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On the performance persistence of European offshore mutual funds

Diogo Miguel Moço Alves

Master in Finance

Supervisor:
PhD António Manuel Corte Real de Freitas Miguel, Associate Professor of Finance, Iscte-Iul

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BUSINESS
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Department of Finance

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Resumo

Usamos dados de fundos de ações geridos de forma ativa, de 26 países de Europa, no período 1995-2019, para estudar diferenças na persistência da performance de fundos offshore e onshore.

Os nossos resultados não indicam diferenças estatisticamente significativas nos alfas gerados por fundos offshore e onshore, mas verificamos maior persistência da performance em fundos offshore. Analisando a persistência da performance em toda a escala de desempenho, verificamos que os fundos offshore com pior e melhor performance persistem menos que as suas contrapartes onshore.

Seguidamente, examinamos as diferenças nas sensibilidades da relação fluxo-desempenho entre fundos onshore e offshore. Os nossos resultados não mostram diferenças para fundos com pior desempenho, mas verificamos que investidores de fundos offshore tendem a comprar mais fundos de melhor desempenho. Este facto sugere que a diferença de persistência evidenciada nos fundos com melhor desempenho é explicada pelo incentivo para gerar alfa e, assim, captar mais fluxo, em linha com o modelo de Berk e Green, e é também consistente com um comportamento menos sofisticado por parte de investidores offshore. Quando testamos se a diferença entre os coeficientes de desempenho superior e inferior são estatisticamente diferentes para fundos offshore e fundos onshore, os nossos resultados mostram uma relação fluxo-desempenho mais convexa para fundos offshore, o que confirma que os investidores offshore são menos sofisticados do que as suas contrapartes onshore.

Palavras-Chave: Fundos de Investimento, Fundos Offshore, Persistência de Performance em Fundos de Investimento, Relação Fluxo-Performance

Classificação JEL: G11, G15

Abstract

We use a sample of actively managed equity mutual funds from 26 European countries, in the 1995-2019 period, to study differences in the performance persistence of offshore and onshore funds.

Our results show no statistically significant difference in the alphas generated by offshore and onshore funds, but we find more performance persistence for offshore funds. When looking at performance persistence across the fund performance scale, we find that bottom and top performing offshore funds persist less than their onshore peers.

We next look at differences in the flow-performance sensitivities between onshore and offshore funds. Our results show no differences for bottom-performing funds, but we find that offshore investors tend to buy more top-performing funds. This result suggests that the difference in performance persistence at the top is explained by flow-induced incentives to generate alpha, in line with the Berk and Green model, and it is also consistent with a less sophisticated behaviour from offshore investors. When we test whether the difference between the coefficients of top and bottom performers are statistically different for offshore funds and onshore funds, our results show a more convex flow-performance relationship for offshore funds, which confirms that offshore investors are less sophisticated than their onshore counterparts.

Keywords: Mutual Funds, Offshore Funds, Mutual Fund Performance Persistence, Flow-Performance Relationship

JEL Classification: G11, G15

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Glossary

4f Alpha – Four-Factor Alpha

CAPM – Capital Asset Pricing Model

ESG – Environmental, Social & Governance

HML – High Book-To-Market Equity Minus Low Book-To-Market Equity

MGT - Management

MOM - Momentum

SMB – Small Market Equity Minus Big Market Equity

TER – Total Expense Ratio

TNA – Total Net Assets

UK – United Kingdom

US – United States

CHAPTER 1

Introduction

The mutual fund industry has grown substantially in the past decade. According to the Investment Company Institute (2020), the total net assets of worldwide regulated open-end funds at the end of 2019 are nearly $55 trillion, being the United States (US) and Europe homes to the world's largest regulated fund markets. The US maintained its leading position, with $25.7 trillion (approximately 47%) of the world's total net assets, while Europe managed assets approaching $19 trillion, representing around 34% of the world's total net assets.

The mutual fund industry is being influenced by different market trends, including the gradual shift into passive funds (Investment Company Institute, 2020) and, more recently, the increasing concerns about ESG factors (Global Sustainable Investment Alliance, 2020). Furthermore, fund families are gradually shifting from solo managed funds into team managed funds (Bär et al., 2011a; Bliss et al., 2008).

We also observe an increasing offer of offshore mutual funds, particularly in Europe.[1,2] Despite this, the literature on offshore funds is rather scarce, and there are virtually no studies on the performance persistence of offshore mutual funds. In this paper, we use data from Lipper Hindsight to study the performance persistence of European offshore mutual funds. We also compare the performance persistence of offshore mutual funds to that of onshore funds and test whether differences in persistence are explained by differences in the flow-performance sensitivities between offshore and onshore investors.

Our results show no significant differences in the performance of onshore and offshore funds, but we find evidence of higher persistence in offshore funds. When we look at differences in persistence across the fund performance scale, we find that bottom and top performing offshore funds persist less than their onshore counterparts. We next look at the flow-performance sensitivity for both onshore and offshore funds. Our results indicate no differences in the flow-performance for bottom-performing funds, but we find that offshore investors tend to buy more top-performing funds, which is consistent with a less sophisticated behaviour from offshore investors. Finally, when we test whether the difference between the coefficients of top and bottom performance quintiles are statistically different for offshore funds and onshore

[1] See Figure 3.1.

[2] The hedge fund industry has also experienced rapid growth and, in particular, the offshore funds segment (Aragon et al., 2014).

funds, our results show a more convex flow-performance relationship for offshore funds, which confirms that offshore investors are less sophisticated than their onshore peers.

Our study makes different contributions to the mutual fund literature. First, to the best of our knowledge, we are the first to study both the performance persistence and the flow-performance sensitivity of offshore mutual funds. Second, we use a global sample of equity mutual funds from 26 jurisdictions that include both onshore and offshore funds, which allow us to test for differences in the performance persistence and the flow-performance sensitivity between onshore and offshore investors. Third, our research is important to retail investors, which try to direct their capital into the most lucrative investments, but also to fund families, which manage a large pool of funds around the world. Mutual funds are an extremely important investment vehicle for households, as, according to the Investment Company Institute (2020), 73% of mutual fund-owning households identified retirement as the primary reason for owning and investing in mutual funds. In summary, our study provides relevant insights for mutual fund investor's strategic decisions.

The remainder of the study is structured as follows. Section 2 presents the literature review. Section 3 describes the data and the variables. In Section 4, we present the methodology. In Section 5, we present our empirical findings. Section 6 presents some robustness tests and Section 7 concludes.

CHAPTER 2

Literature Review

Over the last years, many authors have tried to explain different features of the mutual fund industry. In this section, we summarize the main research. Most research focuses on the US mutual fund industry, the oldest and most developed industry in the world.

Firstly, we approach the literature about fund performance, followed by the literature on performance persistence, the flow-performance relationship and, lastly, on offshore funds related studies.

2.1. Fund performance

The performance of mutual funds is the most important aspect for fund selection. Rational investors try to maximize their wealth and debate if actively managed funds add value. To that extent, they analyse whether fund past performance is above or below a particular benchmark and whether there is fund performance persistence across time. Although there is some contradicting evidence, most studies conclude that actively managed equity mutual funds, on average, underperform their benchmarks (see, e.g., Gruber, 1996, and Berk & Green, 2004, for the US and Ferreira et al., 2013, outside the US) . Despite this underperformance, Gruber (1996) finds evidence that the aggregate pattern of consumer investing behaviour is rational. The author concludes that when investors invest in funds receiving inflows and disinvest from those experiencing outflows, they earn a risk-adjusted return that beats indexed funds, even after fees.

Many authors have tried to explain the performance of mutual funds. Ferreira et al. (2013) show that funds located in countries with liquid stock markets and strong legal institutions achieve better performance. Other studies analyse fund level characteristics, namely fund size, age, fees and expenses, loads, turnover, flows, returns and management structure. For example, Ferreira et al. (2013) and Khorana et al. (2009) show that the realized performance of mutual funds and the fees charged by mutual funds show substantial variation across countries. Ippolito (1989) shows that portfolio turnover and management fees are unrelated to fund performance.

Bliss et al. (2008), Dass et al. (2013), Karagiannidis (2010), Prather and Middleton, (2002, 2006) and Wang (2017) find no significant difference in performance across different management structures. Other studies conclude that team managed funds exhibit lower performance than solo managed ones (e.g., Chen et al., 2004; Ferreira et al., 2013; Hornstein &

Hounsell, 2016; Massa et al., 2010) and that icy-hand funds tend to have larger management teams (Berkowitz et al., 2017).[3] Solo managed funds tend to hold more concentrated investments, allowing for more extreme performances, while team managed funds present less risk and more stable performances over time (Bär et al., 2011a, 2011b; Bliss et al., 2008; Ciccotello, 2010; Goldman et al., 2016).[4]

2.2. Performance persistence

The presence of skill in active management is probably the most debated subject in the mutual fund literature. Berk and Green (2004) derive a rational model of the mutual funds industry. Besides finding that actively managed funds on average underperform, they find that performance is not persistent. They argue that skilled mutual fund managers with positive performance attract new funds until the additional costs and complexity of managing those extra funds drive alphas down to zero, i.e., most managers have skill and investors compete away to capture this value, gradually decreasing the alpha attainable. In fact, in the US mutual fund industry, there is little evidence of performance persistence in actively managed funds (e.g., Berk & van Binsbergen, 2015; Fama & French, 2010; Jensen, 1969). Fama & French (2010) argue that ranking funds on short-term past performance can be an inconsistent approach, since the allocation of funds to winner and loser portfolios is largely based on noise. Using histories of individual fund returns and bootstrap simulations of return histories, they still conclude that the net return to investor is negative for most if not all active funds.

Carhart (1997), on the other hand, using a survivorship bias sample and a four-factor model that accounts for market, style, size and momentum, finds persistence in the worst-performing but not in the top-performing funds. This is because the performance persistence, or the "hot hands" effect, is mostly driven by the exposure to the Jegadeesh and Titman (1993) MOM

[3] Other studies concur with this view, for example Bär et al. (2011b), Ciccotello (2010) and Goldman et al. (2016), while more recent studies find the opposite, for example, Han et al. (2017) and Patel & Sarkissian (2017, 2020). Adams et al. (2018) find evidence that team-managed funds do not generate superior returns relative to individual-managed funds, but that benefits of team management are likely to be demonstrated in the presence of strong board monitoring.

[4] Karagiannidis (2012) and Agarwal & Ma (2012) show that having more members, longer tenure and more members with graduate business training contributes to having lower risk in portfolios, i.e., member diversity is related to less extreme style decisions. According to the author, teams whose members engage in side-by-side management see the opposite effect. Ciccotello (2010) finds that team managed funds tend to have less tournament behaviour.

factor. Berk & Tonks (2007) argue that this persistence is caused by an unwillingness of investors in these funds to react by withdrawing their capital. Concurrently, there are other studies that show evidence of fund performance persistence in short-term periods (e.g., Brown & Goetzmann, 1995; Hendricks et al., 1993; Huij & Verbeek, 2007) and also in longer time horizons (e.g., Elton et al., 1996; Grinblatt & Titman, 1992; Wermers, 2005).[5] Brown et al. (2017) find some evidence of a seasonal component in the aggregate underperformance.

More recently, Ferreira et al. (2019) use a global sample of mutual funds, to find that net performance persistence is present in the majority of fund industries. They use a regression-based approach and a performance gap approach which computes differences between present year winners and prior year losers. Overall, they find evidence of performance persistence in 19 out of 27 countries, whether on the bottom performing funds, top performing funds or both bottom and top performing funds. Following the intuition of Hoberg et al. (2018), Khorana et al. (2009), Khorana & Servaes (2005) and Wahal & Wang (2011), they show that industry competition is an important determinant of performance persistence, since more competition makes remaining a winner fund more difficult and keeping a loser fund at the bottom of the performance ranks more likely. Miguel (2021) finds that decreasing returns to scale only affects a minority of countries and that performance persistence is present in the majority of the countries, even in those that evidence decreasing returns to scale, in line with the findings in Ferreira et al. (2013, 2019), and contradicting the predictions of the Berk & Green (2004) model and those of Chen et al. (2004).

2.3. Flow-performance relationship

Another important topic for the mutual fund literature is the flow-performance relationship, i.e., the relation between performance and net inflows, which is determined by the sales and purchases of funds. Multiple authors have studied how flows depend on past performance in the US industry (e.g., Cashman et al., 2012; Sirri & Tufano, 1998), in China (Ko et al., 2014) and also around the world (Ferreira et al., 2012). Most authors observe that flows are highly related with past performance and that investors chase winners more than they sell poorly

[5] There are other studies on performance persistence, including, Bauer et al. (2011), that find that winner portfolios in domestic equity exhibit persistence for up to one year, fixed income show persistence for up to three years and international equity portfolios show no persistence; and Benos & Jochec (2011), that find short-term persistence in the most poorly performing and only the top well performing funds.

performing funds, i.e., the flow-performance relationship is convex.[6] Chevalier & Ellison (1997) study how this type of relationship creates incentives for mutual fund companies to alter the riskiness of the fund at the end of the year in order to increase inflows. Sirri & Tufano (1998) show that flows are directly related to the size of the fund's complex and to marketing expenses, which lower consumers' search costs and evidence a steeper relation between funds and prior performance.

Ferreira et al. (2012) show that the flow-performance relationship shows substantial differences across countries. They find that the more sophisticated investors are, and the lower participation costs they face, the less convexity is observed. They also show that investor sophistication is associated with higher economic and financial development and with the development of the mutual fund industry in a country. Chen et al. (2021) conclude that investor sophistication is an important determinant of the effect of family size on the response of fund flows to performance. Large family sizes increase (decrease) the convexity of the flow-performance relationship in countries with less (more) sophisticated investors.

Multiple authors study how this relationship varies in funds that are managed by a single manager or by a team. On one hand, Bär et al. (2011b), Bliss et al. (2008) and Ciccotello (2010) suggest that team-managed funds experience higher inflows, while Patel & Sarkissian (2020), Jin et al. (2020) and Wang (2017) suggest the opposite.[7]

2.4. Offshore funds related studies

Offshore locations are generally areas that offer more favourable conditions, including tax avoidance, relaxed regulations or asset protection. These conditions are attractive to entities to set up corporations, investments and deposits, and to individuals, primarily, to avoid capital gains tax. Most major hedge funds in the US have an offshore vehicle which is set up to invest alongside US based limit partnerships, *pari passu* (Brown et al., 1999). Most offshore funds are

[6] There are other studies that argue that the relation is not convex, for example Jun et al. (2014), Schiller et al., (2020) and Spiegel & Zhang (2013). Spiegel & Zhang (2013) argue that the flow return relation is linear, concluding that the convexity of the flow response function found in other studies is due to a misspecification of the empirical models.

[7] Wang (2017) concludes that a manager receives less fund flow when joining a large team, than when this manager manages a fund individually. Jin et al. (2020) refers that overconfidence is more predominant in solo-managed funds, which leads to more extreme performance outcomes. This behavior is rewarded with higher net inflows when the performance is good, but no pronounced penalties when the performance is bad.

hedge funds (Kim & Wei, 2002), even though mutual funds are also often domiciled in offshore locations, for example in Luxembourg or Ireland.

As referred previously, the literature involving offshore mutual funds or offshore funds in general, outside of the US, is very scarce to non-existent. There are a few studies on offshore hedge funds, which, although different, are like mutual funds in many ways. But, hedge funds have broader flexibility, for example in the usage of derivatives, leverage or in selling short, and also have a different compensation scheme generally composed by a fixed fee plus a variable fee as a percentage of the profits – higher risk-taking incentives. Brown et al. (1999) use a survivorship bias free sample of US offshore hedge funds from the period 1989-1995 to study their performance and survival.[8] The authors find that offshore hedge funds, on an absolute return basis, on average, underperform the S&P 500 index by 3.21% (on a risk-adjusted basis they have done relatively well, achieving 7.25% less standard deviation). Plus, in contrast to the mutual fund industry, they find no evidence of performance persistence in raw returns, risk-adjusted returns or pre-fee returns, nor even when they break the funds based on their investment style or on their fund size.

Aragon et al. (2014) use a sample from the Lipper TASS[9] from the period 1994-2010 that includes 2,939 hedge funds, including US onshore domiciled funds and offshore hedge funds from nine low-tax jurisdictions in the Caribbean and Mauritius. They find that liquid asset holdings and share restrictions are more prevalent among US domiciled onshore funds. They also find that the flow-performance sensitivity is higher in offshore funds due to higher constraints in marketing efforts in onshore funds, especially in high-performing funds, in accordance to the evidence in Huang et al. (2007) and Sirri & Tufano (1998). Finally, they conclude that onshore funds outperform offshore funds persistently over the first half of the sample period (1994-2001), meaning that offshore funds conform more closely to the predictions in the Berk & Green (2004) model, delivering lower risk-adjusted performance than their onshore counterparts because offshore fund profits are chased away by unrestricted capital flows.

[8] Data is from the US Offshore Funds Directory. The authors note that it contains most of the major hedge funds and managers and is thus representative of the industry. However, survivorship bias might be higher since the attrition rate in hedge funds is higher and data is unable to account for funds that disappear within one year.

[9] The Trading Advisor Selection System (TASS), or Lipper TASS, is one of the most representative databases for hedge funds.

CHAPTER 3

Data and Variables Description

This section presents the description of the mutual funds' database and the variables employed in our study.

3.1. Data description

We use data of open-end actively managed equity mutual funds that are sold mainly in Europe, in the period starting from 1995 until 2019. Mutual fund data is provided by the Lipper Hindsight database which collects information directly from fund management companies. The same data is employed in other studies, for example, in Ferreira et al. (2012, 2013) and Cremers et al. (2016). The data is survivorship bias free, as it includes data on both active and defunct funds.[10] The database includes monthly data of different fund-level and country-level characteristics.

We follow the same data cleaning method performed in Ferreira et al. (2012), excluding funds with multiple share classes to prevent double counting, as well as exchange traded funds, funds of funds and index tracking funds. In 2015, the Investment Company Institute reported a total of 32,797 worldwide regulated open-end equity funds with net assets corresponding to, approximately, $16 trillion. At the end of 2019 this number had grown to $24.5 trillion.[11] Our initial sample accounts for 24,012 unique funds at the end of 2019, corresponding to $11.5 trillion of assets under management. Thus, this sample is significant since it covers about 47% of the TNA of worldwide equity funds.[12] In this study, we focus on the funds that are mainly sold in Europe, since these account for most of our global sample of offshore mutual funds. According to our sample, 73.59% of offshore funds are domiciled in Europe. In this way, we can target a specific group of investors, with individual characteristics, and tax and regulatory environments. As referred previously, the flow-performance relationship is knowingly different across countries and regions.

[10] Brown et al. (1992) find that average performance of mutual funds is biased upwards by the fact that poorly performing funds are likely to be liquidated or merged.

[11] The data is from the Investment Company Institute (2020) and the International Investment Funds Association (2020).

[12] See Ferreira et al (2013), Cremers et al. (2016) and Ferreira et al. (2018) for a more in-depth description of Lipper's worldwide data coverage.

Our final sample registers a total of 20,822 unique funds, from 26 countries, from which 12,536 are onshore funds and 8,286 are offshore funds, as presented in Table 3.1. Besides, it also shows the total TNA for onshore and offshore funds at the end of 2019.

Table 3.1 - Number and size of mutual funds by type of fund

This table presents the number of unique funds in our sample across the 1995-2019 period and the TNA under management in millions of US dollars at the end of 2019 for both onshore and offshore funds. See Appendix A for variable definitions.

Funds	Number of funds	TNA ($ million)
Onshore	12,536	1,608,374
Offshore	8,286	1,013,645
Total	20,822	2,622,019

Our final sample registers 8,356 active funds, 6890 liquidated funds and 5,576 merged funds, i.e., about 40% of active funds and around 60% liquidated or merged funds. Regarding the TNA ($ million) of onshore and offshore funds, we can see that onshore funds represent more than half of the TNA under management in our sample, corresponding to 1,608,374 million US dollars, at the end of 2019, as shown in Table 3.1.

3.2. Variables description

In this section we describe the main fund level variables included in our regressions.

3.2.1. Offshore versus non-offshore funds

We use the classification provided by Lipper Hindsight to identify offshore and non-offshore funds. The goal with this variable is to clearly identify the countries or territories that are low-tax jurisdictions. Table 3.2 presents data on the number of funds and respective TNA under management, by jurisdiction.

Our sample includes 17 onshore countries and 9 offshore countries/territories, including Bermuda, British Virgin Islands, Cayman Islands, Guernsey, Ireland, Isle of Man, Jersey, Luxembourg and Liechtenstein. The only exception to the Lipper classification is Ireland, a

well-known low-tax jurisdiction, which Lipper identifies as onshore, but that we classify as offshore for the purpose of this study.

Table 3.2 - Number of funds and TNA under management by country/territory

This table presents the total number of funds and TNA by country/territory at the end of 2019, for all funds and splitting our sample into onshore and offshore funds. See Appendix A for variable definitions.

	All funds		Onshore funds		Offshore funds	
Country/Territory	Number of funds	TNA ($ million)	Number of funds	TNA ($ million)	Number of funds	TNA ($ million)
Austria	222	17,997	222	17,997		
Belgium	275	52,822	275	52,822		
Bermuda	11	10,869			11	10,869
Cayman Islands	12	1,690			12	1,690
Denmark	235	48,166	235	48,166		
Finland	173	36,933	173	36,933		
France	1,201	232,266	1,201	232,266		
Germany	440	172,974	440	172,974		
Greece	39	1,356	39	1,356		
Guernsey	11	710			11	710
Ireland	953	311,010			953	311,010
Italy	95	24,168	95	24,168		
Jersey	9	1,463			9	1,463
Liechtenstein	95	9,037			95	9,037
Luxembourg	2,388	678,867			2,388	678,867
Malta	10	379	10	379		
Netherlands	113	40,192	113	40,192		
Norway	138	51,911	138	51,911		
Portugal	47	2,226	47	2,226		
Spain	328	46,194	328	46,194		
Sweden	270	179,427	270	179,427		
Switzerland	370	83,653	370	83,653		
United Kingdom	1,073	617,711	1,073	617,711		
Total	8,508	2,622,019	5,029	1,608,374	3,479	1,013,645

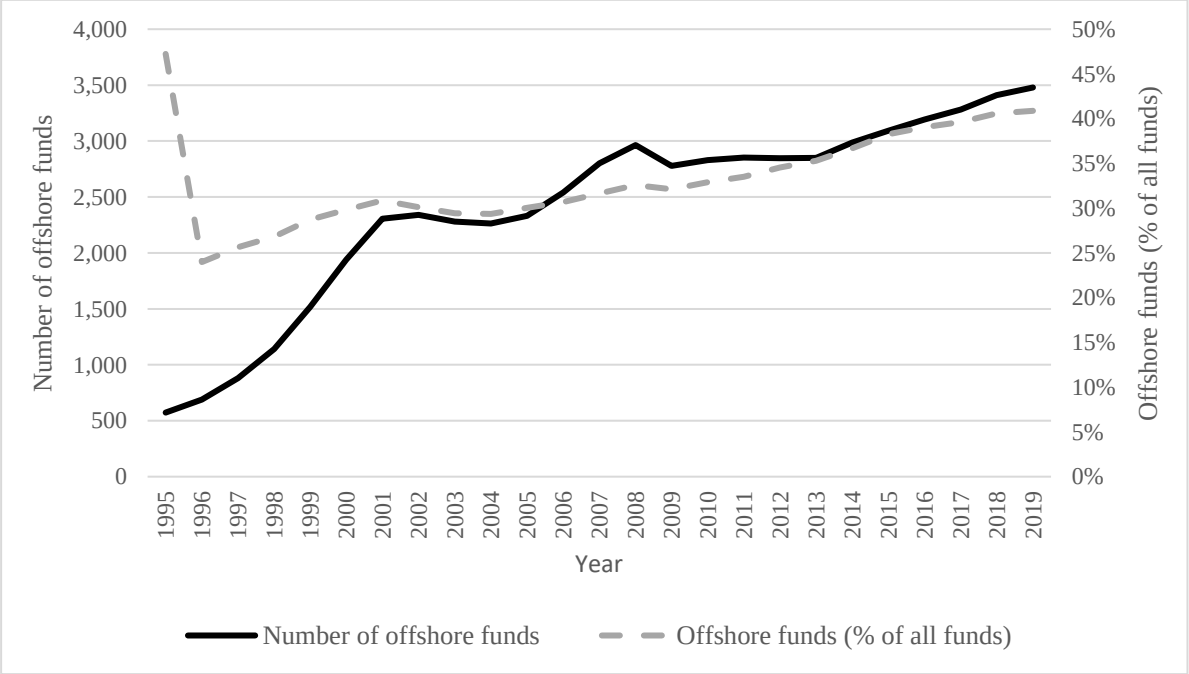
Note: British Virgin Islands, Estonia and the Isle of Man do not report active funds at the end of 2019 but are included in our study based on funds reported in the years prior.

From Table 3.2, we can see that, at the end of 2019, there are a total of 8,508 unique funds, from which 5,029 are onshore funds and 3,479 offshore funds. Table 3.2 also shows that Luxembourg and Ireland are the countries with the higher amount of funds among the offshore jurisdictions. In contrast, at the end of 2019, Jersey, Bermuda and Guernsey report the lower

number of funds. Regarding onshore funds, France and the UK represent the countries with more funds, while Malta and Greece represent the countries with fewer funds. British Virgin Islands, Estonia and the Isle of Man report more than five funds in the previous periods, hence being included in our study. Figure 3.1 presents the number of offshore funds for the 1995–2019 period.

Figure 3.1 – Number of offshore funds for the 1995–2019 period

This figure shows the number of offshore funds for the 1995–2019 period. The solid line presents the number of funds across our sample period while the dashed line presents offshore funds as a percentage of all funds in the sample across the same period. See Appendix A for variable definitions.



From Figure 3.1, we can see that the number of offshore funds increased very significantly (3,479 in 2019 from 573 in 1995), growing gradually almost every year in our sample period (the number of offshore funds increases in 20 out of the 24 years of our sample). The percentage of offshore funds, overall, increased from 24% to 41% from 1996 to 2019.

3.2.2. Flow measurement

We follow the literature (e.g., Chevalier & Ellison, 1997; Sirri & Tufano, 1998) and calculate fund flow as the new money growth rate that is due to new external money. Fund flow for fund *i* in country *c* at month *t* is calculated as follows:

$$Flow_{i,c,t} = \frac{TNA_{i,c,t} - TNA_{i,c,t-1}\left(1 + R_{i,c,t}\right)}{TNA_{i,c,t-1}}, \quad (1)$$

where $TNA_{i,c,t}$ is the total net asset value in the local currency of fund *i* in country *c* at the end of month *t*, and $R_{i,c,t}$ is fund *i*'s raw return from country *c* in month *t*. We winsorize fund flows by country at the top and bottom 1% level of the distribution to minimize the impact of outliers in our results.

Table 3.3 presents detailed information of fund flows by country and shows that the average flow across countries is positive (0.23%), consistent with the findings in, e.g., Ferreira et al. (2019).

Table 3.3 - Descriptive statistics of fund flows by country/territory

This table presents descriptive statistics, in percentage, of monthly fund flows by country across the 1995-2019 sample period, including the mean, the standard deviation, the 10th, 25th, 50th (median), 75th and 90th percentiles, and the number of observations. See Appendix A for variable definitions.

			Percentiles					
Country/Territory	Mean	Standard deviation	10th	25th	50th	75th	90th	Observations
Austria	0.16	7.60	-3.97	-1.34	-0.16	0.81	3.88	53,415
Belgium	-1.29	5.78	-5.17	-2.34	-0.86	-0.13	0.68	101,965
Bermuda	0.10	8.18	-4.74	-1.44	-0.05	0.96	4.62	2,006
British Virgin Islands	-0.34	6.71	-3.63	-1.22	-0.03	0.51	2.31	749
Cayman Islands	-0.02	6.95	-3.78	-0.74	-0.01	0.34	3.19	1,139
Denmark	0.07	7.57	-4.28	-1.62	-0.07	0.99	4.03	38,221
Estonia	0.84	11.21	-6.45	-2.00	-0.25	1.38	7.19	976
Finland	0.74	9.29	-5.67	-1.69	-0.05	1.76	6.99	32,424
France	0.37	7.76	-3.64	-1.22	-0.16	0.67	4.06	247,453
Germany	-0.22	6.76	-3.81	-1.39	-0.25	0.43	2.80	82,162
Greece	0.15	6.17	-2.78	-1.03	-0.28	0.13	2.34	7,557
Guernsey	-0.42	8.85	-6.56	-2.46	-0.43	0.82	4.86	3,476
Ireland	0.49	9.37	-5.37	-1.54	0.00	1.16	5.76	123,717
Isle of Man	-1.07	4.27	-3.18	-1.91	-1.02	-0.10	0.86	540
Italy	-0.41	6.98	-4.70	-2.23	-0.83	0.38	3.18	37,311
Jersey	-0.24	6.62	-3.91	-1.71	-0.40	0.77	3.24	3,615
Liechtenstein	0.34	7.60	-3.73	-1.13	-0.07	0.68	4.16	16,118
Luxembourg	0.47	9.32	-5.53	-1.93	-0.18	1.27	6.14	389,023
Malta	0.55	6.08	-3.43	-1.28	0.00	1.14	5.24	292
Netherlands	-0.14	5.62	-3.30	-1.54	-0.38	0.66	2.92	24,257
Norway	0.41	7.67	-3.73	-1.25	-0.14	1.04	4.36	26,184
Portugal	-0.18	6.97	-4.14	-1.85	-0.57	0.51	3.47	12,045
Spain	0.81	9.98	-5.52	-2.32	-0.32	1.64	7.32	65,123
Sweden	0.54	7.51	-3.49	-1.24	-0.25	1.12	4.71	45,250
Switzerland	0.01	6.90	-3.72	-1.41	-0.12	0.65	3.54	56,854
United Kingdom	0.32	7.30	-3.19	-1.21	-0.21	0.85	3.82	203,669
All countries	0.23	8.14	-4.47	-1.59	-0.23	0.82	4.49	1,575,541

Interestingly the average fund flow varies substantially from country to country (or territory). As shown in Table 3.3, the onshore countries that have, on average, higher inflows are Estonia, Spain and Finland, while Belgium, Italy and Germany are the countries that, on average, see higher outflows. Regarding offshore countries/territories, the ones that see, on average, higher inflows are Ireland, Luxembourg and Lichtenstein. On the other hand, the Isle of Man, Guernsey and the British Virgin Islands have, on average, higher outflows.

3.2.3. Performance measurement

We follow the approach used in Ferreira et al. (2012) and measure fund performance using raw returns and risk-adjusted returns in local currency. The calculation of total returns assumes that dividends are immediately reinvested. Gross benchmark-adjusted returns are calculated for each fund by subtracting from the gross raw return the return of the benchmark given by Lipper. Risk-adjusted performance is calculated using Carhart's (1997) four-factor model that includes market, size, value, and momentum factors. The estimation of the four-factor alpha is an enhancement to CAPM and is given by the following regression:

$$R_{i,t} = \alpha_I + \beta_{oi}RM_t + \beta_{1i}SBM_t + \beta_{2i}HML_t + \beta_{3i}MOM_t + \varepsilon_{it}\,, \qquad (2)$$

where $R_{i,t}$ is the realized return of fund *i* in excess of the 1 month US Treasury bill in month *t*; RM_t is the excess return of the market in month *t*; SMB_t (small minus big) is the average return on the difference between small value portfolio and the average return on the large value portfolio in month *t*; HML_t (high minus low) is the difference in return between the portfolio with high book-to-market stocks and the portfolio with low book-to-market stocks in month *t*; MOM_t (momentum) is the difference in return between the portfolio with the past 12-month winners and the portfolio with the past 12-month losers in month *t*; and ε_{it} is the error term.

We calculate net four-factor alpha in different ways for domestic and international funds. For domestic funds we first regress the previous 36 months of fund excess returns on the fund domicile market excess returns. Thus, we impose a minimum of 36 continuous monthly observations for each fund, to ensure that we have sufficient time series observations to calculate four–factor alphas observations for each fund. The market return is computed using the value-weighted average return in local currency of all stocks in each country in each month. To construct size, book-to-market, and momentum factors for each country in each month, we follow the procedures in Fama & French (1992) and Carhart (1997). For international funds, we employ the same approach as the one described for the domestic funds except that we calculate the market, size, value and momentum factors for each region. The fund investment region is based on the geographic focus field, which can be a single country, a geographic region, or global.

Table 3.4 presents fund-level characteristics by country/territory over the sample period, including the performance measures described previously (raw returns and four-factor alphas).

Table 3.4 – Mutual fund characteristics

This table presents mutual fund descriptive statistics by country/territory across the 1995-2019 sample period. Panel B presents a summary of mutual fund characteristics for offshore and onshore mutual funds. Panel C reports differences in fund characteristics between offshore and onshore funds (t-test results report significance at the 10%, 5%, and 1% level with *, ** and ***, respectively and p-values are reported in parentheses). Panel D, E and F present correlation matrices for all the funds, for onshore and for offshore funds, respectively (significance at the 5% significance level is indicated by *). See Appendix A for variable definitions.

Panel A - Summary statistics of mutual funds characteristics for all funds

Country/Territory	Raw Return (% month)	4f Alpha (% month)	TNA ($ million)	Family TNA ($ million)	Age (years)	TER (% month)	Load (% month)	Mgt. Team	SMB	HML
Austria	0.38	-0.20	38.83	1417.86	8.40	0.15	0.38	0.60	0.13	-0.03
Belgium	0.39	-0.18	48.58	14358.25	5.48	0.11	0.43	0.18	-0.15	-0.05
Bermuda	0.60	0.03	1340.96	5796.06	11.17	0.12	0.10	0.79	0.27	0.25
British Virgin Isl.	0.50	-0.30	180.31	938.70	9.38	0.19	0.06	0.55	0.21	0.17
Cayman Islands	0.61	0.59	217.32	487.99	6.75	0.18	0.06	0.18	0.51	0.06
Denmark	0.68	0.01	134.53	2424.20	9.99	0.13	0.14	0.46	0.08	-0.08
Estonia	0.10	-0.86	34.39	165.95	5.01	0.20	0.17	0.32	0.65	0.34
Finland	0.64	-0.04	132.84	3219.97	7.76	0.15	0.16	0.46	0.19	-0.06
France	0.44	-0.21	124.86	6818.86	9.61	0.15	0.28	0.41	0.12	-0.03
Germany	0.45	-0.22	256.86	12080.54	11.26	0.13	0.35	0.55	0.04	-0.06
Greece	0.25	-0.44	51.84	238.39	11.77	0.25	0.48	0.76	0.26	0.30
Guernsey	0.45	-0.12	100.16	1556.59	6.54	0.18	0.16	0.11	0.28	0.05
Ireland	0.51	-0.14	158.27	5681.44	5.31	0.14	0.29	0.50	0.09	-0.01
Isle of Man	0.44	-0.22	52.78	161.70	9.56	0.16	0.37	0.92	0.14	0.11
Italy	0.44	-0.15	215.16	3823.13	8.57	0.17	0.25	0.47	-0.05	-0.02
Jersey	0.61	-0.05	76.80	801.29	11.32	0.15	0.36	0.10	0.25	0.05
Liechtenstein	0.37	-0.31	74.31	1137.99	6.67	0.18	0.03	0.64	0.16	0.03
Luxembourg	0.41	-0.19	111.68	11470.33	6.69	0.17	0.08	0.53	0.09	-0.03
Malta	0.62	-0.24	86.81	92.82	5.95	0.24	0.00	0.70	0.16	-0.33
Netherlands	0.55	-0.11	363.77	7582.13	10.92	0.10	0.09	0.66	0.06	-0.03
Norway	0.82	0.00	197.30	3044.74	10.31	0.12	0.11	0.47	0.20	0.11
Portugal	0.34	-0.31	36.21	299.24	10.44	0.17	0.16	0.05	0.10	-0.05
Spain	0.35	-0.25	64.69	1504.58	8.41	0.17	0.07	0.54	-0.13	0.03
Sweden	0.72	0.14	375.87	13780.78	11.18	0.12	0.03	0.26	0.05	-0.12
Switzerland	0.61	-0.11	125.91	14348.79	10.58	0.11	0.28	0.55	0.09	-0.02
United Kingdom	0.62	0.00	374.03	11659.88	12.61	0.12	0.25	0.43	0.22	-0.06
All countries	0.49	-0.14	168.21	8799.46	8.81	0.15	0.21	0.47	0.09	-0.03

Panel B - Summary statistics of mutual funds characteristics by offshore and onshore funds

Variable	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations
Onshore funds						
Raw Return (% month)	0.51	0.78	5.42	-6.12	6.79	1,424,069
Four-factor alpha (% month)	-0.12	-0.18	2.70	-3.00	2.85	1,128,465
TNA ($ million)	189.70	44.90	572.44	4.61	420.11	1,084,943
TNA family ($ million)	8,369	2,437	12,632	67	26,186	1,197,063
Flow (% month)	0.11	-0.29	7.50	-4.02	3.79	1,036,076
Age (years)	9.98	7.50	9.16	1.25	21.75	1,422,087
Total expense ratio (%)	1.63	1.61	0.68	0.83	2.39	1,170,254
Loads (%)	3.01	3.00	2.47	0.00	5.50	1,424,069
SMB	0.09	0.02	0.43	-0.36	0.65	1,128,465
HML	-0.04	-0.05	0.48	-0.54	0.46	1,128,465
Offshore funds						
Raw Return (% month)	0.44	0.74	5.48	-6.35	6.72	708,176
Four-factor alpha (% month)	-0.18	-0.22	2.87	-3.20	2.87	517,216
TNA ($ million)	125.90	28.63	396.50	1.43	283.65	555,123
TNA family ($ million)	9,633	2,294	17,519	54	29,987	614,325
Flow (% month)	0.45	-0.10	9.25	-5.43	5.93	540,662
Age (years)	6.47	4.92	5.94	0.75	14.83	707,296
Total expense ratio (%)	1.96	1.88	0.93	1.10	2.75	646,273
Loads (%)	1.56	0.00	2.42	0.00	5.00	708,176
SMB	0.10	0.03	0.43	-0.35	0.67	517,216
HML	-0.02	-0.04	0.55	-0.58	0.54	517,216

Panel C - Differences between offshore and onshore funds

			Offshore minus Onshore	
Fund characteristics	Offshore	Onshore	Difference	(p-value)
Raw Return (% month)	0.44	0.51	-0.08***	(0.00)
Four-factor alpha (% month)	-0.18	-0.12	-0.05***	(0.00)
TNA ($ million)	125.95	189.84	-63.89***	(0.00)
TNA family ($ million)	9,633	8,372	1261***	(0.00)
Flow (% month)	0.45	0.11	0.34***	(0.00)
Age (years)	6.46	9.98	-3.52***	(0.00)
Total expense ratio (%)	1.96	1.63	0.33***	(0.00)
Loads (%)	1.56	3.01	-1.46***	(0.00)
SMB	0.10	0.09	0.01***	(0.00)
HML	-0.02	-0.04	0.01***	(0.00)

Panel D - Pairwise correlations – All funds

		1	2	3	4	5	6	7	8	9	10
Raw Return (% month)	1	1									
Four-factor alpha (% month)	2	0.4165*	1								
TNA ($ million)	3	0.0121*	0.0090*	1							
TNA family ($ million)	4	0.0177*	0.0028*	0.1780*	1						
Flow (% month)	5	0.0586*	0.0348*	-0.0014	-0.0069*	1					
Age (years)	6	0.0118*	0.0015	0.2374*	0.1162*	-0.0822*	1				
Total expense ratio (%)	7	-0.0141*	-0.0267*	-0.0960*	-0.1625*	0.0109*	-0.0241*	1			
Loads (%)	8	-0.0073*	-0.0062*	-0.0431*	0.0353*	-0.0352*	0.0029*	-0.0849*	1		
SMB	9	0.0039*	0.0269*	-0.0125*	-0.0755*	0.0119*	-0.0068*	0.1113*	-0.0091*	1	
HML	10	0.0085*	-0.0226*	-0.0226*	-0.0102*	0.0057*	0.0107*	0.0057*	0.0002	-0.0967*	1

Panel E - Pairwise correlations – Onshore funds

		1	2	3	4	5	6	7	8	9	10
Raw Return (% month)	1	1									
Four-factor alpha (% month)	2	0.4065*	1								
TNA ($ million)	3	0.0116*	0.0102*	1							
TNA family ($ million)	4	0.0193*	0.0058*	0.2334*	1						
Flow (% month)	5	0.0521*	0.0297*	-0.0008	-0.0248*	1					
Age (years)	6	0.0101*	-0.0001	0.2487*	0.1656*	-0.0720*	1				
Total expense ratio (%)	7	-0.0097*	-0.0243*	-0.0777*	-0.2152*	0.0164*	0.0371*	1			
Loads (%)	8	-0.0109*	-0.0146*	-0.0875*	0.0619*	-0.0412*	-0.0657*	-0.0333*	1		
SMB	9	0.0064*	0.0317*	-0.0017	-0.0844*	0.0185*	0.0053*	0.0966*	-0.0249*	1	
HML	10	0.0090*	-0.0229*	-0.0334*	-0.0244*	0.0098*	0.0109*	0.0105*	0.0047*	-0.0931*	1

Panel F - Pairwise correlations – Offshore funds

		1	2	3	4	5	6	7	8	9	10
Raw Return (% month)	1	1									
Four-factor alpha (% month)	2	0.4376*	1								
TNA ($ million)	3	0.0123*	0.0042*	1							
TNA family ($ million)	4	0.0168*	-0.0009	0.1034*	1						
Flow (% month)	5	0.0698*	0.0433*	0.0008	0.0115*	1					
Age (years)	6	0.0134*	-0.0012	0.1527*	0.0702*	-0.1110*	1				
Total expense ratio (%)	7	-0.0178*	-0.0273*	-0.1151*	-0.1280*	-0.0037*	-0.0071*	1			
Loads (%)	8	-0.0064*	0.0029*	0.0113*	0.0325*	-0.0131*	-0.0170*	-0.0217*	1		
SMB	9	-0.0012	0.0175*	-0.0402*	-0.0644*	0.0008	-0.0400*	0.1317*	0.0333*	1	
HML	10	0.0078*	-0.0217*	0.0064*	0.0088*	-0.0004	0.0235*	-0.0058*	0.0029*	-0.1045*	1

From Table 3.4, Panel A, we can see that the average raw return is positive (0.49%) and the average four–factor alpha is negative (–0.14%), which is comparable with the findings in Chen et al. (2021). We can see that Norway, Sweden and Denmark present the higher monthly raw returns, on average, while Estonia, Greece and Portugal, on average, present lower monthly raw returns. Cayman Islands, Sweden and Bermuda generate, on average, the higher alphas, while Estonia, Greece and Liechtenstein report, on average, the lower monthly four-factor alphas in our sample.

Table 3.4, Panel A, also presents other fund-level variables, such as the average TNA in millions of dollars, the family TNA in millions of dollars, the average age in years, the average monthly TER, the average monthly load, the average percentage of funds managed by teams, and the SMB and HML loadings. The average fund size presents substantial variation across countries. The territories with the highest average fund sizes are Bermuda, Sweden and the UK and the lowest average fund sizes are observed in Estonia, Portugal and Austria. The average family TNA varies from 14,358.25 million of dollars in Belgium and 92.82 million of dollars in Malta. Fund age varies from 12.61 years and 5.01 years, being, on average, the older funds located in the UK, Greece and Jersey, and the newer funds located in Estonia, Ireland and Belgium. The countries that charge higher fees are Greece, Belgium and Austria, while Malta, Lichtenstein and Sweden charge the lower fees. The countries or territories with higher percentages of funds managed by teams are the Isle of Man, Bermuda and Greece, while Portugal, Jersey and Guernsey present the higher numbers of solo managed funds.

3.2.4. Additional control variables

Following the literature (e.g., Ferreira et al., 2012), we include a set of additional mutual fund characteristics as control variables to help explain flows and their sensitivity to performance.[13] These characteristics include fund size, age, fees, loads and fund investment style measured by the SMB and HML loadings, as widely suggested in the literature (Chevalier & Ellison, 1997; Ferreira et al., 2012; Sirri & Tufano, 1998). We also include past flows to control for the serial correlation of fund flows, following Chen et al. (2021) and Ferreira et al. (2012).

Table 3.4, Panels B-F report additional statistics regarding these variables, more specifically, Panel B provides an overview of mutual fund characteristics for offshore and

[13] See Table 3.4.

onshore funds, Panel C reports t-statistics for the differences between offshore and onshore funds and Panels D-F report pairwise correlation matrices for all funds, onshore funds and offshore funds, respectively. From Table 3.4, Panel B, we can see that both the average monthly raw return and four-factor alpha are higher in onshore funds comparing to offshore funds. The average TNA (in millions of dollars), age and loads are also higher in onshore funds in comparison to offshore funds, while the other characteristics including the TNA of fund family (in millions of dollars), average monthly flow and total expense ratio report, on average, report higher values for offshore funds. In Table 3.4, Panel C, we can see that all the differences reported are significant at the one percent significance level.

Table 3.4, Panel D, shows that fund flows are positively correlated with raw returns, four-factor alpha, the total expense ratio, the SMB and HML loadings, but negatively correlated with age and loads. The results are in line with those in Chen et al. (2021), with the exception of the correlation results for the SMB loading, which is shown to be negative. The correlation coefficients are significant at the five percent significance level. Multicollinearity among these variables does not appear to be a serious concern as most correlation coefficients are low, except for the correlations between raw return and four-factor alpha and between age and size, which are normal, suggesting that these variables may be included together in our regressions. From Panel E, we observe that the same relations hold for onshore funds. Interestingly, in Panel F, we find that the SMB and HML loadings are not correlated with flow in the case of offshore funds.

CHAPTER 4

Methodology

This section provides the details of our empirical tests regarding performance persistence and the flow-performance relationship, which are presented in Sections 4.1. and 4.2., respectively.

4.1. Performance persistence

4.1.1. Linear regression

To test for performance persistence, we start by following Busse et al. (2010) and Ferreira et al. (2019) and use a regression-based approach, where we run the following linear regression:

$$Performance_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 Offshore + \theta X_{i,c,t-1}{}' + \varepsilon_t\,, \qquad (3)$$

where we regress the performance in month *t* on the performance in the prior month *t-1*, an offshore dummy (*Offshore*) that takes the value of one if the country/territory is a low tax jurisdiction and zero otherwise, as well as lagged control variables (in the vector $X_{i,c,t-1}$). The error term is given by ε_t. Following Ferreira et al. (2019) we add several lagged fund specific control variables, including fund size, fund family size, age, fund style and flows. We measure fund style as the loadings of the fund's return on the country specific size (SMB) and value (HML) factors. Regression includes time, investment region, fund type (domestic, foreign, regional, and global) and benchmark fixed effects, and we present robust t-statistics that are clustered by fund and month.

The main parameter of interest in the regression is the coefficient of the offshore dummy variable. The respective signal and significance indicates if there is a difference in the alpha produced between offshore and non-offshore variables, allowing us to understand which funds perform better. Ferreira et al. (2013) find that, outside of the US, fund size is associated with higher performance. In addition, domestic funds located in countries with strong legal institutions, with more rigorous law enforcement, and with liquid stock markets tend to perform better. Aragon et al. (2014) also find that onshore hedge funds outperform offshore funds.

We next test for differences in performance persistence between onshore and offshore funds. To do so, we run a similar regression to that in Equation (3), except that we add an interaction between past performance and the offshore dummy variable. We therefore run the following regression:

$$Performance_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 \left(Performance_{i,c,t-1} \times Offshore\right) + \beta_3 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t . \quad (4)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

The main parameter of interest in this regression is the coefficient of the interaction of the performance variable with the offshore variable, which attempts to measure the additional effect in fund performance persistence of offshore funds versus onshore funds.

4.1.2. Conditioning on past performance

The literature as shown differences in fund performance persistence across the performance scale. In the US, mutual fund persistence originates from bottom–performing funds, while there is evidence of performance reversals for top–performing funds (e.g., Carhart, 1997). Outside of the US, the literature finds persistence for both bottom and top-performing funds (e.g., Ferreira et al., 2019; Miguel, 2021). Thus, we follow the literature (see, e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Ferreira, et al. 2012) and look at differences in performance, splitting past performance into low, mid and top quintiles.

We therefore divide the funds into quintiles and group them in the bottom 20%, the mid 60% (the three mid quintiles are grouped together) and the top 20% funds based on prior performance, following the procedure of Ferreira et al. (2012) and Huang et al. (2007). We therefore run the following regression:

$$Performance_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 Top\ Performance_{i,c,t-1} + \beta_3 Bottom\ Performance_{i,c,t-1} + \beta_4 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t , \quad (5)$$

where:

$Bottom\ Performance_{i,c,t-1} = \min\left(0.2, Rank_{i,c,t-1}\right)$,

$Mid\ Performance_{i,c,t-1} = \min\left(0.6, Rank - Low_{i,c,t-1}\right)$,

$High\ Performance_{i,c,t-1} = Rank - \left(Low_{i,c,t-1} + Mid_{i,c,t-1}\right)$,

and *i* stands for a given mutual fund, *c* represents the country and *t* denotes the month. Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

Next, we run a similar regression to that in Equation (5), except that we add to the regression the interaction between our offshore dummy variable (*Offshore*) and past performance, as follows:

$$Performance_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 \left(Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_3 Top\ Performance_{i,c,t-1} + \beta_4 \left(Top\ Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_5 Bottom\ Performance_{i,c,t-1} + \beta_6 \left(Bottom\ Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_7 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t \,. \quad (6)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

4.2. Flow-performance relationship

4.2.1. Linear regression

The literature shows that the flow-performance sensitivity determines fund performance persistence. Berk and Green (2004) show that fund performance persistence is determined by the way flows respond to past performance. More capital invested in top–performing funds will cause fund size to grow, which in turn will result in less persistence, while less capital to bottom-performers will improve the performance persistence in poor-performing funds.

We therefore test whether the differences in performance persistence are explained by differences in the flow-performance sensitivity between offshore and onshore investors. We run the following regression:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t \,, \quad (7)$$

where we regress fund flow in month *t*, for country *c*, on the performance in the prior period *t-1*, the offshore dummy variable (*Offshore*), as well as lagged control variables (in the vector $X_{i,c,t-1}$). The error term is given by ε_t . Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

Next, we add to Equation (7) the interaction between the offshore dummy variable (*Offshore*) and past performance. Thus, we run the following regression:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 \left(Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_3 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t \,. \quad (8)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

The main parameters of interest are the coefficients on the interactions between past performance and the offshore dummy. These coefficients allow us to compare the difference in the flow-performance sensitivities of offshore and onshore investors. Because offshore investors are usually high net worth individuals that want to benefit from investing in low-tax jurisdictions, we therefore would expect these investors to be, in general, more sophisticated, and, thus, to actively seek out and process better the information about funds. In this way, since the flow-performance relationship is convex, we would expect these investors to be less sensitive to past performance in comparison to onshore investors. Contrarily, Aragon et al. (2014) argues that offshore investors are more sensitive to past performance due to higher constraints in marketing efforts for onshore funds (Huang et al., 2007; Sirri & Tufano, 1998). Since the number of offshore mutual funds is increasing rapidly, we could also make the case that investors are more easily persuaded to invest in these funds more than in onshore funds because of the increased offer or solely based on the tax advantages, ignoring other more important aspects like performance.

4.2.2. Conditioning on past performance

The literature also shows that the flow-performance relationship is convex and that the flow-performance sensitivities can vary at different levels of performance (Ferreira et al., 2012).

We therefore test the flow-performance sensitivities at different levels of performance, by estimating the flow-performance relationship according to the following equation:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2 Top\ Performance_{i,c,t-1}$$
$$+\beta_3 Bottom\ Performance_{i,c,t-1} + \beta_4 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t \,, \quad (9)$$

where:

$Bottom\ Performance_{i,c,t-1} = \min\left(0.2, Rank_{i,c,t-1}\right)$,

$Mid\ Performance_{i,c,t-1} = \min\left(0.6, Rank - Low_{i,c,t-1}\right)$,

$High\ Performance_{i,c,t-1} = Rank - \left(Low_{i,c,t-1} + Mid_{i,c,t-1}\right)$.

Thus, we regress the flow of fund *i*, in month *t*, for country *c* on the performance in the prior period *t-1* split into low, mid and top quintiles, the offshore dummy variable (*Offshore*), as well as lagged control variables (in the vector $X_{i,c,t-1}$). Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

Next, we run a similar regression to that in Equation (9), except that we add to the regression the interaction between our offshore dummy variable (*Offshore*) and past performance, as follows:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance_{i,c,t-1} + \beta_2\left(Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_3 Top\ Performance_{i,c,t-1} + \beta_4\left(Top\ Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_5 Bottom\ Performance_{i,c,t-1} + \beta_6\left(Bottom\ Performance_{i,c,t-1} \times Offshore\right)$$
$$+\beta_7 Offshore + \theta X_{i,c,t-1}{}' + \varepsilon_t\,. \quad (10)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

To assess if the difference between the coefficients of top and bottom performance quintiles are statistically different for offshore funds and onshore funds, we run a Wald test. More specifically, the difference in convexity of offshore and onshore funds, allows us to conclude on the level of sophistication of investors. Using the same intuition explained before, we expect offshores' flows to be less sensitive to past performance, i.e., we expect offshore investors to be sophisticated. If this is the case, offshore investors will not chase winners, but they will promptly sell losers, meaning that coefficients for the top performing funds should be negative or non-significant and for the bottom performing the coefficient should be negative and significant. If the opposite occurs, offshore investors can be considered as less sophisticated than their onshore counterparts.

4.2.3. Allowing for non-linearities in sensitivities

We also run the same regressions allowing for non-linearities in the sensitivity to raw returns and compute fund flow-performance specifications in the manner of Guercio & Reuter (2014),

which consists of using both performance measures (raw returns and four-factor alpha) simultaneously, as the next regression shows:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance\mu_{i,c,t-1} + \beta_2 Performance\delta_{i,c,t-1}$$

$$+\beta_3\left(Performance_{i,c,t-1} \times Offshore\right) + \beta_4 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t\,, \qquad (11)$$

where:

$Performance\mu_{i,c,t-1}$ represents performance measured by the four-factor alpha,

$Performance\delta_{i,c,t-1}$ represents performance measured by raw returns,

and we regress fund flow of fund *i* in month *t*, for country *c*, on the performance in the prior period *t-1* measured by raw returns and four-factor alpha, the interaction between our offshore dummy variable (*Offshore*) and past performance, the offshore dummy variable, as well as lagged control variables (in the vector $X_{i,c,t-1}$). The error term is given by ε_t. Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

Next, we run a similar regression to that in Equation (11), except that we add to the regression the top and bottom past performance quintile variables, as follows:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance\mu_{i,c,t-1} + \beta_2 Performance\delta_{i,c,t-1}$$

$$+\beta_3\left(Performance_{i,c,t-1} \times Offshore\right) + \beta_4 Top\ Performance\delta_{i,c,t-1}$$

$$+\beta_5 Bottom\ Performance\delta_{i,c,t-1} + \beta_6 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t\,. \qquad (12)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

Lastly, we run a similar regression to that in Equation (12), except that we add to the regression the interaction between our offshore dummy variable (*Offshore*) and past performance, as follows:

$$Flow_{i,c,t} = \alpha + \beta_1 Performance\mu_{i,c,t-1} + \beta_2 Performance\delta_{i,c,t-1}$$

$$+\beta_3\left(Performance_{i,c,t-1} \times Offshore\right) + \beta_4 Top\ Performance\delta_{i,c,t-1}$$

$$+\beta_5\left(Top\ Performance\delta_{i,c,t-1} \times Offshore\right) + \beta_6 Bottom\ Performance\delta_{i,c,t-1}$$

$$+\beta_7\left(Bottom\ Performance\delta_{i,c,t-1} \times Offshore\right) + \beta_8 Offshore + \theta {X_{i,c,t-1}}' + \varepsilon_t\,. \qquad (13)$$

Regression also includes time, investment region, fund type and benchmark fixed effects, and we present robust t-statistics clustered by fund and month.

CHAPTER 5

Empirical Results

In this section we present the results of the empirical tests described in the previous section. In Section 5.1, we describe the results regarding performance persistence, followed by the results regarding the flow-performance relationship, in Section 5.2.

5.1. Performance persistence

The results of our repression-based persistence tests are presented in Table 5.1. The results of the regression in Equation (3) are presented in Table 5.1, Column (1). We regress performance on past performance and control variables. We also include a dummy variable that is equal to one when the fund is an offshore fund and zero otherwise (*Offshore*). Results show that the coefficient on last month four-factor alpha is not significant, which indicates that there is no performance persistence when we pool both offshore and onshore funds. From Column (1) we also observe that the performance of offshore funds is not statistically significant from that of onshore funds.

Table 5.1 – Mutual fund performance persistence

This table presents the results of panel regression-based performance persistence tests presented in Equations (3)-(6). The dependent variable is the fund's monthly performances, measured as four-factor alpha. Independent variables include past performance and lagged control variables, including a team management dummy variable and measures of size, family's fund size, age, fees, SMB and HML. In Columns (1)-(4) we add an offshore dummy variable that takes the value of one if the fund is in a low-tax jurisdiction and zero otherwise. Column (1) presents the result of Equation (3). Column (2) presents the result of Equation (4), where we add the interaction between past performance and the offshore dummy variable. Column (3) presents the result of Equation (5), where we the top and bottom past performance quintile variables. Column (4) presents the result of Equation (6), where we add the interactions between past performance split into low, mid and top quintiles with the offshore dummy variable. Robust t-statistics clustered by month and country are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	(1)	(2)	(3)	(4)
Net flow (t-1)	0.0030***	0.0030***	0.0030***	0.0030***
	(8.02)	(7.90)	(8.03)	(7.91)
4f alpha (t-1)	-0.0016	-0.0103***	-0.0105***	-0.0271***
	(-1.00)	(-5.49)	(-4.27)	(-9.64)
4f alpha (t-1) in Top 20%			0.0004***	0.0009***
			(4.71)	(8.93)
4f alpha (t-1) in Bottom 20%			-0.0005***	-0.0009***
			(-5.79)	(-8.71)
4f alpha (t-1) x Offshore		0.0244***		0.0538***
		(7.41)		(10.18)
Top 4f alpha (t-1) x Offshore				-0.0017***
				(-8.75)
Bottom 4f alpha (t-1) x Offshore				0.0014***
				(6.93)
Offshore	-0.0039	-0.0039	-0.0040	-0.0035
	(-1.41)	(-1.37)	(-1.41)	(-1.24)
Team	0.0002***	0.0002***	0.0002***	0.0002***
	(3.72)	(3.75)	(3.73)	(3.76)
TNA (log)	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-7.11)	(-7.09)	(-7.16)	(-7.15)
TNA family (log)	0.0001***	0.0001***	0.0001***	0.0001***
	(7.99)	(7.98)	(7.95)	(7.92)
Age (log)	0.0002***	0.0002***	0.0002***	0.0002***
	(6.31)	(6.26)	(6.29)	(6.25)
Fees	-0.0641***	-0.0640***	-0.0637***	-0.0637***
	(-17.82)	(-17.81)	(-17.73)	(-17.72)
SMB	0.0002**	0.0002**	0.0002**	0.0002**
	(2.31)	(2.32)	(2.36)	(2.40)
HML	0.0001	0.0001	0.0001	0.0001
	(1.55)	(1.56)	(1.57)	(1.59)
Benchmark fixed effects	Yes	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.044	0.045	0.044	0.045
R-squared	0.044	0.044	0.044	0.044
Number of observations	1085254	1085254	1085254	1085254

Regarding the coefficient on the remaining control variables, these are in line with those observed in Ferreira et al. (2013, 2019). We find that fund size has significant explanatory power and is negatively correlated with fund performance. Empirical evidence on the relation between mutual fund performance and fund size is mixed, for example, Chen et al. (2004) and Miguel (2021) try to shed light on this question. We also find that fees are negatively related with fund performance, in line with the literature (e.g., Carhart, 1997; Ferreira et al., 2013). On the other hand, we find that funds from large fund families perform better, in line with the findings in Ferreira et al. (2013). We can conclude the same regarding funds that are team managed and older, in contrast with the literature (e.g., Ferreira et al., 2013). Lastly, we find that funds that overweight small-cap stocks also perform better.

Table 5.1, Column (2), presents the results of the regression presented in Equation (4). In this regression, we add to the regression in Equation (3) the interaction between past four-factor alpha and the offshore dummy. By doing this, the coefficient on lagged four-factor alpha now represents the performance persistence of onshore funds, while the coefficient on the interaction between past four-factor alpha and offshore represents the difference in performance persistence between offshore and onshore funds. Our results show reversals for the performance persistence of onshore funds. Our results also show that the performance of offshore funds persists significantly more than that of onshore funds.

The literature has shown differences in fund performance persistence across the performance scale. Carhart (1997) shows that, in the US, fund persistence originates from bottom-performing funds, while top performers revert their performance. Ferreira et al. (2019) find performance persistence for poor-performing funds, but they also find performance persistence at the top of the performance scale for many mutual fund industries outside the US. Therefore, we next run the regression in Equation (5), where we repeat the regression in Equation (3) allowing the coefficients on lagged four-factor alpha to be different if a fund's lagged four-factor alpha is in the bottom 20%, the mid-60% and the top 20% of funds in the prior month. From Table 5.1, Column (3), we find that there is evidence of performance persistence in our sample and that this persistence originates from both, top and bottom-performing funds. This is therefore in line with the results in Ferreira et al (2019), but in contrast with the findings in Carhart (1997). Our results are also in contrast with those observed in Berk & Green (2004) that argue that fund performance is not persistent.

Finally, to test whether there are differences in performance persistence between offshore and onshore funds across the performance scale, we also interact lagged four-factor alpha in the bottom 20%, the mid-60% and the top 20% of funds with our dummy variable offshore, as shown in Equation (6).

The results presented in Column (4) confirm the results obtained in Column (3) for onshore funds, i.e., onshore funds persist at the bottom of the performance scale, while top-performing funds revert their performance in the following month. In the case of offshore funds, we find that offshore funds persist less at the top and at the bottom of the performance scale, meaning that neither the top nor the bottom funds remain in those ranks in the following month, which is negative for top-performing funds and positive for bottom performers. Our results also show that offshore funds in the middle of the performance distribution persist significantly more than their onshore peers. Overall, our results show that the stronger persistence reported in offshore funds comes from the middle of the performance distribution, where most funds are included.

The observed differences in performance persistence between offshore and onshore funds are not only statistically significant but also economically significant. In Column (2) the coefficient on lagged four-factor alpha interacted with our offshore dummy is 0.0244 (significant at the 1% significance level), which indicates that, compared to onshore funds, offshore funds carry over around 2.5% more of their past performance into the next month.

5.2. Flow-performance relationship

Table 5.2 presents our results for the flow-performance relationship. Panels A and B report the results using raw returns and four-factor alpha as a performance measure, respectively. In Panels A and B, Columns (1) to (4), we present the results of the regressions presented in Equations (7)-(10), respectively, with the only difference being the performance measure we use. At the bottom of both panels, Panel A and Panel B, in Column (4), we compute the differences in the convexity (Top-Bottom) between offshore and onshore funds.

Table 5.2 - Fund flow-performance sensitivity

This table presents the results of flow-performance regressions, as presented in Equations (7)-(10). Dependent variable includes the fund's monthly flows. Independent variables include past performance measured by raw returns in Panel A and four-factor alpha in Panel B, and lagged control variables, including a team management variable and measures of size, family's fund size, age, fees, SMB and HML. In Columns (1)-(4) we add an offshore dummy variable. Column (1) presents the result of Equation (7). Column (2) presents the result of Equation (8), where we add the interaction between past performance and the offshore dummy variable. Column (3) presents the result of Equation (9), where we add the top and bottom past performance quintile variables. Column (4) presents the result of Equation (10), where we add the interactions between past performance split into low, mid and top quintiles with the offshore dummy variable. Robust t-statistics clustered by month and country are reported in parentheses. p-value from a Wald test of the equality of coefficients on top and bottom performance quintiles interacted with the offshore variable is reported at the bottom of the table. *, **, and *** indicate significance at the 10 %, 5%, and 1% level, respectively. See Appendix A for variable definitions.

Panel A - Fund flow–performance sensitivity: raw returns

	(1)	(2)	(3)	(4)
Net flow (t-1)	0.1513***	0.1510***	0.1512***	0.1509***
	(76.01)	(75.88)	(75.97)	(75.83)
Net return (t-1)	0.1683***	0.1552***	0.1210***	0.1089***
	(60.71)	(53.99)	(28.29)	(25.14)
Net return (t-1) in Top 20%			0.0037***	0.0030***
			(16.48)	(12.58)
Net return (t-1) in Bottom 20%			-0.0016***	-0.0015***
			(-7.36)	(-6.20)
Net return (t-1) x Offshore		0.0372***		0.0292***
		(12.09)		(8.64)
Top return (t-1) x Offshore				0.0022***
				(5.06)
Bottom return (t-1) x Offshore				-0.0006
				(-1.51)
Offshore	-0.0107**	-0.0109***	-0.0112***	-0.0120***
	(-2.54)	(-2.60)	(-2.66)	(-2.84)
Team	0.0009***	0.0009***	0.0009***	0.0009***
	(6.39)	(6.41)	(6.41)	(6.45)
TNA (log)	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	(-12.87)	(-12.88)	(-12.80)	(-12.81)
TNA family (log)	0.0003***	0.0003***	0.0003***	0.0003***
	(5.72)	(5.76)	(5.72)	(5.77)
Age (log)	-0.0032***	-0.0032***	-0.0032***	-0.0032***
	(-30.06)	(-30.06)	(-30.02)	(-30.03)
Fees	-0.1030***	-0.1033***	-0.1030***	-0.1030***
	(-9.80)	(-9.82)	(-9.79)	(-9.80)
SMB	0.0000	0.0000	-0.0001	-0.0000
	(0.04)	(0.10)	(-0.26)	(-0.22)
HML	0.0003**	0.0003**	0.0003**	0.0003**
	(2.08)	(2.09)	(2.06)	(2.06)
Benchmark fixed effects	Yes	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Change in convexity (Top–Bottom)				0.0028***
Wald test Top = Bottom (p–value)				(0.00)
Adjusted R-squared	0.043	0.043	0.043	0.043
R-squared	0.042	0.042	0.042	0.043
Number of observations	1081751	1081751	1081751	1081751

Panel B - Fund flow–performance sensitivity: four-factor alpha

	(1)	(2)	(3)	(4)
Net flow (t-1)	0.1529***	0.1528***	0.1529***	0.1528***
	(76.72)	(76.67)	(76.72)	(76.67)
4f alpha (t-1)	0.1468***	0.1279***	0.1157***	0.1002***
	(49.00)	(37.03)	(25.10)	(19.61)
4f alpha (t-1) in Top 20%			0.0022***	0.0018***
			(9.78)	(7.45)
4f alpha (t-1) in Bottom 20%			-0.0010***	-0.0010***
			(-4.62)	(-4.18)
4f alpha (t-1) x Offshore		0.0526***		0.0401***
		(8.16)		(3.84)
Top 4f alpha (t-1) x Offshore				0.0012**
				(2.38)
Bottom 4f alpha (t-1) x Offshore				-0.0001
				(-0.15)
Offshore	-0.0103**	-0.0101**	-0.0106**	-0.0108**
	(-2.47)	(-2.42)	(-2.52)	(-2.57)
Team	0.0009***	0.0009***	0.0009***	0.0009***
	(6.37)	(6.40)	(6.37)	(6.41)
TNA (log)	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	(-12.19)	(-12.18)	(-12.12)	(-12.11)
TNA family (log)	0.0003***	0.0003***	0.0003***	0.0003***
	(5.78)	(5.77)	(5.83)	(5.85)
Age (log)	-0.0032***	-0.0032***	-0.0032***	-0.0032***
	(-29.97)	(-30.01)	(-29.89)	(-29.94)
Fees	-0.1034***	-0.1032***	-0.1034***	-0.1032***
	(-9.82)	(-9.81)	(-9.82)	(-9.81)
SMB	-0.0000	-0.0000	-0.0001	-0.0001
	(-0.16)	(-0.15)	(-0.32)	(-0.33)
HML	0.0006***	0.0006***	0.0006***	0.0006***
	(3.96)	(3.97)	(3.94)	(3.94)
Benchmark fixed effects	Yes	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Change in convexity (Top–Bottom)				0.0013*
Wald test Top = Bottom (p–value)				(0.09)
Adjusted R-squared	0.041	0.041	0.041	0.041
R-squared	0.041	0.041	0.041	0.041
Number of observations	1081751	1081751	1081751	1081751

We start by presenting the results of Table 5.2, Panel A, where we use raw returns as performance measure. In Column (1), we present the results for the regression in Equation (7). We regress flow on past performance and control variables. We also include a dummy variable that is equal to one when the fund is an offshore fund and zero otherwise (*Offshore*). From Column (1), we see that, as expected, past performance increases flows. We also observe that, on average, offshore funds receive less flows than onshore funds, given the negative, significant, coefficient of the offshore dummy variable.

Regarding the coefficients of the control variables, our results are broadly in line with the literature. We conclude that past flows increase flows in line with the literature (e.g., Chen et al., 2021; Ferreira et al., 2012), funds from larger fund families get more flow, in line with Chen

et al. (2021), and identically funds that load more on value stocks (Ferreira et al., 2012). Funds managed by teams also receive more flows, consistent with Bliss et al. (2008). We also find that larger funds, older funds or funds that charge more fees receive less flow, which is consistent with the conclusions of Ferreira et al. (2012), Chevalier & Ellison (1997) and Sirri & Tufano (1998).

In Table 5.2, Column (2), we run the regression in Equation (8), which is identical to that in Equation (7), except that we now also interact past performance with the offshore dummy variable. The results show that offshore funds react more to past performance, since the coefficient of the interaction is positive (0.0372) and significant at the 1% significance level.

Regarding Column (3), we run the regression in Equation (9), where we allow the flow-performance sensitivities to vary at the bottom, mid and top performance ranges. In line with the literature (e.g., Chevalier & Ellison, 1997), we conclude that the flow-performance relationship is convex, i.e., investors buy winner funds more than they sell losers. The absolute value of the bottom coefficient is less than half than the top coefficient (0.0016 at the bottom and 0.0037 at the top).

The results of Equation (10) are presented in Column (4). We find that offshore funds are more sensitive to past performance, as in Column (2) and, additionally, that offshore funds are more sensitive in the top performing funds, in line with the findings of Aragon et al. (2014) regarding hedge funds. From the Wald test, we also observe that the difference between the coefficients of top and bottom performance quintiles reported in Column (4) are statistically different for offshore funds and onshore funds, which indicates that offshore investors are less sophisticated than their onshore peers. The change in convexity that is due to a fund being located offshore is 0.0028 (p-value of 0.000).[14]

In Table 5.2, Panel B, we run the same regressions using four-factor alpha rather than raw returns as the performance measure. Overall, the results in Panel B confirm all our previous conclusions. Our results are also economically important. Based on the Panels A and B of Table 5.2, we find that funds being domiciled in offshore locations increase the convexity of the Top-

[14] To compute the change in convexity (Top-Bottom) we compute the difference between the coefficients on the Top x Offshore and Bottom x Offshore interactions variables. As an example (from Column (4) of Panel A of Table 5.2): 0.0028=0.0022-(-0.0006).

Bottom performance range by 62% and 46%, respectively, using raw returns and four-factor alpha as performance measures.[15]

In Table 5.3 we follow Guercio & Reuter (2014) and compute fund flow-performance specifications that allow for non-linearities in sensitivity to raw returns, following the regressions presented in Equations (11)-(13). In this case, we use both performance measures together in the regressions. The variables for the bottom and top quintiles in Panels A and B are based on raw returns. In Panel A we interact the offshore dummy variable with past performance measured by raw returns and in Panel B we do the same using four-factor alpha.

[15] To compute the economic impact of (Top-Bottom) performance range we divide the change in convexity that is due to a fund being located offshore (change in convexity (Top-Bottom)) – computed as the difference between coefficients on the Top x Offshore and Bottom x Offshore interactions variables – by the level of convexity associated with onshore funds (Top-Bottom) – calculated as the difference between the coefficient of Top and Bottom. As an example (from Column (4) of Panel A of Table 5.2): 62%=0.0028/0.0045; where 0.0028=(0.0022-(-0.0006)); and 0.0045=(0.0030-(-0.0015)).

Table 5.3 - Fund flow–performance specification that allows for nonlinearities in sensitivities

This table presents the results of flow-performance regressions, as presented in Equations (11)-(13). The dependent variable is the fund's monthly flows. Independent variables include past performance measured both by raw returns and four-factor alpha, and lagged control variables, including a team management variable and measures of size, family's fund size, age, fees, SMB and HML. Column (1) presents the regression in Equation (11), where we add an offshore dummy variable, past performance measured by raw returns and four-factor alpha and the interaction between past performance and the offshore dummy variable. Column (2) presents the regression in Equation (12), where we also add past performance the top and bottom past performance quintile variables. Column (3) presents the regression in Equation (13), where we also add the interactions between past performance split into low, mid and top quintiles with the offshore dummy variable. Robust t-statistics clustered by month and country are reported in parentheses. p-value from a Wald test of the equality of coefficients on top and bottom performance quintiles interacted with the offshore variable is reported at the bottom of the table. *, **, and *** indicate significance at the 10 %, 5%, and 1% level, respectively. See Appendix A for variable definitions.

Panel A - Fund flow–performance sensitivity: raw returns

	(1)	(2)	(3)
Net flow (t-1)	0.1510***	0.1509***	0.1509***
	(75.89)	(75.85)	(75.84)
4f alpha (t-1)	0.0295***	0.0288***	0.0287***
	(7.19)	(7.02)	(7.00)
Net return (t-1) x Offshore	0.0370***	0.0366***	0.0291***
	(12.01)	(11.88)	(8.59)
Net return (t-1)	0.1362***	0.0903***	0.0907***
	(35.18)	(18.02)	(18.11)
Net return (t-1) in Top 20%		0.0037***	0.0030***
		(16.33)	(12.52)
Net return (t-1) in Bottom 20%		-0.0016***	-0.0015***
		(-7.14)	(-6.17)
Top return (t-1) x Offshore			0.0022***
			(5.04)
Bottom return (t-1) x Offshore			-0.0006
			(-1.48)
Offshore	-0.0108***	-0.0114***	-0.0119***
	(-2.58)	(-2.70)	(-2.82)
Team	0.0009***	0.0009***	0.0009***
	(6.40)	(6.42)	(6.43)
TNA (log)	-0.0007***	-0.0007***	-0.0007***
	(-12.83)	(-12.76)	(-12.76)
TNA family (log)	0.0003***	0.0003***	0.0003***
	(5.75)	(5.75)	(5.76)
Age (log)	-0.0032***	-0.0032***	-0.0032***
	(-30.08)	(-30.03)	(-30.04)
Fees	-0.1026***	-0.1026***	-0.1024***
	(-9.76)	(-9.76)	(-9.74)
SMB	0.0000	-0.0001	-0.0001
	(0.05)	(-0.25)	(-0.27)
HML	0.0004**	0.0004**	0.0004**
	(2.30)	(2.27)	(2.26)
Benchmark fixed effects	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Difference in convexity (Top–Bottom)			0.0028***
Wald test Top = Bottom (p–value)			(0.00)
Adjusted R-squared	0.043	0.043	0.043
R-squared	0.042	0.043	0.043
Number of observations	1081751	1081751	1081751

Panel B - Fund flow–performance sensitivity: four-factor alpha

	(1)	(2)	(3)
Net flow (t-1)	0.1512***	0.1511***	0.1510***
	(75.98)	(75.93)	(75.91)
4f alpha (t-1)	0.0130***	0.0121***	0.0213***
	(2.93)	(2.74)	(4.69)
4f alpha (t-1) x Offshore	0.0486***	0.0491***	0.0220***
	(7.54)	(7.62)	(2.84)
Net return (t-1)	0.1484***	0.1017***	0.0991***
	(39.05)	(20.49)	(19.95)
Net return (t-1) in Top 20%		0.0037***	0.0029***
		(16.46)	(11.87)
Net return (t-1) in Bottom 20%		-0.0016***	-0.0013***
		(-7.30)	(-5.64)
Top return (t-1) x Offshore			0.0028***
			(6.18)
Bottom return (t-1) x Offshore			-0.0011***
			(-2.68)
Offshore	-0.0104**	-0.0109***	-0.0118***
	(-2.48)	(-2.60)	(-2.78)
Team	0.0009***	0.0009***	0.0009***
	(6.39)	(6.41)	(6.43)
TNA (log)	-0.0007***	-0.0007***	-0.0007***
	(-12.81)	(-12.74)	(-12.75)
TNA family (log)	0.0003***	0.0003***	0.0003***
	(5.70)	(5.70)	(5.73)
Age (log)	-0.0032***	-0.0032***	-0.0032***
	(-30.11)	(-30.06)	(-30.07)
Fees	-0.1022***	-0.1022***	-0.1021***
	(-9.72)	(-9.72)	(-9.71)
SMB	-0.0000	-0.0001	-0.0001
	(-0.00)	(-0.30)	(-0.31)
HML	0.0004**	0.0004**	0.0004**
	(2.31)	(2.28)	(2.27)
Benchmark fixed effects	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Change in convexity (Top–Bottom)			0.0038***
Wald test Top = Bottom (p–value)			(0.00)
Adjusted R-squared	0.043	0.043	0.043
R-squared	0.042	0.043	0.043
Number of observations	1081751	1081751	1081751

From Table 5.3, Panel A, Column (1), we find that offshore funds react more to raw returns. The results presented in Column (2) confirm the results obtained in Table 5.2, i.e., we conclude that the flow-performance relationship is convex, since investors buy winner funds more than they sell loser funds. Looking at Column (3), we find no significant difference between offshore and onshore funds for the funds at the bottom of the performance ranks, in line with the findings of Table 5.2 in both specifications.

In Table 5.3, Panel B, we also find that offshore funds react more to the four-factor alpha. However, in Panel B, Column (3), we find that offshore funds react more to the top, as well as to the bottom performing funds, meaning investors buy more the top and sell more the bottom

performing funds, contrarily to our findings in both Panels of Table 5.2 and in Table 5.3, Panel A. Since only being significant in one of the regressions (Panel B of Table 5.3), we conclude that the difference for the bottom performance funds is not robust and that managers of offshore funds at the bottom ranks are more skilled than those of onshore funds.

We conclude that there is a stronger incentive to increase the four-factor alpha at the top, which generates more flows into these funds, but also generates diseconomies of scale, explaining the lower persistence of this group of funds – in line with the Berk and Green model. Since there is no significant difference in the bottom performing funds between offshore and onshore funds, the lower performance persistence of offshore funds in the bottom ranks cannot be explained by the Berk and Green model. Berk & Green (2004) argue that by selling more bottom performing funds, these funds have less assets under management, which allows them to improve performance. However, in this case, our results do not match the predictions of the model but are consistent with offshore fund managers having more skill at the bottom ranks.

In sum, our conclusions are broadly in line with the conclusions of Aragon et al. (2014). Offshore funds' sensitivity is higher, especially in high-performing funds.

Looking at the change in convexity shown in Table 5.3, we confirm our conclusion that there is in fact a significant difference between the top performing and bottom performing offshore funds (both Panel A and B report a convexity change that is significant at the 1% significance level). Panels A and B report coefficients of 0.0028 and 0.0038, respectively (and p-values of 0.0000). Since offshore investors buy the top performers more than they sell the losers, we conclude that these investors are less sophisticated than their onshore counterparts, following the intuition of Ferreira et al. (2012). The relationship is convex for non-offshore funds but is even more convex for offshore funds, in contrast with our initial hypothesis. One possible explanation can be the higher constraints in marketing efforts of onshore funds, which further research can help shed light on.

CHAPTER 6

Robustness Tests

In this section we perform additional tests to check the robustness of our main findings. The main question that arises from our empirical results is the coefficient regarding the bottom performing offshore funds. Thus, we run an additional specification using both mid-range performance measures in the same regression. The results are presented in Table 6.1.

Table 6.1 - Fund flow–performance sensitivity using both mid-range performance measures

This table presents the result of panel regression-based flow-performance tests presented where we use as the dependent variable the fund's monthly flow and as independent variables the past performance measured both by raw returns and four-factor alpha, lagged control variables, including a team management variable and measures of size, family's fund size, age, fees, SMB and HML. This specification adds the mid-range past performance measured by four-factor alpha interacted with the offshore dummy variable, but otherwise is the same specification in Equation (13). Robust t-statistics clustered by month and country are reported in parentheses. p-value from a Wald test of the equality of coefficients on top and bottom performance quintiles interacted with the offshore variable is reported at the bottom of the table. *, **, and *** indicate significance at the 10 %, 5%, and 1% level, respectively. See Appendix A for variable definitions.

Net flow (t-1)	0.1509***
	(75.84)
4f alpha (t-1)	0.0256***
	(5.62)
4f alpha (t-1) x Offshore	0.0088
	(1.11)
Net return (t-1) x Offshore	0.0282***
	(8.20)
Net return (t-1)	0.0911***
	(18.17)
Net return (t-1) in Top 20%	0.0031***
	(12.65)
Net return (t-1) in Bottom 20%	-0.0015***
	(-6.33)
Top return (t-1) x Offshore	0.0020***
	(4.39)
Bottom return (t-1) x Offshore	-0.0004
	(-0.98)
Offshore	-0.0119***
	(-2.80)
Team	0.0009***
	(6.44)
TNA (log)	-0.0007***
	(-12.76)
TNA family (log)	0.0003***
	(5.76)
Age (log)	-0.0032***
	(-30.05)
Fees	-0.1024***
	(-9.74)
SMB	-0.0001
	(-0.27)
HML	0.0004**
	(2.27)
Benchmark fixed effects	Yes
Fund type fixed effects	Yes
Investment region fixed effects	Yes
Country fixed effects	Yes
Time fixed effects	Yes
Change in convexity (Top–Bottom)	0.0020***
Wald test Top = Bottom (p–value)	(0.00)
Adjusted R-squared	0.043
R-squared	0.043
Number of observations	1081751

From Table 6.1, we conclude that there is no significant difference in the persistence of bottom performing funds between offshore and onshore, since the bottom performance coefficient interacted with the offshore dummy variable is not significant. Therefore, the results are consistent with our main conclusions.

Additionally, we also rerun our main regressions, including time, investment region, fund type and benchmark fixed effects and clustering the t-statistics by country and month, instead of fund and month. In unreported results, we find that our main results hold when we cluster by country and month.

Overall, we conclude that our main results are robust.

CHAPTER 7

Conclusion

In this paper, we use a sample of actively managed equity mutual funds from 26 European countries, to study differences in the performance persistence of offshore and onshore funds. We also analyse whether these differences are explained by differences in the flow-performance sensitivities between offshore and onshore investors.

Our results show no significant difference in the alphas generated between offshore and onshore funds, but we find evidence of higher performance persistence in offshore funds. When looking at differences in the performance persistence across the fund performance scale, we find that bottom and top performing offshore funds persist less than their onshore counterparts.

We next examine whether these differences are explained by investor preferences, as the literature shows that the performance persistence is determined by the sensitivity of investor flows to fund past performance. Our results indicate no differences in the flow-performance sensitivity for bottom-performing funds, but we find that offshore investors tend to buy more top-performing funds, which is in line with previous studies on offshore hedge funds (Aragon et al., 2014), and consistent with a less sophisticated behaviour from offshore investors. These results are also in line with the predictions of the Berk & Green (2004) model that shows that less performance persistence at the top of the fund performance scale can be explained by flow-induced incentives to generate alpha.

When we test whether the difference between the coefficients of top and bottom performance quintiles are statistically different for offshore funds and onshore funds, our results show a more convex flow-performance relationship for offshore funds, which confirms that offshore investors are less sophisticated than their onshore peers. Our results are not only statistical, but also economically important.

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Appendix

Appendix A. Variable definitions

Variable	Definition
Raw return	Fund net return in local currency (percentage per month) (Lipper).
Four-factor alpha	Net four–factor alpha (percentage per quarter or year) estimated as indicated in Equation (1).
Flow	Percentage growth in TNA (in local currency) in a month, net of internal growth (assuming reinvestment of dividends and distributions) into funds with the same investment style, i.e., geographical focus. We follow Chevalier and Ellison (1997) and Sirri and Tufano (1998) and fund flow for fund *i* at period *t* is calculated as: $Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net asset value in US dollars of fund i at the end of month t, and $R_{i,t}$ is fund i's raw return in month t. Net annual fund flow is the sum of net monthly fund flows.
Size	Total net assets in millions of US dollars (Lipper).
Family size	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (Lipper).
Age	Number of years since the fund launch date (Lipper).
Total expense ratio	Total annual expenses as a fraction of TNA (Lipper).
Loads	Sum of front–end and back–end loads (Lipper).
SMB	Loadings on the small–minus–big size factor (SMB) from four–factor alpha regressions.
HML	Loadings on the high–minus–low factor (HML) from four–factor alpha regressions.
Mgt. Team	Dummy that takes the value of one if fund located in managed by more than one manager and zero otherwise (Lipper).
Offshore	Dummy that takes the value of one if fund located in offshore and zero otherwise (Lipper).