PF has begun to be used for research purposes, European authorities have not proposed extending such a privilege to researchers. New data that contain position and leverage level information would allow researchers to carry out more granular test such as, for instance, which subcomponents of regulation affect alternative investment fund risk and performance.

Data Availability Statement

The hedge fund data used in this article are owned by third parties. The hedge fund data underlying this article were provided by BarclayHedge, Eurekahedge, eVestment, HFR, Lipper TASS, Morningstar, and Preqin under license.

Conflict of interest

Both authors confirm that they do not have a conflict of interest.

Appendix

Table A1. Matching estimator across investment strategies

This table presents the matching estimator results for each investment strategy. Results are based on the baseline matching procedure presented in Table II. In all panels, for each UCITS hedge fund, we match three corresponding funds characterized by the lowest distance. All measures are estimated for each fund having at least twenty-four return observations.

	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Variable	Credit (#UCITS = 90)		Equity (#UCITS = 429)	
Global alpha (% pa)	−3.96	−3.03	−2.67	−3.11
t-statistics	−0.89	−3.29	−0.75	−6.25
Stepwise alpha (% pa)	−4.73	−4.40	−2.86	−3.46
t-statistics	−1.12	−3.40	−0.90	−6.27
Smoothing-adjusted alpha (% pa)	−3.30	−2.84	−3.13	−4.11
t-statistics	−0.84	−2.12	−1.05	−4.57
	Event-driven (#UCITS = 24)		Macro (#UCITS = 123)	
Global alpha (% pa)	−6.99	−3.69	−1.69	−0.92
t-statistics	−1.76	−3.56	−0.76	−3.15
Stepwise alpha (% pa)	−6.06	−3.47	−2.01	−1.64
t-statistics	−1.91	−3.40	−0.78	−3.05
Smoothing-adjusted alpha (% pa)	−6.39	−3.41	−1.44	−1.18
t-statistics	−1.28	−1.78	−0.82	−2.98
	Managed futures (#UCITS = 42)		Multistrategy (#UCITS = 21)	
Global alpha (% pa)	−10.29	−5.91	−4.72	−1.79
t-statistics	−1.50	−6.93	−1.00	−2.19
Stepwise alpha (% pa)	−7.43	−4.49	−3.33	−1.70
t-statistics	−1.40	−5.40	−1.08	−2.27
Smoothing-adjusted alpha (% pa)	−7.00	−4.46	−2.37	−1.04
t-statistics	−1.07	−2.23	−1.46	−1.86
	Other (#UCITS = 8)		Relative value (#UCITS = 70)	
Global alpha (% pa)	2.18	0.69	−8.75	−3.09
t-statistics	−1.14	−1.76	−1.80	−4.64
Stepwise alpha (% pa)	4.36	0.92	−8.62	−3.57
t-statistics	−1.82	−2.04	−2.15	−4.14
Smoothing-adjusted alpha (% pa)	3.44	0.67	−7.03	−2.90
t-statistics	−2.78	−2.39	−1.65	−2.98

Table A2. Statistical tests for performance persistence tests

This table shows the (annualized) global alphas for the UCITS hedge funds and matched conventional hedge funds. It displays the top twenty-five and top fifty fund portfolios' VW global alphas across rebalancing frequencies. Using *t*-statistics of the global alpha, funds are sorted into top twenty-five and top fifty portfolios that are rebalanced at 1, 2, 3, 4, 6, and 12 month frequencies. The *t*-statistics are estimated using the twenty-four most recent return observations. Statistical inference is based on Newey and West (1987) standard errors. The out-of-the sample period is from January 2007 through December 2016.

Panel A: Net-of-fees returns

		Top twenty-five funds						Top fifty funds					
		Holding period (months)						Holding period (months)					
Portfolio	Measure	1	2	3	4	6	12	1	2	3	4	6	12
UCITS	Alpha (%)	−5.77	−4.41	−5.76	−4.68	−3.37	−7.38	−5.12	−5.03	−4.34	−4.75	−3.62	−5.17
	t-statistic	(−2.64)	(−2.08)	(−2.67)	(−2.18)	(−1.59)	(−3.09)	(−2.92)	(−2.81)	(−2.40)	(−2.55)	(−1.93)	(−2.54)
Conventional	Alpha (%)	−0.82	0.20	0.49	1.26	1.18	−0.16	−0.35	−1.06	−0.47	−1.50	−0.48	−0.93
	t-statistic	(−0.37)	(0.09)	(0.22)	(0.55)	(0.52)	(−0.07)	(−0.17)	(−0.52)	(−0.23)	(−0.75)	(−0.24)	(−0.44)
Spread	Alpha (%)	−4.95	−4.60	−6.25	−5.93	−4.55	−7.22	−4.77	−3.96	−3.87	−3.25	−3.14	−4.24
	t-statistic	(−1.89)	(−1.76)	(−2.42)	(−2.17)	(−1.70)	(−2.61)	(−2.27)	(−1.84)	(−1.81)	(−1.51)	(−1.41)	(−1.83)

Panel B: Gross-of-fees returns

		Top twenty-five funds						Top fifty funds					
		Holding period (months)						Holding period (months)					
Portfolio	Measure	1	2	3	4	6	12	1	2	3	4	6	12
UCITS	Alpha (%)	−2.29	−0.99	−1.67	−1.30	−0.63	−3.19	−1.99	−2.20	−1.96	−2.34	−1.29	−2.61
	t-statistic	(−1.07)	(−0.45)	(−0.75)	(−0.58)	(−0.28)	(−1.31)	(−1.07)	(−1.17)	(−1.02)	(−1.21)	(−0.65)	(−1.26)
Conventional	Alpha (%)	3.23	4.02	3.79	4.51	3.84	2.36	3.13	2.80	2.09	2.52	2.54	1.12
	t-statistic	(1.29)	(1.61)	(1.39)	(1.81)	(1.40)	(0.82)	(1.36)	(1.17)	(0.89)	(1.05)	(1.07)	(0.45)
Spread	Alpha (%)	−5.51	−5.01	−5.46	−5.82	−4.47	−5.55	−5.11	−4.99	−4.06	−4.86	−3.83	−3.73
	t-statistic	(−2.01)	(−1.80)	(−1.94)	(−2.10)	(−1.59)	(−1.94)	(−2.28)	(−2.21)	(−1.85)	(−2.12)	(−1.74)	(−1.60)

Table A3. Feasibility and performance persistence

This table presents the (annualized) global alphas for the UCITS hedge funds and matched liquid conventional hedge funds. It displays the top twenty-five and top fifty fund portfolios' VW global alphas across rebalancing frequencies. Using *t*-statistics of the global alpha, funds are sorted into top twenty-five and top fifty portfolios that are rebalanced at 1, 2, 3, 4, 6, and 12 month frequencies. The *t*-statistics are estimated using the twenty-four most recent return observations. Statistical inference is based on Newey and West (1987) standard errors. The out-of-the sample period is from January 2007 through December 2016.

Panel A: Net-of-fees returns

		Top twenty-five funds						Top fifty funds					
		Holding period (months)						Holding period (months)					
Portfolio	Measure	1	2	3	4	6	12	1	2	3	4	6	12
UCITS	Alpha (%)	−5.77	−4.41	−5.76	−4.68	−3.37	−7.38	−5.12	−5.03	−4.34	−4.75	−3.62	−5.17
	t-statistic	(−2.64)	(−2.08)	(−2.67)	(−2.18)	(−1.59)	(−3.09)	(−2.92)	(−2.81)	(−2.40)	(−2.55)	(−1.93)	(−2.54)
Conventional	Alpha (%)	−0.25	−0.37	0.25	0.14	−0.27	−0.64	−0.74	−0.94	−0.79	−1.54	−0.91	−1.29
	t-statistic	(−0.10)	(−0.14)	(0.09)	(0.05)	(−0.10)	(−0.21)	(−0.32)	(−0.38)	(−0.32)	(−0.62)	(−0.38)	(−0.49)
Spread	Alpha (%)	−5.52	−4.04	−6.01	−4.82	−3.10	−6.74	−4.38	−4.09	−3.55	−3.21	−2.71	−3.88
	t-statistic	(−1.82)	(−1.33)	(−2.01)	(−1.57)	(−1.01)	(−2.14)	(−1.98)	(−1.81)	(−1.52)	(−1.40)	(−1.16)	(−1.56)

Panel B: Gross-of-fees returns

		Top twenty-five funds						Top fifty funds					
		Holding period (months)						Holding period (months)					
Portfolio	Measure	1	2	3	4	6	12	1	2	3	4	6	12
UCITS	Alpha (%)	−2.29	−0.99	−1.67	−1.30	−0.63	−3.19	−1.99	−2.20	−1.96	−2.34	−1.29	−2.61
	t-statistic	(−1.07)	(−0.45)	(−0.75)	(−0.58)	(−0.28)	(−1.31)	(−1.07)	(−1.17)	(−1.02)	(−1.21)	(−0.65)	(−1.26)
Conventional	Alpha (%)	4.37	3.59	2.59	3.22	3.59	0.89	3.37	3.34	2.84	2.93	2.27	1.20
	t-statistic	(1.68)	(1.37)	(0.96)	(1.15)	(1.27)	(0.28)	(1.41)	(1.39)	(1.19)	(1.16)	(0.94)	(0.46)
Spread	Alpha (%)	−6.65	−4.58	−4.26	−4.52	−4.22	−4.08	−5.35	−5.54	−4.80	−5.26	−3.55	−3.81
	t-statistic	(−2.28)	(−1.56)	(−1.39)	(−1.50)	(−1.32)	(−1.31)	(−2.33)	(−2.41)	(−2.15)	(−2.24)	(−1.57)	(−1.62)

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