Measuring Skills in European Actively Management Funds

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Abstract

This paper examines the evolution and the determinants of fund skills for European actively managed funds. Using a model based on industry returns to scale, we estimate fund skills by extracting fund fixed-effect from panel regressions. The results show that new funds have higher skills than older ones and fund skills grows over time. We point out that fund skills are a fund family and fund governance concerns. The more expensive funds and the small and mid-cap funds are also those with the highest initial skills. This is not the case for emerging, multi-manager and outsourced funds. Large and more diversified fund families are those who bring out new skilled funds.

JEL Classification: G11, G15, G18, G23

Keywords: Performance evaluation, Economies of scale, European mutual funds, Fund skills

1 Introduction

Since Jensen (1968) [14], Malkiel (1995) [16] and Gruber (1996) [13], who established that, on average, actively managed funds underperform market, the issue of funds performance and therefore their skills has been raised. Traditionally, researchers has focused on Jensen's alpha and/or risk-adjusted returns measured with one or more factors as a proxies of fund skills. More recently, Berk and Green (2004) and Pastor et al. (2012) pointed out that alpha is an inadequate measure of fund skill. They gives a convincing proof that alpha is subject to decreasing returns to scale, based on fund and/or industry size, respectively. From a theoretical perspective, when the size is small, the fund generates a positive alpha, which attracts investors' capital flows. This leads in turn to an increase the costs of active management due to an increase transaction costs related to higher liquidity constraints and the extent of the competition between funds. As a consequence, this reduce its subsequent performance and lead the gross alpha closed to zero and net alpha become negative. From an econometric perspective, fund skills can be estimated by a fixed-effect extracted from a panel regression clustered at the fund level. Fund skills are therefore time-invariant and represents the fund's gross alpha when size is zero and before they face the negative effect of the time-varying decreasing returns to scale. In the literature, most studies have focused on the estimation of decreasing returns to scale and its main determinants. Paradoxically, few are devoted to explore the determinants of fund skills. This while it seems established that the coefficient estimating the decreasing returns to scale varies a little or not at all between the funds, that is not the case for fund skills. This is the aim our paper.

In line with our previous work that explore the scale performance dynamics for European actively managed funds, we propose to examine the evolution and determinants of European fund skills.To do this, we adopt an industrial approach by focusing on skill at the fund level and not at the manager's level, who are, from this point of view, only one component among others of the fund skills. Following Brown and Wu (2016)[4], we consider that skills correspond to all the elements which contribute to the ability of funds to generate performance: manager specific skills, characteristics of the funds they manage, and all the resources provided by the family. Funds are then seen as products, designed and marketed by competing fund families, which endow them with a set of characteristics that support the development of skills. In this way, the largest families, i.e. those with the most resources, are the most likely to put the highest initial skills into the fund. More precisely, as the fund skill is time-invariant, then it is the organizational and competitive context in which the fund families are embedded at the time they design and launch new funds that will determine skills. So, the subsequent evolution of the fund family will impact the fund's ability to manage the negative effects of size and the possible impacts of experience. The aims of this research is to explore the first part of this story.

Using monthly data covering all funds marketed in Europe between 2001 and 2016 to compute fund family characteristics, and focusing on the 1325 Equity actively managed funds, we empirically examine the relationships between fund and their family characteristics on skills. To deal with endogeneity problem between funds size and performance (Reuters and Zitzewitz, 2013[21].), we use Pastor et al. (2014) framework to compute skills. In a second step, following Khorana and Servaes (1999, 2000) [15] which assume that families established their product strategies each June or December before funds launch date, we run cross-sectional regressions. The purpose is to identify relationships between funds family organizational characteristics and skills for a subsample of 388 funds for which we could compute these characteristics at this date. Our results can be summarized in the following four points.

First, we examine the evolution of fund skills and observe a significant upward trend. Despite the growth in the industry size and the extent of competition, fund skills increase by 8.8 bp per year on average. This result is consistent with those of Pastor et al.(2015)[19] who stated that new funds have higher skills than older ones. Moreover, we confirm the positive relation between fund age and fund skills. For each additional age, fund skills grows by 18.7 bp per year. These results confirms that skills grows over time due to greater know-how, experience et also the introduction of new tools and technologies.

Second, we find strong evidence that price and fees are not set at fund level but more a fund family concern. Price and funds skills relation is positive. Fund families with more expensive fund prices are also those that offer the highest skills. This result is consistent with those of Gaspar et al. (2006)[10]. It seems that the higher price is a compensation for higher coordination and/or hierarchical costs.

Third, we show mixed evidence related to relation between fund skills, fund style and governance. The relation is positive for small and mid-cap funds. Small and mid-cap funds have a higher initial skills. It seems that fund families invest more resources in them in order to implement an effective monitoring mecanism to take the opportunity of a higher possible performance and, at the same time, control moral hasard and frequent valuation errors. Conversely, the relation is negative for emerging funds. Consistent with Chuprinin et al. (2015)[7], the fragmentation and the existing barriers in European industry make that emerging funds do not benefit resources from fund family due to the existence of local high information rents. The other results related to outsourced to master fund are mixed. The number of country of sales and multi-manager funds are non-significant. These results can be explained by the presence of information asymmetries.

Fourth, we decisively validate that fund skills are organized at the family level. For all three fund family variables used, cross-sectional regressions display highly significant. We observe a positive relation between funds skills and fund family resources. This result confirms our underlying idea that fund families contribute to funds' skills by allocating the resources (financial and organizational) at their disposal during the design of the fund. . We observe also that fund skills are primarily based on the extent of diversification of the fund family. Large and more diversified fund families are those who bring out new skilled funds. Large fund families can easily transfer know-how and experiences due to their mature internal organizational structure, a proven track record and sources of diversified information related to the activity of its members. These results show the importance of fund governance and internal organization in designing and launching a fund that is likely to be better than its predecessors.

The rest of the paper is organized as follows. Section 2 outlines the theoretical background and some relevant empirical issues. Section 3 presents the data and the methodology for extraction of fund skills. Section 4 presents our empirical results related to the evolution of funds and its main determinants and results. Section 5 presents our conclusion and our contributions to the literature.

2 Background

2.1 Theoretical background

The literature dedicated to the measure of fund skills is closely related to the literature on decreasing return to scale (DRS hereafter), based of the theoretical framework of Berk and Green. Fund's (or manager's) ability to actively outperform a passive benchmark decline as the fund size increase and can be modeling as follow :

$$\alpha_{t+1} = a_i - bq_t \tag{1}$$

A positive gross alpha (α_t) attract investors capital inflow, increasing fund size (q_t), and increasing in turn active management transaction cost. This effect then reducing subsequent performance (α_{t+1}) proportionally to coefficient b, which measures the DRS. DRS occurs at the fund level due to the negative effect of the fund liquidity constraints following the increase in asset price. Pastor and al. (2012) demonstrate that DRS occur at the industry level, which represent competitive intensity between actively managed funds. A great competition between active funds leaves fewer investment opportunities to generate positive alphas. Thus, fund performance declines as the industry size (q_t) and consequently competition grows. The two theoretical framework represent skills with the coefficient a_i, which is fund specific and time-invariant. This measure of fund skills correspond to the average gross alpha that is adjusted for any potential time-varying fund-level and/or industry-level DRS, i.e. when $q_t = 0$. That is the gross alpha when fund faces no competition from other funds or faces any transactions costs. The analysis of DRS is outside the scope of this paper, and has already been the subject of several studies. Therefore, ignoring the time-varying effects of DRS, its remain the fund specific skills, a_i, which also display significant cross-sectional variability which deserves to be examine further. Funds are primarily firms organized to “produce” alpha and/or attract investor capital inflow. They have a set of resources that serve to make the most of manager’s skill, and at the same time give the efficient incentive to maximize effort. Since skill is not directly observable, and given that active management are risky and costly, funds face an agency conflict with managers which could prefer to passively manage funds with very low cost. Moreover funds have incentive to exploit non-sophisticated investors with marketing and distribution strategy rather than to produce alpha.

2.2 Empirical evidence

In this section, we present a selected evidence on fund skills studies in the literature. According to Berk et al. (2017)[2], fund families have access to privileged private information on the day-to-day behavior of their funds, allowing them to exploit this informational advantage to assess fund skills and manage DRS. Massa and Rehman (2008)[17] find that the lending activity of banks benefits the investment activities of funds belonging to the same banking group. Chen et al. (2013)[6] state that in-house funds perform better than outsourced funds, partly because they share the same information system. Brown and Wu (2016)[4] show that funds belonging to the same family share *“common skills”*, making them tend to be similar. The increase in active fund management costs resulting from the increase in fund size and/or industry size will in turn impact upon the fund manager’s incentives to carry out active management rather than passive management. Brown and Davies (2017)[3] describe the agency relationship between fund managers and investors and show that the extent of moral hazard is increasing with DRS. [1] Fund governance mechanisms within fund families serve to moderate moral hazard through the internalization of hierarchical and coordination costs (Chen et al., 2004)[5]. Fund families are then seen as delegated monitors of managers, to the benefit of investors (Gervais et al. (2005)[11], Dangl et al. (2008)[8]), and monitoring activity is more efficient if the family is large in terms of both number of funds and financial resources. All in all, fund families

[1] The extent of the manager’s incentives to maximize effort depends on flow-performance sensitivity. When this is low, generally when the clientele is essentially composed of unsophisticated investors, managers are not systematically penalized by a bad performance. So it reduces their incentives to conduct effective and costly active management.

contribute to the performance of their funds, on the one hand by moderating decreasing returns to scale related to industry size dynamics, and on the other hand by contributing to the funds' initial skills at the moment of the fund design prior to launching. The empirical study of Pastor et al. (2015)[19] shows that new funds tend to outperform old ones, through the effect of technical progress.

As in Brown and Wu (2016)[4], we view funds as a set of common and specific characteristics which form their Skills. We assume that family with the most resources, are the most likely to put the highest skills into the fund. Their size gives them an effective human resource management strategy that enables them to attract more skilled managers and assign their funds to them. Their size allows them to put in place effective governance to internalize agency costs and implement an efficient internal information system capable of coordinating the actions of all their fund managers.

2.3 Econometric issues

According to Reuter and Zitzewitz (2010)[21] and Pastor et al. (2015)[19], standard OLS can be used to correctly estimate the relationship between size and future performance if and only if the size is independent of the fund skills. However, human resource management practices by fund families mean that it is very likely that skilled managers will be assigned to the largest funds, or that they will invest more resources to generate performance, resulting in a positive relationship between size and skills. Thus, without being able to directly observe skills, which are correlated with both performance and size, we have to deal with an omitted variable bias and the coefficients calculated through standard OLS are biased downward. Furthermore, the estimation of the causal effect between industry size and performance is not subject to this omitted variable bias. Finally, considering that skills are time-invariant, which is the case in the Berk and Green (2004)[1] and Pastor and Stambaugh (2012)[18] models, an estimation using a fund level fixed-effect model will make it possible to separate the time-series relationships resulting from time-varying variables (including industry size) and the cross-sectional relationships resulting from time-invariant variables (including skills).

We follow this methodology in a first step to perform the following model:

$$\alpha_{it} = a_i - \beta_1 \cdot IndSize_{t-1} + \sum_{k=2}^{K} \beta_k x_{ikt-1} + \varepsilon_{it} \tag{2}$$

Where x_{ikt-1} is a vector of time-varying control variable at the funds and family of dimension $k-1$. The introduction of a fund level fixed-effect a_i allows us to separate all the effects on fund performance α_{it} due to the cross-sectional differences between the funds, i.e. the fund's observable characteristics and all unobservable time-invariant variables, especially fund-specific skills. It is therefore an intra-fund time-series estimate. Note that decreasing returns to scale at the industry level therefore imply that $\beta < 0$.

From the model (2), we can calculate fund fixed-effects as following :

$$\hat{a}_i = \bar{\alpha}_i - \beta_1 \overline{IndSize} - \sum_{2}^{K} \beta_k \bar{x}_i - \bar{\varepsilon} \tag{3}$$

By definition, a_i corresponds to the performance of the funds when the industry size is equal to zero (i.e., with no DRS). This is the starting value from which DRS cause fund performance to decline, i.e., when the fund enters the active funds industry and faces competitors.

Following Pastor et al. (2015)[19], it is therefore a measure of the fund's skills. We consider that skills consist of all elements that contribute to the fund's stock-picking ability. Since mutual fund families have the ability to design funds by defining their observable (management and load fees, style) and unobservable (manager's skill, information system, monitoring) characteristics at the moment when they determine their strategy, the type of fund on the market is a function of the characteristics of the family, and should be an explanation of cross-sectional differences in skills between funds.

To capture this potential effect, in a second step we carry out the following regression:

$$\hat{a}_i = \delta_t + (\delta_f +) \sum_{1}^{M} \gamma_m z_{imL} + \eta_i \tag{4}$$

Where δ_t is a years fixed-effect and (δ_f) a family fixed effect that we will introduce in models which not use variable at the family level.[2]

z_{im} is a vector of time-invariant explanatory variables of dimension m for funds i. In this study, we perform a two-step analysis via the fund's i characteristics (as price, style and a set of funds organizational proxies) and the fund family variables at moment L when it defines its design, which we estimate to be the semester preceding the fund launch date.

3 Data and methodology

3.1 Data management

In this study, we use three main databases: Lipper - Reuters, Factset and Eurofidai. We extract monthly data from the Lipper-Reuters, our main database composed of all European mutual funds, classified by the ISIN code at the share class level, i.e., 70,518 funds from 2000 to 2016. This database is free from survivorship bias and lists all active and inactive funds. From this database, we excluded all funds with incomplete information. The funds' total assets under management are calculated as the sum of all funds' share classes (TNA, denoted *FundSize* hereafter). Fund charges have been calculated using the TNA weighted average of share class.

We build a sample composed of all actively managed European mutual funds. We follow the same fund selection criteria proposed by Pastor et al. (2015)[19]. We build up a sample composed of all actively managed european equity funds. We exclude all ETFs and all funds which display "Index" or "Index Tracking" in their fund name or in their fund feature. We remove all observations with a fund size inferior to 5 million euros, as well as funds with less than 36 observations. Ultimately, we obtain a database containing 1,325 equity funds distributed across 16 Lipper Global Classifications.

We use the FactSet database to calculate the index related to the active management industry in Europe (denoted *IndSize* herafter). We estimate the risk-adjusted perfor-

[2]Individual Fixed Effect models use only within variance for estimation and not between variance, and fail to allow the estimation of time-invariant variables. We could use the Plümper and Troeger (2007)[?] efficient Fixed Effect Vector Decomposition (FEVD) methodology to avoid this problem. However, Green (2011) [?] and Breusch et al. (2011)[?] state that FEVD gives an excessively small standard error.

mances using the gross returns of all 1,325 funds based on the three standard performance valuation models, namely the 1-factor CAPM (1F), the 3-factors Fama-French model (3F) and the 4-factors Carhart model (4F). We use the MSCI Europe Index and the MSCI World Index as the market benchmarks for the Equity Europe and Equity Global Funds, respectively. The 1-month Euribor rate is used as a risk-free rate. From the Eurofidai database covering 24 European countries, we extract all data on common factors such as size (Small minus Big, SMB), style (High minus Low, HML) and Momentum (MOM). [3] The table A2 in the appendix reports the summary statistics related to our main database.

3.2 Methodology

In this section, we run the estimation of the fund skills following the methodology developped by Pastor et al. (2015)([19]). In our framework, fund skills are measured by the fund fixed-effects extracted from the following regression model :

$$\begin{aligned}\alpha_{i,t} = \beta_1 \times Age_{i,t-1} + \beta_2 \times IndSize_{t-1} + \beta_3 \times FamSize_{i,t-1} + \beta_4 \times IndSize_{t-1} \times FamSize_{i,t-1} \\ + \beta_5 \times IndSize_{t-1} \times SmdCap + \beta_6 \times IndSize_{t-1} \times Emerging + \varepsilon_{i,t} \quad (5)\end{aligned}$$

These fixed-effects are specific to each fund and correspond to a_i coefficient in equation 2, which is time-invariant. a_i measures the fund's performance when it faces no competition in the industry (i.e. *IndSize* is equal to zero). The fixed-effects correspond to gross alphas adjusted for all time-varying effects at the industry level and controlling for individual fund and fund family characteristics. Table A3 in the appendix reports panel regressions for various models that we use to extract fixed-effects.

In line of the seminal work developped by Pastor et al. (2015)([19]) and our previous paper[4] , we run panel regressions based on alphas obtained from the three standard

[3] Beforehand, we compare these data with those provided in the Fama-French Library database. We did not observe any significant difference.

[4] Veasna Khim & Razafitombo Hery (2021) S̈cale and Skills in European Active Management: The impact of a new Regulatory Context", Under review in The Journal of Banking and Finance, Forthcoming.

evaluation models and using three specifications to extract the fund skills. The first specifications are used to find if the scale effect is at the fund level or at the industry level. As a result, we observe the *FundSize* is not significant for all three regressions (columns 1 to 3) indicating an industry-level returns to scale. The next six columns report panel regression results after controlling for fund specific and family characteristics that are likely to have impacts on scale. We use Family Size ($FamSize$)[5]as a proxy of the financial resources that the family fund can make available to its members in order to maximize the overall performance. We use two dummy variables, Small and mid-cap($SmdCap$) and Emerging to capture the impacts of the liquidity constraints on scale. It is well known that small and mid-cap stocks are inherently illiquid and so are likely to have strong effects on scale. (Chen et al. (2004)[5], Pollet and Wilson (2008)[20], Pastor et al. (2012)[18]. The dummy variable Emerging refers to funds invested in Emerging European stocks. It is worth to notice that one of the main features of the European industry is the existence of a fragmented market with large developed countries on one side and Emerging countries on the other. "Emerging stocks" seems to display two stylized attributes sides, as a niche and/or an opportunistic investments likely to generate higher performance but also as a more risky with high transaction costs assets. Here, we observe that the results are almost similar whether it is the level of R^2 or the value and the significance of the coefficients for all variables. We observe that the adjusted performance has a negative relation with *IndSize* and *SmdCap*, a positive relation with *Emerging* and a mixed one with *FamSize*. Based on these results, we will use the model (8) to the rest of our study. Indeed, the significance of all coefficient are slightly more pronounced, namely for *FamSize* and the *SmdCap*. Moreover, as indicated in table A4 in the appendix, the correlations of fixed-effects extracted from various specifications are high and more acute with a_i from model (8).

[5]The total AUM for all equity funds belonging to the family after deducting the size of the fund itself.

4 Empirical investigations

The aim of this section is to examine the evolution and the explore the main determinants of fund skills.

4.1 The evolution of fund skills

We begin by examining the evolution of fund skills, denoted a_i. To do this, we calculate for each month the average fixed-effects of each fund in the industry. Thus, we obtain a database with a subsample formed by 1262 funds from our initial database. It is worth to notice that since a_i is time-invariant, any variation in this series corresponds to new funds entering the industry during the month. As a consequence, we expect a constant and positive trend for a_i indicating a consolidation of learnings and experiences in the industry.

Figure 1 shows the evolution of fund skills from 2002 to 2016. As expected, we observe that the trend for average funds skills is positive, as are the median or the decile values, Q_1, Q_3, D_1 and D_9. Thus, despite the growth in the industry size and the extent of competition, fund skills increase by 0.71% per month on average. The interquartile gaps follow the same trend with a 0.52% increase per month.[6] These results are consistent with those of Pastor et al.(2015)[19] which indicate that new funds entering the industry have higher skills than older ones. The new funds have greater know-how, probably linked to better education among fund managers and the introduction of new technologies in fund administration. Moreover, we report in table A3 a positive relationship between fund age and performance after controlling for industry size. This indicates that experiences or, what Pastor et al. (2015)[19] call "learning on the job" effects, explain why funds become more skilled over time. This potential "learning on the job" effects can be observed on figure 2 which shows the age-varying skills within funds. The age-varying skills is measured using coefficient estimates from model (8) A3.[7] As a result, we observe a more

[6]We confirm this upward trend by performing a regression between the average fixed-effect and time trend. The slope estimate is significantly positive at the 1% level.

[7]Age-Varying Skills equal $a_i + Age \times 0.001546$. 0.001546 is the coefficient associated to fund age form model (8) A3

This figure plots the month's mean and quantiles of estimated fund skills a_i across all funds operating during that month in the industry. Skills are extracted from the 3-factors model of the previous panel regression (model (8) in appendix table A3).

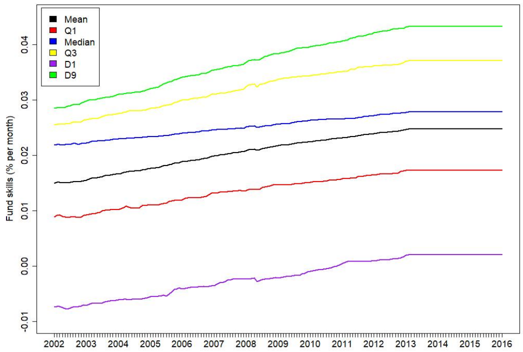

Figure 1: Constant skills within funds

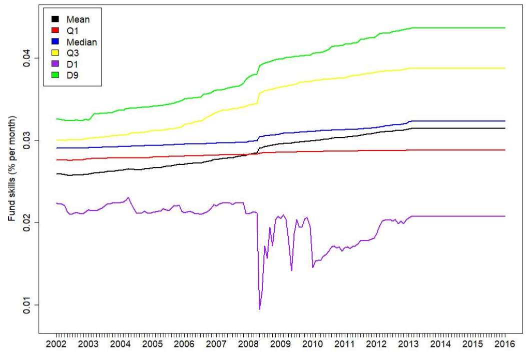

Figure 2: Age-varying skills within funds

consistent and significant trend than in figure 1. For each additional year, the fund's skill grows by 1.546 bp per month, or 18.7 bp per year.

4.2 The determinants of fund skills

In this section, we examine the main determinants of fund skills. To do so, we explore the cross-sectional distribution of skills a_i, focusing on the impacts of fund-specific and fund family characteristics. More precisely, we carry out a two step analysis. First, we perform cross-sectional regression to explore the relation between fund skills and price. Second, we expand regression by controlling for fund specific and fund family variables. According to Khorana and Servaes (1999)[15], family characteristics at the time that they launch a new fund have an effect on the fund's profile and future performance. Thus, we assume that fund families define their productive strategy 6-months prior to the launch date. Thereby, we use this hypothesis to collect information related to fund specific and fund family characteristics. For each fund in our sample, family variables are recorded at this date. We exclude funds launched before January 2001. Furthermore, since the alphas are calculated in a 36-months rolling window, we discard all funds launched after 2013. At the end, we obtain a sample formed by 388 funds from the previous database.

4.2.1 Price and fund skills relation

In the litterature, the relationship between performance and price which include management fees, subscription and redemption fees and ongoing charges is considered as a puzzle. There is two main points of view. On the one hand, the relation is assumed to be positive. A high-priced fund will have value for its family, which will therefore tend to invest more resources in it to produce higher performance (Gaspar et al., 2006)[10]. On the other hand, Gil-Bazo and Verdu (2009)[12] find evidence of a negative relationship. High prices are intended for marketing and distribution expenditure targeted to unsophisticated investors, who are assumed to be less sensitive to performance. Here, we propose an alternative way to explore this relation using fund skills (a_i) instead of the adjusted performance (α_i). We use several fees: subscription and redemption fees, and the annual fees related to funds' expenses and management fees. Following Gil-Bazo and Verdu (2009), we also use a global variable: Total Operational Cost (TOC).[8] We carry out cross-sectional regressions with year fixed-effect with robust t-statistics clustered at the fund sector level. We also use family fixed-effects to control for all unobserved heterogeneity between the families. This allows us to highlight the impact on fund skill within and outside the fund family.

The table 1 reports our results. We observe a significant and positive relation between price and skills (columns 1 to 4). Overall, skilled funds have a higher prices. The slope coefficients are slighlty the same for the three variables TOC, AnP and $Price$. The introduction of family fixed-effects drastically changes the results (columns 5 to 8). All slope coefficients flip from positive to negative and lose their significance. This indicates that there is no difference in skills between funds according to the price criterion within families. The cross-sectional relation between fund skills and price is in fact due to the variations among fund families. All in all, these results give a strong evidence that price and fees are not set at fund level but more a fund family concern. Fund families with more expensive fund prices are also those that offer the highest skills. It seems that the higher price is a compensation for higher coordination and/or hierarchical costs.[9]

[8] $TOC = AnP + \frac{Price}{7}$ (Tuffano and Sevick, 2007)[]Tufano2007.

[9] For robustness check, we run the same cross-sectional regression using all 1262 funds from our initial

Table 1: **Price and fund skills relation**

This table reports cross-sectional regressions between fund skills, measured by fund fixed-effects estimated from model (8) in table (A3). The independant variables are formed by *Price* (the Subscription + Redemption fees), the annual price (*AnP*: Management fees + total Expense) and the Tuffano and Sevick indicator *TOC*. Regressions use year fixed-effects with a robust t-statistics clustered at the fund sector level. Family fixed-effects are added for specifications 5 to 8. ***/**/* indicate statistical significance at the 1%, 5%, 10% level.

	Dependent variable: Fund skills a_i							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TOC	0.0009***				−0.0001			
	(0.0003)				(0.0005)			
AnP		0.0009**		0.0008**		−0.0002		−0.0002
		(0.0004)		(0.0004)		(0.0005)		(0.0006)
price			0.0004**	0.0003			−0.00003	−0.000004
			(0.0002)	(0.0002)			(0.0003)	(0.0003)
Year fixed effect ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family fixed effect ?	No	No	No	No	Yes	Yes	Yes	Yes
Observations	388	388	388	388	388	388	388	388
R^2	0.1595	0.1579	0.1536	0.1601	0.4797	0.4797	0.4796	0.4797
Adjusted R^2	0.1349	0.1332	0.1288	0.1332	0.1396	0.1396	0.1394	0.1359
Note:								*p<0.1; **p<0.05; ***p<0.01

4.2.2 Fund skills and fund specific characteristics

Following our previous results, we expand regression by controlling for fund specific variables. We use a set of 6 fund specific variables which provide information on fund style and/or their fund governance. More precisely, we use dummies variables related to small and mid-cap funds(*SmdCap*), funds investing in European emerging stocks (*Emerging*), to outsourced fund companies (*CompOut*)[10], to fund that has multiple layers of diversification – across multiple managers, multiple investment styles and in some cases multiple asset classes (*Multi_Mgr*) and to master fund (*MasterFund*).[11] We use also the number of countries in which the fund are marketed (*Nb_Sales*). As before, for each regression, we introduce a year fixed-effect with robust t-statistics clustered at the fund sector level.

database. The results are reported in table A7 are quite similar and do not need to be overemphasized because of a lack of theoretical foundation.

[10] To construct *CompOut* variable, we use the methodology of Chuprinin et al. (2013)[7] in order to identify fund companies that are not directly affiliated with the fund family. To do this, we use the FactSet and Lipper database. For each fund, we identified and compared the "ultimate parent" provided by FactSet, and the "fund master" provided by Lipper. We then compared with fund names to find those whose family name appears. Marginally, we carried out a manual check via the FactSet data and online if necessary. In our sample, we find 98 outsourced funds.

[11] A Master fund in a special structure master-feeder fund is a common special purpose entity utilized to raise capital or subscription from investors into a centralised vehicle known as a master fund.

We also use family fixed-effects to control for all unobserved heterogeneity between the families, except for models using family variables.

Table 2: **Skills, price, fund specific and family characteristics**

This table reports cross-sectional regressions between fund skills, measured by fund fixed-effects estimated from the model (8) in table (A3). The independant variables are formed by the Tuffano and Sevick indicator (TOC), fund specific variables (*Nb_Sales*, *SmdCap*, *Emerging*, *CompOut*, *Multi_Mgr*, *Master_Fund*) and lagged independent variables, measured 6-months before their launch date, related to fund family ($FamSize$; $Large$ and HHI_M_FS). Regressions use year fixed-effects with robust t-statistics clustered at the fund sector level. ***/**/* indicate statistical significance at the 1%, 5%, 10% level.

	Dependent variable: Fund skills a_i							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TOC	0.0006**	0.0005***	0.0007**	0.0005***	0.0005***	0.0006***	0.0006***	0.0006***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
SmdCap	0.0040***	0.0041***	0.0039***	0.0043***	0.0041***	0.0042***	0.0043***	0.0043***
	(0.0011)	(0.0006)	(0.0010)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Emerging	−0.0305***	−0.0315***	−0.0316***	−0.0316***	−0.0315***	−0.0315***	−0.0316***	−0.0316***
	(0.0019)	(0.0007)	(0.0009)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Multi_Mgr	−0.0056***	−0.0013	−0.0007	−0.0014	−0.0014	−0.0016	−0.0017*	−0.0017*
	(0.0014)	(0.0010)	(0.0021)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0009)
MasterFund	−0.0035*	−0.0019***	−0.0005	−0.0018***	−0.0020***	−0.0019***	−0.0019***	−0.0019***
	(0.0018)	(0.0005)	(0.0013)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Nb_Sales	0.0001	0.0001	0.00005	0.0001	0.0001*	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CompOut	0.0006	0.0006	−0.0022*	0.0005	0.0005	0.0007	0.0005	0.0005
	(0.0010)	(0.0006)	(0.0011)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
FamSize				0.0043**			0.0031*	0.0032*
$\times 10^6$				(0.0018)			(0.0019)	(0.0019)
Large					0.0016***		0.0003	0.0003
					(0.0004)		(0.0006)	(0.0007)
HHI_M_FS						−0.0035***	−0.0030**	−0.0030**
						(0.0011)	(0.0015)	(0.0015)
U4								−0.0007
								(0.0010)
Constant	0.0371***							
	(0.0008)							
Year fixed effect ?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family fixed effect ?	No	No	Yes	No	No	No	No	No
Observations	388	388	388	388	388	388	388	388
R^2	0.6875	0.8549	0.8950	0.8558	0.8563	0.8575	0.8581	0.8582
Adjusted R^2	0.6817	0.8482	0.8217	0.8488	0.8493	0.8506	0.8504	0.8501
Note:								*p<0.1; **p<0.05; ***p<0.01

The first three columns (1 to 3) of table 2 reports the results of our regressions related to fund specific variables. We observe interesting results for all three specifications. The R^2 is high, greater that 85%, except for model 1 using standard OLS. All coefficients are stable regardless of the fixed-effects considered, except for *CompOut* and *MasterFund*. As expected, we observe that the price coefficients are positive for all models. Contrary to our previous results, the coefficient remain significant even after using fund family fixed-effect (column 3) and controlling for fund specific variables. This indicates that the cross-sectional relation between skills by price can be partly explained by the variations among fund families but also by some fund specific characteristics, mainly fund style. All variables related to fund style, such as small and mid-cap and emerging, are highly significant. The slope coefficients related to *SmdCap* are positive. This indicates that small and mid-cap funds have higher initial skills. Indeed, this type of fund is subject to strong liquidity constraints, and therefore must have a significant stock-picking ability. Otherwise, small and mid-cap funds are subject to the most frequent valuation errors from financial markets. They are therefore a significant source of alpha, but also of moral hazard. Thus, fund families must invest many of their resources in them and put in place an effective monitoring mechanism to control moral hazard. Conversely, we observe the opposite relationship between fund skills and emerging funds. All coefficients are negative. It seems that emerging funds receive a low level of resources from families during the fund design phase. It is worth to recall that the European mutual funds market was known to be fragmented before the adoption of the UCITS IV directive in 2011. This fragmentation can be explained by various entry barriers, including the obligation to domicile funds for commercialization in the country, but more particularly a cultural barrier. All these barriers generally require the hiring of a local manager to identify profitable opportunities more easily. As a result, emerging funds have high market power at the domestic level, and their managers benefit from high information rents. This increases the difficulty of monitoring and makes resource investment less attractive to fund families. This result is consistent with those of Chuprinin et al. (2015)[7] who find that fund companies that do not share a language with their family enjoy less preferential treatment. For master fund and outsourced fund, the results are mixed. Both display a negative relation with fund skills. On the one hand, the significance of the *MasterFund*'s coefficient desapear in the model (3) using family fixed-effects. Thus, the negative relation between fund skills and Master fund is not explained by variation "within" family but "between" fund families. On the other hand, *CompOut* is significance only without family fixed-effects specifications. This result bears out the presence of information asymmetries inherent to the outsourcing relationship. It means that these outsourced funds do not have access to the family's resources and to valuable information. These results confirm the findings of Chen et al. (2013)[6] and Chuprinin et al. (2015)[7] who document the underperformance of outsourced funds. Last, the others variables related to fund organization (*Nb_Sales* and *MultiMgr*) are non-significant. For the number of country sales, we would have expected a significant effect, as skilled funds are supposed to be the major provider of investment flows and geographical diversification, so families should invest heavily in them. Notwithstanding the above, this result is consistent with the findings of Ferreira et al. (2013) [9]. In the same way, we would expected a kind of synergetic effect for multi-managers funds with a combination of "skilled managers". This is surprinsingly not the case. We do not to overemphasize this latter because of absence of clear empirical arguments.

4.2.3 Fund skills and fund family characteristics

Here, we expand regression by controlling for fund family variables. Following Khorana and Servaes (1999)[15] conclusions, we collect the fund family characteristics 6-months before the launch date. The underlying idea is that the productive strategies set by families depend on the available resources at their disposal at this time. To do so, we use three main variables: the fund family resource (*FamSize*), the family degree of specialization measured with a Herfindall Hirschmann Index according to the size of the fund sectors of all funds in the family (HHI_M_FS) and a dummy variable (*Large*) which give information on the scope of the family in terms of number of fund members. The main intuition is that a fund family with a lot of resources, more diversified (with a low HHI) and/or "large" should put funds with the highest skills on the market.

Columns 4 to 5 in table 2 reports the results of our regressions. The result decisively validates that fund skills are organized at the family level. For all three fund family variables used, cross-sectional regressions display highly significant coefficients with a R^2 up to 85%. Moreover, the slope coefficients related to fund specific variables remain stable. As expected, we observe a positive relation between funds skills and fund family resources. This result from model (4) confirms our underlying idea that fund families contribute to funds' skills by allocating the resources (financial and organizational) at their disposal during the design of the fund. It validates the idea that there is a transfer of know-how and experiences. We observe also that large fund families are also those with high skills (model 5). More precisely, according to our subsample, this result validates our main hypothesis that large fund families tend to bring out new skilled funds. Thus, fund skills are primarily based on the extent of diversification of the fund family. Indeed, a large family is supposed to have a mature internal organizational structure with longstanding experience, a proven track record and sources of diversified information related to the activity of its members. This conclusion is reinforced by the negative and significant coefficient associated HHI_M_FS (model 6). Let's recall that HHI_M_FS measures Herfindall Hirschmann concentration index based on the fractions of market shares for each fund sector in which the family funds are invested. So, HHI_M_FS gives its degree of specialization. A HHI equal to 1 indicates a highly concentrated fund family, i.e. investing heavily in a few sectors and vice versa for a family with an HHI equal to 0. Thus, the negative coefficient associated to HHI_M_FS in our regression indicates that the more diversified is the family, the more skilled are its (new) funds. Beyond confirming that skills are determined at the family level, this result shows the importance of fund governance and internal organization. These two elements appears to be helpful in designing and launching a fund that is likely to be better than its predecessors.

5 Conclusion

In this paper we examine the evolution and the main determinant of fund skills. In light of the seminal works of Berk and Green (2004) [1] and Pastor et al. (2012, 2015)[18][19] As a starting point we focus on fund'skills and not manager's skill considering this latter only as one of its various components. Using a model based on industry returns to scale, we estimate fund skills by extracting fund fixed-effect from panel regressions. As results, we clearly bring out that fund skills are a fund family concerns and fund governance. We show that new funds have higher skills than older ones and fund skills grows over time. Fund families with more expensive fund prices are also those that offer the highest initial skills. We point out that small and mid-cap funds have a higher initial skills that is not the case for emerging, multi-manager and outsourced funds. It seems that family invest more resources in promising funds to compensate possible higher coordination and/or hierarchical costs. On the contrary, they neglect funds with greater information asymmetries. We confirm that large and more diversified fund families are those who bring out new skilled funds.

All in all, this study provide some significant contributions to the literature. First, it allows us to investigate the relationship between the firm's organizational form, the resulting agency rents and performance. Indeed, the analysis of the fund industry has the advantage, through Jensen's alpha, which is public information, to compute directly the manager's output and by extent the organizational performance. Berk et al. 2017 for example, show that the best performing funds are those whose families are organized in such a way that they have an informational advantages that allow them to efficiently match capital to skill. Secondly, this study clearly distinguishes the manager's skill from the fund's skill. The difference is not so clear in the literature. Sometimes studies tend to confuse the two. Our study show therefore that fund structure has its own resources, like a car for which the fund manager is merely their pilot. Managers come and go, funds stay and remain stable in times. Finally, by allowing a deeper understanding of funds performance, our results will give decision making tools to investor for their need to assess and classification of funds sold and marketed.

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Table A1: **Variables definition**

Variables	Label	Definition
Alpha 1-Factor	α_{1F}	Alpha (percentage per month) estimated with 3 years of past monthly fund returns with 1 factor model (CAPM).
Alpha 3-Factor	α_{3F}	Alpha (percentage per month) estimated with 3 years of past monthly fund returns with the Fama-French 3-factors model.
Alpha 4-Factor	α_{4F}	Alpha (percentage per month) estimated with 3 years of past monthly fund returns with the Carhart 4-factors model (CAPM).
Fund Size	FundSize	The sum of AUM across all fund share class (in Euro millions, Lipper).
Family Size	FamSize	The sum of AUM of the fund family (parent management company) to which the fund belongs (in Euro billions, Lipper).
Industry Size	IndSize	The sum of AUM across all active European equity mutual funds divided by the total market value of all European stocks. (FactSet, Lipper???) Note that IndustrySize equals Number of Funds times Average Fund Size divided by the total stock market capitalization at the end of 2011 (PST 2014, p.41)
Fund Age	Age	Inflated to millions of 2016 euros using the total market cap of European stocks in FactSet. Number of years since the fund launch date (Lipper).
UCITS IV	U4	Refers to subperiod after UCITS directive adoption, after 06/2011
Small Cap Funds	SmdCap	Dummy variable that equals one if the fund is classified as a small-cap fund (i.e. a fund trading small-capitalization stocks) and zero otherwise (Lipper).
Emerging Funds	Emerging	Dummy variable that equals one if the fund is classified as Emerging fund (i.e. a fund trading European Emerging stocks) and zero otherwise (Lipper).
Large Fund	Large	Dummy variable that equals one if the number of fund members of the fund family to which the fund belong is superior to 10, and zero otherwise.
Fund Sector	HHI_M_FS	Herfindall Hirschmann concentration index based on the sum of the squares of the fractions of market shares (TNA) for each fund sector in which the family funds are invested.

Table A2: **Summary Statistics**

This table shows summary statistics of our sample of active European equity mutual funds from January 2000 to October 2016. The unit of observation is the fund/month. The first three rows show the benchmark-adjusted return estimated with the three standard performance evaluation models (1, 3 and 4-factor models). FundSize is the fund's total AUM aggregated across all its share classes. IndustrySize (IndSize) is the sum of all European active management funds' AUM divided by the total market value of all European stocks in the same month. FundAge (Age) is the number of years since the fund's first offer date. FamilySize (FamSize) is the sum of fundSize across funds belonging to the same family. *Nb of Fund members* is the number of funds belonging to the fund family master. In all of our tests, adjusted R^2 are high, around 90% on average.

	Mean	Stdev	Min	Q1	Median	Q3	Max
Alpha 1F (α_{1F})	0.0028	0.0179	-1.4175	0.0001	0.0022	0.0059	0.7049
Alpha 3F (α_{3F})	0.0019	0.0219	-1.4998	-0.0007	0.0019	0.0059	1.0279
Alpha 4F (α_{4F})	0.0024	0.0366	-2.3039	-0.0001	0.0026	0.0067	1.6913
FundSize ($\times 10^6$)	710.09	2012.10	15.00	59.07	172.16	599.24	91644.5
IndSize	0.0784	0.0186	0.0429	0.0600	0.0860	0.0950	0.1022
Age	11.29	8.52	0.083	5.25	9.67	15.25	86.08
FamSize ($\times 10^9$)	71.942	99.312	0.0004	3.197	27.413	104.986	716.143
Nb of Fund members	148.95	202.88	1	23	67	202	1278

Table A3: **Models for the extraction of fund skills**

This table reports the results from panel regressions of fund performance on fund size. The dependent variables measure the alpha coefficients estimated with 3 years of past monthly fund returns with the three main performance evaluation models: α_{1F}, α_{3F} and α_{4F}. The independant variables are the lagged fund age (Age), fund size (*FundSize*), industry size (*IndSize*), and various fund specific and fund family variables : fund family size (*FamSize*), dummy for small and mid-cap funds *SmdCap*, a dummy for emerging funds (*Emerging*). We multiply the slopes on fund size and fund family size by 10^6 to make them easier to read. The reported slopes on fund size thus equal the change in alpha, in units of bp per month, associated with a 100 million increase in *FundSize*. All panel regressions use OLS with fund fixed-effects. The sample period is from December 2000 to October 2016. Robust standard errors clustered by sector × month are reported in parentheses. ***/**/* indicate statistical significance at the 1%, 5%, 10% level.

	Dependent variable:								
	1F	3F	4F	1F	3F	4F	1F	3F	4F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lag(ageym)	0.001***	0.001***	0.002***	0.001***	0.002***	0.002***	0.001***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0005)
lag(FundSize) $\times 10^6$	0.106	0.042	−0.169	−0.007	−0.069	−0.275			
	(0.068)	(0.094)	(0.273)	(0.082)	(0.086)	(0.213)			
lag(IndSize)	−0.383***	−0.428***	−0.383**	−0.436***	−0.483***	−0.458***	−0.435***	−0.482***	−0.454***
	(0.034)	(0.053)	(0.143)	(0.063)	(0.082)	(0.148)	(0.062)	(0.081)	(0.150)
lag(FamSize) $\times 10^6$				−0.283*	−0.415*	−0.106	−0.284*	−0.418*	−0.122
				(0.161)	(0.243)	(0.372)	(0.164)	(0.245)	(0.362)
lag(IndSize) × lag(FamSize) $\times 10^6$				2.649**	3.766	0.122	2.651*	3.782	0.189
				(1.309)	(2.303)	(4.398)	(1.320)	(2.311)	(4.347)
lag(IndSize) × lag(SmdCap)				0.022	−0.060*	0.324	0.022	−0.060*	0.324
				(0.018)	(0.030)	(0.422)	(0.018)	(0.030)	(0.422)
lag(IndSize) × lag(Emerging)				0.353**	0.360**	0.390**	0.353**	0.358**	0.381**
				(0.158)	(0.167)	(0.148)	(0.155)	(0.164)	(0.145)
Observations	126,923	126,923	126,163	126,923	126,923	126,163	126,923	126,923	126,163
R^2	0.300	0.288	0.216	0.310	0.295	0.220	0.310	0.295	0.220
Adjusted R^2	0.292	0.280	0.208	0.302	0.287	0.212	0.302	0.287	0.212

Note: *p<0.1; **p<0.05; ***p<0.01

Table A4: **Fund fixed effets Correlation Matrix**

This table reports the correlation between a_i coefficients, *i.e.* fund fixed effects, extracted from various panel regressions 1 to 8 in table A3.

	FE.m1	FE.m2	FE.m3	FE.m4	FE.m5	FE.m6	FE.m7	FE.m8	FE.m9
FE.m1	1.00								
FE.m2	0.96	1.00							
FE.m3	0.81	0.88	1.00						
FE.m4	0.87	0.84	0.69	1.00					
FE.m5	0.84	0.88	0.77	0.96	1.00				
FE.m6	0.71	0.79	0.89	0.79	0.82	1.00			
FE.m7	0.87	0.84	0.69	1.00	0.96	0.79	1.00		
FE.m8	0.84	0.89	0.77	0.96	1.00	0.82	0.96	1.00	
FE.m9	0.71	0.79	0.89	0.78	0.82	1.00	0.78	0.82	1.00

Table A5: **Summary statistics fund skills and fund characteristics**

This table reports summary statistics for fund skills extracted from panel regression model 7 to 9 in table A3 and all fund specific and fund family characteristics used in our empirical investigation.

	Min	Max	Median	Mean	Std.dev
			All sample: 1262 funds		
FundSize $\times 10^6$	0.100	22688.30	53.539	401.96	1392.34
Age	0.083	72.083	1.167	4.359	6.756
FamSize $\times 10^6$	0.617	465590.04	14080.25	53640.09	80550.75
HHI_M_FS	0.040	1.000	0.172	0.256	0.224
Nb_Sales	1.000	20.000	1.000	2.691	3.235
Management fees (Mgtfee)	0.000	5.000	1.100	0.963	0.934
Submission fees (Subfee)	0.000	15.000	2.000	2.225	2.078
Expense	0.000	12.740	1.728	1.790	0.810
Redemption fees (redfee)	0.000	5.000	0.000	0.286	0.758
AnP	0.000	14.840	2.515	2.753	1.355
price	0.000	19.000	2.000	2.510	2.252
TOC	0.000	15.269	2.950	3.112	1.478
FE.m7	-0.084	0.084	0.025	0.022	0.016
FE.m8	-0.148	0.071	0.028	0.025	0.018
FE.m9	-0.299	0.071	0.021	0.017	0.023

Table A6: **Summary statistics fund skills and fund characteristics**

This table is the same as table A5 related to subsample formed by all funds launched after 2001 from our main database.

	nbr.val	min	max	median	mean	std.dev
FundSize $\times 10^6$	388	0.100	2973.258	24.712	120.137	285.760
Age	388	0.083	8.667	0.083	0.232	0.781
FamSize $\times 10^6$	388	48.41	444903.7	34870.15	75490.12	94079.98
Nb_Sales	388	1.000	20.000	1.000	2.691	3.235
HHI_N_FS	388	0.025	1.000	0.059	0.092	0.114
Management fees (Mgtfee)	388	0.000	4.000	1.100	0.992	0.933
Submission fees (subfee)	388	0.000	15.000	2.000	2.487	2.181
Redemption fees (redfee)	388	0.000	5.000	0.000	0.337	0.818
Expense	388	0.000	5.710	1.710	1.718	0.773
AnP	388	0.000	8.210	2.485	2.709	1.347
price	388	0.000	19.000	2.875	2.824	2.431
TOC	388	0.000	8.710	2.936	3.113	1.477
FE.m8	388	-0.038	0.070	0.038	0.036	0.012

Table A7: **Price and fund skills relation**

This table is the same as table 1 using all sample. It is used for robustness check. The cross-sectional regressions are run using all 1262 funds after relaxing the hypothesis based on 6-months before launching funds period to collect fund specific and fund family variables.

	Dependent variable: Fund skills a_i							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TufSev	0.0007**				−0.0004			
	(0.0003)				(0.0012)			
AnP		0.0006		0.0004		−0.0007		−0.0010
		(0.0004)		(0.0004)		(0.0013)		(0.0013)
price			0.0005***	0.0005***			0.0006*	0.0007**
			(0.0001)	(0.0001)			(0.0004)	(0.0003)
Observations	1,266	1,266	1,266	1,266	1,266	1,266	1,266	1,266
R^2	0.2660	0.2650	0.2673	0.2680	0.4911	0.4918	0.4932	0.4951
Adjusted R^2	0.2590	0.2580	0.2603	0.2604	0.2783	0.2793	0.2813	0.2831

Note: *p<0.1; **p<0.05; ***p<0.01