DOI: 10.1111/eufm.12160

ORIGINAL ARTICLE

WILEY EUROPEAN FINANCIAL MANAGEMENT

The payback of mutual fund selectivity in European markets

Feng Dong[1] | **John A. Doukas**[2]

[1] Department of Finance, Strome College of Business, Old Dominion University, Constant Hall, Suite 2169, Norfolk, VA 23529-0222, USA
Email: fodng@odu.edu

[2] Department of Finance, Strome College of Business, Old Dominion University, Constant Hall, Suite 2080, Norfolk, VA 23529-0222, USA
Email: jdoukas@odu.edu

Abstract

Is European fund management selectivity skill $(1 - R^2)$ profitable (*alpha*)? To examine this question, we use a sample of 2,947 actively managed domestic equity mutual funds from 11 European countries. We find that high fund selectivity generates significant investor gains. The results are robust to investor sentiment and stock-market dispersion conditions. Moreover, we investigate the moderating effect of country characteristics on the profitability of fund selectivity and find that managers' selectivity ability is more valuable in countries with high economic development, strong legal system, small but highly liquid equity markets, and young mutual fund industries.

KEYWORDS

European fund selectivity skill, fund manager skill, fund performance

JEL CLASSIFICATION

*G*11, *G*14, *G*20, *G*23

1 | INTRODUCTION

Since their invention in 1924, mutual funds have become an increasingly important investment instrument, attracting a large amount of capital from individual investors. By the end of 2014, the total value of assets managed by mutual funds exceeded US$31 trillion, which represented a 20% growth rate since 2007 (Investment Company Institute, 2015). While numerous studies have acknowledged the extremely important role of the mutual fund industry in the context of the US financial markets, they have also investigated the relation between mutual fund performance and fund managers' skills (Amihud & Goyenko, 2013; Berk & van Binsbergen, 2015; Brands, Brown, & Gallagher, 2005;

Carhart, 1997; Cremers, Ferreira, Matos, & Starks, 2016; Cremers & Petajisto, 2009; Daniel, Grinblatt, Titman, & Wermers, 1997; Kacperczyk, Sialm, & Zheng, 2015; Malkiel, 1995). Despite the depth of this literature, there is still no consensus with respect to the sources behind the performance of mutual funds. While the most recent studies (Amihud & Goyenko, 2013; Berk & van Binsbergen, 2015) stress the importance of fund management selectivity (skill), they only do so in the context of the US mutual fund industry.

As of the end of 2014, the European mutual fund industry had more than US$9.5 trillion in assets under management, which was 31% of the world's total mutual fund industry. To date, while the mutual fund industry in Europe is the second largest mutual fund industry in the world and plays an important role in the world economy, it is unknown whether fund performance is attributed to fund management selectivity skill. To the best of our knowledge, no empirical study has analyzed the performance and skill of European fund managers. Whether European fund performance is linked with fund managers' selectivity remains unanswered and represents the main objective of this study. In this paper we ask the following natural question: Does fund management selectivity lead to superior fund performance across the European fund industry?

This paper attempts to fill this void by addressing this question using a unique dataset from 11 European countries. Unlike several previous studies that have investigated the determinants of the performance of the European mutual fund industry at a very macro level, we investigate whether fund management selectivity, an established measure of fund management skill, is associated with superior fund performance for actively managed equity mutual funds.[1,2] In addition, research focus on the more interesting question of whether European skilled fund managers can generate superior risk-adjusted excess returns has received considerably less research attention thus far.[3] To the best of our knowledge, no study has dealt with the measurement of mutual fund managers' skill (i.e., fund selectivity) in a European context to examine whether superior fund performance is related to fund management skill. The aim of our analysis is to address this important question.

Empirical studies based on the US mutual fund industry show that mutual fund managers with high managerial skills improve fund performance by selecting valuable stocks (Carhart, 1997; Daniel et al., 1997; Gruber, 1996; Zheng, 1999). Fund selectivity skill has been attributed to fund managers' superior analytical ability to anticipate macro or micro fundamental information (Kacperczyk, Van Nieuwerburgh, & Veldkamp, 2011) or special knowledge of specific industries or companies (Cohen, Frazzini, & Malloy, 2007; Kacperczyk et al., 2015). Petajisto (2013) uses active share, which is measured as the aggregate stockholding dispersion between a manager's portfolio and the benchmark

[1]For example, Grünbichler and Pleschiutschnig (1999) and Otten and Bams (2002), conducting aggregate research on the European mutual fund industry's performance, report that, unlike the evidence of US mutual funds, European mutual funds as a group slightly outperform the market benchmark. Banegas, Gillen, Timmermann, and Wermers (2013) report that European mutual fund performance can be explained by macroeconomic state variables, such as the default yield spread, the term spread, and the dividend yield. Ferreira et al. (2013), using the data of actively managed equity mutual funds from 27 countries, find that both fund-level variables and country characteristics can determine fund performance. In addition, they show that the superior performance of mutual funds is associated with countries with highly liquid markets and strong legal investor protection.

[2]Several studies, such as Dermine and Röller (1992), Shukla and van Inwegen (1995), Blake and Timmermann (1998), Dahlquist, Engström, and Söderlind (2000), and Cesari and Panetta (2002) focus on specific European countries.

[3]Abinzano, Muga, and Santamaria (2010) use stochastic dominance techniques to show that some European mutual fund managers do possess management skills. Cuthbertson, Nitzsche, and O'Sullivan (2008) employ a cross-sectional bootstrap methodology and find that some top-performing UK equity mutual fund managers have stock-picking abilities. Furthermore, Franck and Kerl (2013) point out that European fund managers actively change their portfolio allocations based on sell-side analyst information and that this strategy benefits fund performance.

index, to capture fund managers' selectivity skill and finds a strong relation between active management and fund performance. Amihud and Goyenko (2013), using a lower fund R^2-value from regressing its returns on multifactor benchmark models to proxy for higher selectivity skill, find similar results. One advantage of Amihud and Goyenko's method is that it does not require knowledge of fund holdings or the fund's benchmark index. Following their methodology and using a special sample of 2,947 actively managed domestic equity mutual funds from 11 European countries over the years 2000–2015, we add to this literature by estimating fund manager's stock-picking skill directly and investigating the relation between managerial skills and fund performance.

To measure fund manager skill, we first construct the benchmark factors in the Fama and French (1993) and Carhart (1997) four-factor model (FFC model) for each individual country, using all the stocks included in the Bloomberg database, and calculate fund selectivity following Amihud and Goyenko (2013). Consistent with previously recorded US evidence (Amihud & Goyenko, 2013; Berk & van Binsbergen, 2015), our European evidence reveals a significantly positive relation between fund selectivity and fund performance, suggesting that the fund management skill predictability of fund *alpha* is universal. Furthermore, evidence that fund management skill predicts fund *alpha* outside the United States (out of sample) makes data mining unlikely to be a primary explanation for the in-sample (US) management selectivity predictability. That is, the fact that European fund management skill generates significant abnormal returns outside of the United States can be viewed as an out-of-sample (US) robustness check of fund management skill.

Moreover, our empirical evidence remains robust to investor sentiment and market dispersion, which have been shown to influence fund performance. Previous literature on investor sentiment has shown that it can affect both overall market returns and individual stock returns (Amromin & Sharpe, 2009; Antoniou, Doukas, & Subrahmanyam, 2015; Daniel, Hirshleifer, & Subrahmanyam, 1998; Hong & Stein, 1999); consequently, it can affect the profitability of a fund manager's skill. During high-sentiment periods, the equity market is filled with greater noise than during low-sentiment periods. Hence, asset prices are more likely to be noisy and it is more difficult to identify good investment opportunities. On average, stock-picking ability during high-sentiment periods is limited, resulting in fund underperformance. During low-sentiment periods, stocks are traded around their fundamental values and overall mutual fund performance should be higher during low-sentiment periods, when asset prices are less noisy. The above argument suggests that the relation between fund selectivity and fund performance could be affected by market sentiment. Therefore, we estimate market sentiment for each country based on the European market Consumer Confidence Indicator (CCI) and test the sensitivity of our results by replacing the major sentiment index with four alternative market sentiment measures. The results are shown to be consistent with the pattern of our main findings on the relation between fund selectivity and fund performance.

Second, von Reibnitz (2013) shows that market dispersion can also influence the market state and consequently impact the effectiveness of fund manager skill. If fund managers' skills result from their great insight and analytical ability, average mutual funds cannot yield high risk-adjusted returns during periods of low market dispersion, when access to firm-specific information is costly. Thus, mutual fund manager selectivity should be more profitable during periods of high stock-return dispersion, when more firm-specific information is available in the market, due to the payoff from increasing weights in stocks that have the potential to outperform the market. The results of this test are also consistent with this prediction.

Last, we study how the profitability of fund selectivity relates to country-level characteristics. Unlike previous studies, which examine the direct effects of country-level variables on fund performance (e.g., Ferreira, Keswani, Miguel, & Ramos, 2013), we examine whether these factors, such as equity market development or legal protection strength, influence fund manager skills and mutual fund performance. We employ a two-step regression procedure and find that fund manager skill is more valuable and profitable for fund investors if the fund is domiciled in countries with high economic development, strong legal protection, small but highly liquid equity markets, and a young mutual fund industry.

The remainder of the paper is organized as follows. Section 2 describes the data and empirical methodology. Section 3 presents the empirical findings, along with a discussion of the results. Section 4 concludes with a discussion of the implications of this study for the literature on mutual fund performance and managerial skill.

2 | DATA AND METHODOLOGY

In this section, we describe our sample selection procedure and then present the methodology used to calculate fund performance and fund management selectivity. Lastly, we describe the other market variables and country-level characteristics used in our analysis.

2.1 | Sample description

We first collect data for European actively managed domestic equity mutual funds. The source is the Bloomberg mutual fund database and the sample period is from January 1998 to December 2015 (the first 24 months of data are used to estimate fund selectivity and fund performance as of January 2000). The criteria used to collect the data require determining that: (1) the fund status is active or dead; (2) the country of domicile is European; (3) the asset focus is equity; (4) the inception date is before 31 December 2013; and (5) the fund type is an open-end mutual fund. To eliminate index funds or international funds, we delete funds with a description containing any of the partial terms such as *index*, *ind*, *global*, *fixed-income*, *international*, *sector*, *balanced*, *bond*, *money-market*, and *convertible debt*. In addition, each fund must have more than 25 months of continuous data. Our final sample consists of 3,388 mutual funds from 17 European countries. The list of countries and the number of mutual funds in each country is shown in Table 1.

To ensure the reliability of our results, we narrow down the list of countries to those with more than 100 months of available mutual funds data. Of the 17 European countries, 12 meet this criterion. We then delete Luxembourg, because it often functions as an offshore mutual fund market for other countries. The final sample consists of 11 countries with 2,947 actively managed mutual funds. The summary statistics for these funds are reported in Table 2. The average monthly raw return for all European mutual funds is 0.49%, Sweden has the highest average monthly return (0.81%) and Austria has the lowest (0.36%). The average of total net assets (TNA) for all funds in the sample is US\$235.15 million and the average age is 10.11 years.

2.2 | Measuring fund selectivity and performance

The next step is to estimate fund performance (fund *alpha*) and fund selectivity for all mutual funds in our sample. Following Amihud and Goyenko (2013), we use logistically transformed $1 - R^2$ to measure fund selectivity, where R^2 is obtained from regressing each fund's returns on the multifactor benchmark model (i.e., the FFC model). According to Amihud and Goyenko (2013), a low R^2 indicates a low level of co-movement with the market benchmark and fund management's superior selectivity ability, because highly skilled fund managers manage funds based on private information, which makes funds less sensitive to variations in public information. The model to estimate R^2 is the following:

$$R_{i,t} = \alpha_i + \beta_{1,i}(RM_t - Rf_t) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}MOM_t + \varepsilon_{i,t} \tag{1}$$

TABLE 1 List of European countries in the database

This table lists all the European countries in the Bloomberg actively managed domestic equity mutual fund database, along with the number of mutual funds within each country. In total we have 3,388 actively managed European domestic equity mutual funds, both active and dead status, from January 2000 to December 2015.

Country	Number of funds
Austria	371
Belgium	13
Denmark	138
Finland	156
France	15
Germany	339
Greece	74
Ireland	641
Italy	308
Luxembourg	207
Netherlands	111
Norway	83
Portugal	49
Spain	399
Sweden	147
Switzerland	185
United Kingdom	152
Total	3,388

where $R_{i,t}$ is the return in US dollars of fund i in month t over the 1-month US Treasury bill rate in month t; $RM_t - Rf_t$ is the market excess return in US dollars in month t; SMB_t (small minus big) is the return difference between a large capitalization portfolio and a small capitalization portfolio in month t; HML_t (high minus low) is the return difference between a high-book-to-market ratio portfolio and a low-book-to-market ratio portfolio in month t; and MOM_t (momentum) is the return difference between the past 12 months' winners and the past 12 months' losers. To employ this model, we first construct the monthly benchmark factors from the FFC model for each country using all equity values included in the Bloomberg equity database traded in each country. The variable *RM* is calculated as the value-weighted average return of all stocks, active or dead. We then form the *SMB*, *HML*, and *MOM* factors following the method described by Fama and French (1993) and Carhart (1997). To test the validity of our estimation, we calculate the correlation between each market return factor with each country's major market index return.[4] The summary statistics are shown in Table 3.

[4]The following are the major markets: Austrian Traded Index (ATX Index) for Austria, OMX Copenhagen Index (KFX Index) for Denmark, OMX Helsinki Index (HEX Index) for Finland, German Stock Index (DAX Index) for Germany, Irish Stock Exchange Overall Index (ISEQ Index) for Ireland, FTSE Italia All-Share Index (FTSEMIB Index) for Italy, Amsterdam Exchange Index (AEX Index) for the Netherlands, Spanish Continuous Market Index (IBEX Index) for Spain, Stockholm Stock Exchange Index (OMX Index) for Sweden, Swiss Market Index (SMI Index) for Switzerland, and FTSE 100 Index (UKX Index) for the United Kingdom.

TABLE 2 Summary statistics of actively managed equity mutual funds' characteristics from 11 selected European countries

This table reports the means of mutual funds' descriptive statistics and the number of funds for each of the 11 European countries with more than 100 mutual funds obtained from the Bloomberg actively managed domestic mutual fund database. Age refers to the number of years after the inception date. TNA is each fund's total net assets in millions. Expense ratio is the annual expense ratio of each fund. Our sample contains 2,947 actively managed equity mutual funds over the period from January 1998 to December 2015.

Country	Age (years)	TNA ($ million)	Expense ratio (%)	Raw return (%)	Number of funds
Austria	10.87	81.93	1.68	0.36	371
Denmark	13.19	173.71	1.93	0.78	138
Finland	8.66	169.66	1.84	0.51	156
Germany	11.69	208.98	2.27	0.57	339
Ireland	7.74	599.02	1.83	0.46	641
Italy	10.90	181.62	2.24	0.39	308
Netherlands	10.93	170.71	1.57	0.57	111
Spain	8.98	76.20	2.05	0.41	399
Sweden	14.17	433.88	1.63	0.81	147
Switzerland	11.13	186.60	1.73	0.54	185
United Kingdom	7.98	171.96	1.83	0.59	152
All	10.11	235.15	1.95	0.49	2,947

We calculate fund performance (the fund's *alpha*), past performance (the fund's $alpha_{t-1}$), and fund selectivity (logistically transformed $1 - R^2$) using a 24-month moving window regression based on the estimated FFC model for each individual country. The fund *alpha* is the difference between the fund's return in month t and the expected return of the same month. The expected return for each fund in month t is calculated by multiplying the FFC model factor loadings from the preceding 24-month estimation period (months $t-24$ to $t-1$) by the FFC model factors in the current month. The process repeats by moving the estimation and test period 1 month at a time. The fund's $alpha_{t-1}$ is the intercept from the preceding 24-month estimation period (months $t-24$ to $t-1$). As Amihud and Goyenko (2013) explain, the distribution of R^2 is negatively skewed, which means that the distribution of $1-R^2$ should be heavily positively skewed. Therefore, we use the following logistic transformation of $1-R^2$ to measure fund manager selectivity skill:

$$Selectivity = \log\left(\frac{1-R^2}{1-\left(1-R^2\right)}\right) = \log\left(\frac{1-R^2}{R^2}\right). \tag{2}$$

One thing to note here is that, based on the argument of Berk and Green (2004), the performance measure based on fund return (the fund's *alpha*) is inaccurate due to economic scale, since superior performance can be detected by investors and funds with such performance can attract capital inflows. Consequently, managers with more capital must choose suboptimal investment opportunities due to the limited number of investment opportunities in the market, which harms fund performance. However, Ferreira et al. (2013) show that this scale effect is not present outside the US mutual fund industry.

TABLE 3 Market risk factor summary and correlations between market premium and major market index return for each country

This table reports the average value of the risk factors in the estimated Fama and French (1993) and Carhart (1997) model (FFC model) for each European country. The table also reports the correlations between the market return factor (*RM*) and the major market index return for each country (Austrian Traded Index (ATX Index) for Austria, OMX Copenhagen Index (KFX Index) for Denmark, OMX Helsinki Index (HEX Index) for Finland, German Stock Index (DAX Index) for Germany, Irish Stock Exchange Overall Index (ISEQ Index) for Ireland, FTSE Italia All-Share Index (FTSEMIB Index) for Italy, Amsterdam Exchange Index (AEX Index) for Netherlands, Spanish Continuous Market Index (IBEX Index) for Spain, Stockholm Stock Exchange Index (OMX Index) for Sweden, Swiss Market Index (SMI Index) for Switzerland, and FTSE 100 Index (UKX Index) for United Kingdom). ***Pearson's *p*-value at 1% significance level.

Country	*RM*	*SMB*	*HML*	*MOM*	Market index	Correlation
Austria	1.203	−0.238	0.150	0.510	ATX Index	0.928***
Denmark	1.774	0.388	−1.008	0.698	KFX Index	0.868***
Finland	1.548	−0.170	0.296	0.555	HEX Index	0.987***
Germany	1.111	1.032	1.152	0.873	DAX Index	0.926***
Ireland	0.969	−0.325	0.166	0.062	ISEQ Index	0.749***
Italy	0.637	−0.063	1.293	0.101	FTSEMIB Index	0.963***
Netherlands	0.800	0.018	−0.158	0.581	AEX Index	0.951***
Spain	0.951	0.113	0.748	0.660	IBEX Index	0.972***
Sweden	1.315	0.184	0.306	0.531	OMX Index	0.985***
Switzerland	0.994	−0.192	0.393	0.332	SMI Index	0.865***
United Kingdom	0.787	0.390	0.284	0.656	UKX Index	0.966***
All	1.099	0.103	0.329	0.505		
Std. dev.	0.341	0.391	0.622	0.249		

2.3 | Investor sentiment and market dispersion

In this section, we estimate market sentiment and market dispersion and incorporate these two factors into the analysis. To measure European market sentiment, we use the CCI, a survey-based index designed to measure consumer confidence in European countries. This index is available through the European Commission database. To ensure that the sentiment measure is free of macroeconomic influences, we use the residual from the regression of the CCI index on a set of macroeconomic variables.[5] The data reflect the period from January 2000 through December 2015.

We also estimate the market dispersion for each European country in our sample. Market dispersion, as argued by von Reibnitz (2013), measures how the level of stock price is affected by firm-specific information. Following von Reibnitz (2013), we measure market dispersion using the standard deviation of stock returns for all stocks in each country in month t:

[5]The variables include Europe's (1) inflation rate; (2) the growth rate of the employment rate; (3) the growth rate of industrial production; (4) the growth rate of durable consumer goods production; (5) the growth rate of nondurable goods production; (6) the consumer price index change of the service industry; and (7) European recession indicators from the Organisation for Economic Co-operation and Development (OECD).

$$Dispersion_{j,t} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{i,j,t} - R_{m,j,t}\right)^2} \tag{3}$$

where n is the number of stocks traded within country j in month t, $R_{i,j,t}$ is month t's return for each stock i in country j, and $R_{m,j,t}$ is the equally weighted average return of all stocks traded in country j for month t. The data for both active and delisted stocks are from the Bloomberg database and our data for market dispersion range from January 2000 to December 2015.

2.4 | Country-level characteristics

Previous studies have documented that, besides fund-level variables, country-level characteristics are essential determinants of mutual fund performance (Ferreira et al., 2013; Otten & Bams, 2002). Rather than investigate the direct relation between funds' domicile country characteristics and fund performance, we investigate whether those country-level variables can influence the profitability of fund selectivity skill. To address this issue, we use a two-step regression procedure. First, for each year from 2001 to 2015, we regress fund performance (fund *alpha*) on fund selectivity, controlling for other fund-level variables using monthly data for the current year and the prior year. Only funds with data for the full 24-month period are considered. Then, we collect the coefficients of fund selectivity for each year from the prior regression, which is used as a proxy of fund selectivity profitability, and run a regression of the coefficients on various country-level variables. Similar to the country-level variables used by Ferreira et al. (2013), we classify our country characteristics into different groups: economic development, equity market development, investor protection and legal strength, and mutual fund industry development. The details of country-level characteristics can be found in the Appendix.

First, we use the gross domestic product (GDP) per capita and the percentage of Internet users to capture economic development. Both sets of data are collected from the World Development Indicators (WDI) database. The GDP per capita is the GDP divided by the mid-year population, while the percentage of Internet users measures the percentage of individuals who have used the Internet in each country in the last year. Greater economic development is associated with higher income and education levels and, in our scenario, we expect a positive relation between fund selectivity, profitability, and country economic development, since information quality should be higher with better-informed and more educated investors, which places more value on the accuracy of fund managers' selectivity ability.

To capture equity market development, we use equity share turnover and the total size of equity markets. These two variables are also accessible from the WDI database. Share turnover, which is the value of domestic shares traded divided by their market capitalization, measures the liquidity of the equity market in each country. A higher share turnover ratio, that is, higher equity market liquidity, will help fund managers to establish and change portfolios based on new information. This argument indicates a positive relation between fund selectivity profitability and the share turnover ratio. On the other hand, a large equity market size may have an ambiguous effect on the implementation of fund managerial skill. First, a large equity market means more investment opportunities, which allows skilled managers to find profitable investment opportunities much more easily. On the other hand, a large equity market contains more noise, which hinders selectivity skills from being profitable.

We use a dummy variable that equals one for a common-law country and zero otherwise to capture common-law countries and securities regulation to capture investor protection and a country's legal strength. According to La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999), common-law systems provide more protection for investors than civil-law systems do and enhance the enforcement of business contracts. Another variable used as a proxy for a country's legal strength is securities regulation, which combines disclosure requirements, liability standards, and public enforcement, introduced by La Porta, Lopez-de-Silanes, and Shleifer (2006). We expect a strong positive relation between fund selectivity profitability and investor protection and legal strength, since strong legal strength and strong securities market regulation limit insider trading activities and promote informed arbitrage, which makes fund managerial skill based on analytical ability more valuable (Morck, Yeung, & Yu, 2000). In addition, stock markets in countries with weak property rights protection are more influenced by political events and rumors, which create more noisy markets and harm the profitability of fund managers' selectivity ability.

Finally, we use fund industry age and the mutual fund industry's proportion of the equity market to capture mutual fund industry development. We collect mutual fund industry age data from Ferreira et al. (2013). We argue that the older the mutual fund industry, the more competitive it is and the harder it is, therefore, for fund managers to achieve superior performance, since they will generate fewer risk-adjusted returns due to higher market competition. To estimate the mutual fund industry proportion, which is calculated as the percentage of total mutual fund equity within the total capitalization of the equity market, we collect mutual fund industry equity data from the annual Asset Management Report of the European Fund and Asset Management Association. From our perspective, a larger mutual fund industry proportion means a more competitive mutual fund industry, which will hurt the profitability of fund managers' selectivity skills.

3 | EMPIRICAL FINDINGS

3.1 | Effect of fund selectivity on fund performance

We begin our examination of whether fund management selectivity, based on the lagged logistically transformed value of $1 - R^2$, leads to superior mutual fund performance (fund *alpha*) across 11 European countries. The model we estimate is as follows:

$$\begin{aligned} Fund\,Alpha = {} & \beta_1 * Selectivity + \beta_2 * Alpha_{t-1} + \beta_3 * Expense\,Ratio + \beta_4 * \log(TNA) \\ & + \beta_5 * \log(TNA)^2 + \beta_6 * \log(Age) + Fund\,Strategy \end{aligned} \tag{4}$$

where the dependent variable is the fund *alpha*, which is the difference between the fund's excess return in month t and the expected excess return for the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the preceding 24-month estimation period (months $t - 24$ to $t - 1$) by the FFC model factors in the current month. This process is repeated by moving the estimation and test period 1 month at a time. The main independent variable is fund selectivity, which is the logistically transformed value of $1 - R^2_{t-1}$. Fund-level control variables contain the fund $alpha_{t-1}$, which is the intercept from the preceding 24-month estimation period (months $t - 24$ to $t - 1$), the expense ratio, the log value of fund age, the value of TNA, and the squared log value of TNA. All control variables are lagged by 1 month. Following Amihud and Goyenko (2013), we report the results with and without $alpha_{t-1}$ as a control variable. Our sample period ranges from January 2000 through December 2015. If a positive relation between fund selectivity and fund performance exists in the European mutual fund industry, we expect to observe $\beta_1 > 0$. The regression results are reported in Table 4.

TABLE 4 The effect of fund selectivity on fund performance

This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics. The dependent variable is fund *alpha*, which is the difference between fund excess return in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the 24-month preceding estimation period ($t-24$ to $t-1$) by the FFC model factors in the current month. This estimation procedure is repeated by moving the estimation and test period 1 month at a time. The main independent variable is fund selectivity, which is the logistic transformed value of $(1 - R^2_{t-1})$. Fund-level control variables contain fund $alpha_{t-1}$, which is the intercept from the 24-month preceding estimation period ($t-24$ to $t-1$), expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, *Significance at the 1%, 5%, or 10% level.

	Fund *alpha*	
Intercept	−0.162**	−0.083
	(0.022)	(0.241)
Fund Selectivity	0.113***	0.088***
	(<0.0001)	(<0.0001)
$Alpha_{t-1}$		0.101***
		(<0.0001)
Expense Ratio	−0.009	−0.008
	(0.387)	(0.407)
Log(Age)	0.131***	0.120***
	(<0.0001)	(<0.0001)
Log(TNA)	0.064***	0.053**
	(0.003)	(0.012)
Log(TNA)^2	−0.005**	−0.005**
	(0.038)	(0.042)
Strategy Control	YES	YES
Adj. R^2	0.12%	0.17%

Consistent with the above prediction, the results in Table 4 show that selectivity in all regression specifications is positive and significantly related with fund *alpha* ($p < 0.0001$). These results provide strong evidence in support of a positive association between fund selectivity and fund performance in the European mutual fund industry. The consistency of this result with evidence from the US mutual fund industry (Amihud & Goyenko, 2013) suggests that the logistically transformed value of $1 - R^2$ is a reliable measure of fund management selectivity whose validity remains robust outside the US framework.

Next, we replicate the previous regression analysis (Equation 4) by country and report the coefficients of fund selectivity along with p-values in Table 5.

The results in Table 5 show that the positive relation between fund selectivity and fund performance gains significant support in 7 out of the 11 European countries. While this evidence indicates that fund management skill does not lead to excess risk-adjusted returns in Finland, Italy, Spain, or the United Kingdom, none of the management selectivity coefficients in these countries is significantly negative. Jointly, the evidence demonstrates that managerial skill is prevalent in the European mutual fund industry, which, in turn, leads to value-increasing performance in most European actively managed domestic mutual funds.

TABLE 5 The effect of fund selectivity on fund performance for each country

This table reports the coefficients of fund selectivity by regressing fund *alpha* on manager's selectivity controlling for other fund characteristics for each country. Sample period covers from January 2000 through December 2015. The *p*-value for each coefficient is also reported. ***, **, *Significance at the 1%, 5%, or 10% level.

	Selectivity coefficient
Austria	0.106***
	(<0.0001)
Denmark	0.127***
	(0.007)
Finland	−0.013
	(0.819)
Germany	0.236***
	(<0.0001)
Ireland	0.166***
	(<0.0001)
Italy	0.039
	(0.110)
Netherlands	0.263***
	(0.002)
Spain	−0.029
	(0.128)
Sweden	0.146***
	(<0.0001)
Switzerland	0.298***
	(<0.0001)
United Kingdom	0.030
	(0.549)

3.2 | Effect of selectivity, market sentiment, and market dispersion on fund performance

We then re-examine the effect of fund management skill on fund performance, accounting for market sentiment and market dispersion in the analysis. The purpose of this analysis is to determine whether fund management selectivity still contributes to fund performance after controlling for investor sentiment and market dispersion. First, we divide the sample period into periods of high and low investor sentiment based on the median number of the monthly CCI index orthogonalized with respect to a set of macroeconomic conditions. If month *t*'s CCI is higher (lower) than the median number of the monthly CCI for all sample periods (January 2000–December 2015), we define month *t* as a period of high (low) sentiment. Then, we estimate the model, as shown in Equation 4, in periods of high and low investor sentiment separately. The results are reported in Table 6, columns (1) and (2), respectively. As predicted, fund selectivity has a stronger relation with fund performance during low-sentiment periods (0.154, $p < 0.0001$), when the equity market is less noisy and asset prices trade close to fundamental

TABLE 6 The effect of fund selectivity on fund performance in high vs. low market sentiment and market dispersion periods

This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics during high/low market sentiment periods and during high/low market dispersion periods. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk-free rate) in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the 24-month preceding estimation period ($t-24$ to $t-1$) by the FFC model factors in the current month. This estimation procedure is repeated by moving the estimation and test period 1 month at a time. The main independent variable is fund selectivity, which is the logistic transformed value of $(1-R^2_{t-1})$. Consumer Confidence Indicator (CCI) free of macroeconomic influences is used to capture the market sentiment for all countries. If month t's CCI is higher (lower) than the median number of monthly CCI for all sample periods, we define month t as high-(low-) sentiment period. Market dispersion is measured as the stock return standard division for all stocks in each country in month t. Then, if the country's dispersion for this month is higher (lower) than the median market dispersion of this country for all sample periods, we define this month as high (low) market dispersion period. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, *Significance at the 1%, 5%, or 10% level.

	Fund *alpha*			
	High sentiment	**Low sentiment**	**High dispersion**	**Low dispersion**
Intercept	−0.005	−0.141	−0.671***	0.476***
	(0.962)	(0.129)	(<0.0001)	(<0.0001)
Fund Selectivity	0.001*	0.154***	0.230***	−0.051***
	(0.094)	(<0.0001)	(<0.0001)	(<0.0001)
$Alpha_{t-1}$	0.222***	0.029**	0.039**	0.166***
	(<0.0001)	(0.038)	(0.016)	(<0.0001)
Expense Ratio	0.017	−0.022*	−0.014	−0.002
	(0.273)	(0.086)	(0.339)	(0.892)
Log(Age)	0.134***	0.108***	0.262***	−0.041
	(<0.0001)	(<0.0001)	(<0.0001)	(0.102)
Log(TNA)	−0.013	0.097***	0.059*	0.035
	(0.690)	(0.001)	(0.071)	(0.206)
Log(TNA)^2	0.000	−0.008**	−0.003	−0.006**
	(0.973)	(0.012)	(0.520)	(0.049)
Strategy Control	YES	YES	YES	YES
Adj. R^2	0.30%	0.21%	0.42%	0.18%

values, than in high-sentiment periods (0.001, $p = 0.094$), when the equity market is more likely to be exposed to noisy information.

As with investor sentiment, we split our sample into periods of high and low market dispersion based on the median of the market dispersion index for the whole sample period (January 2000–December 2015). If a country's market dispersion for month t is higher (lower) than the median market dispersion of this country for all sample periods, we define month t as a period of high (low) market dispersion. The regression results on the relation between fund selectivity and fund performance during high and low market dispersion periods are presented in Table 6, columns (3) and (4), respectively. Interestingly, during periods of high market dispersion, when private information is more valuable, fund selectivity skill is positively and significantly related to fund performance (0.230, $p < 0.0001$). Hence, this result suggests that skilled fund managers improve fund performance by relying more on private information to make fund investment decisions than on public signals when the market and stock prices are more likely to be affected by private than public information. On the contrary, during periods of low market dispersion, the relation is negative and significant (−0.051, $p < 0.0001$). This result implies that, during periods of low market dispersion, when market-level information (i.e., economic shocks) is more important for estimating stock prices, increased attention to private information (i.e., increased bets on private information) leads to negative abnormal returns by exposing fund portfolios to greater risk. That is, a strategy of building a portfolio deviating from market movements during periods of low market dispersion turns out to be costly due to decreasing fund performance. Next, we incorporate investor sentiment and market dispersion into the main regression (Equation 4) and report the results in Table 7.

First, the regression results in Table 7 show that fund selectivity is still positively related with fund performance (0.124, $p < 0.0001$) after controlling for market sentiment and market dispersion. In addition, we observe that market sentiment harms overall fund performance (−0.039, $p < 0.0001$), but market dispersion, on average, can benefit fund performance (0.014, $p < 0.0001$). Jointly, these results provide additional support for our previous findings that fund selectivity is positively and significantly related to fund performance and this relation remains significant even after controlling for investor sentiment and market dispersion.

Next, we repeat the above analysis for each country and report the coefficients of selectivity, investor sentiment, and market dispersion in Table 8.

After we consider investor sentiment and market dispersion, the results, as shown in Table 8, are consistent with our previous findings. Eight of the 11 European countries show that the association between fund selectivity and fund performance is positive and statistically significant. These results indicate that, after controlling for investor sentiment and market dispersion, fund selectivity still has strong predictive power for future fund performance in the majority of European mutual fund industries. Even though the selectivity coefficients for the remaining three countries are not significant, they still emerge with positive signs (0.007, $p = 0.900$ for Finland; 0.013, $p = 0.502$ for Spain; 0.058, $p = 0.253$ for the United Kingdom). The sentiment coefficients for 9 of the 11 countries appear to be significantly negative, while the market dispersion coefficients for 7 of the 11 countries are significantly positive.[6]

To examine the sensitivity of our findings with respect to the relation between the European mutual fund industry's performance and market sentiment, in this section we replace our major sentiment measure (CCI) used so far with three alternative market sentiment measures: the Economic Sentiment Indicator (ESI), which is from the European Commission's business and consumer surveys and is constructed from the industrial confidence indicator (40%), the service confidence indicator (30%), the CCI (20%), the construction confidence indicator (5%), and the retail trade confidence indicator (5%); the Economic Climate Index (ENOMWLEC), which is drawn from surveys of business conditions in Germany among a broad range of business executives across the manufacturing, construction, wholesale, and retail sectors; and the German Consumer Confidence Index (GECSI), where a value of 100 indicates an equal number of optimists and pessimists and figures below 100 indicate more

[6]We do find four countries (Ireland, Italy, Span, and Switzerland) appear to have negative correlations between market dispersion and fund performance. This is mainly caused by the high pace growth of those countries' macro-economy. Thus, the securities in the equity market move synchronistically, while the mutual funds yield superior performance. This argument is supported by the fact that the average annual GDP growth of Ireland (4.70%), Spain (1.67%), and Switzerland (1.89%) are much higher than the 11-country average (1.75%) from 2000 to 2015. For Italy, we think it might be caused by policy changes or just noisy information.

TABLE 7 The effect of fund selectivity, market sentiment, and market dispersion on fund performance

This table reports the results of regressing fund *alpha* on manager's selectivity controlling for other fund characteristics during high/low market sentiment periods and during high/low market dispersion periods. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk-free rate) in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the 24-month preceding estimation period ($t-24$ to $t-1$) by the FFC model factors in the current month. The process repeats by moving the estimation and test period 1 month at a time. The main independent variables are fund selectivity, which is the logistic transformed value of $(1-R^2_{t-1})$, Consumer Confidence Indicator (CCI) free of macroeconomic influences, and market dispersion, which is the stock return standard division for all stocks in each country in month t. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through December 2015. ***, **, *Significance at the 1%, 5%, or 10% level.

	Fund *alpha*
Intercept	−0.331***
	(<0.0001)
Fund Selectivity	0.124***
	(<0.0001)
Sentiment	−0.039***
	(<0.0001)
Dispersion	0.014***
	(<0.0001)
$Alpha_{t-1}$	0.110***
	(<0.0001)
Expense Ratio	−0.006
	(0.510)
Log(Age)	0.113***
	(<0.0001)
Log(TNA)	0.067***
	(0.002)
Log(TNA)^2	−0.006**
	(0.016)
Strategy Control	YES
Adj. R^2	0.39%

pessimists than optimists (and vice versa). As before with the CCI sentiment index, we use the residual obtained by regressing each index on a set of macroeconomic variables, including Europe's inflation rate, the growth rate of Europe's employment rate, the growth rate of Europe's industrial production, the growth rate of Europe's durable consumer goods production, the growth rate of Europe's nondurable goods production, the consumer price index change in Europe's service industry, and Organisation for Economic Co-operation and Development (OECD) based European recession indicators.

Since no financial market in the world is isolated from the others, especially large and developed ones, we also use the Baker–Wurgler (BW) sentiment index (Baker & Wurgler, 2006) orthogonalized with respect to a set of macroeconomic conditions to replace the European sentiment measures. This index is formed to measure US market sentiment, but the argument is that the US equity market, which

TABLE 8 The effect of fund selectivity, market sentiment, and market dispersion on fund performance for each country

This table reports the coefficients of selectivity, market sentiment, and market dispersion from regressing fund *alpha* on manager's selectivity, market sentiment, and market dispersion, controlling for other fund characteristics for each country. The *p*-value for each coefficient is also presented. Sample period ranges from January 2000 through December 2015. ***, **, *Significance at the 1%, 5%, or 10% level.

	Selectivity coeff.	Sentiment coeff.	Dispersion coeff.
Austria	0.159***	−0.018***	0.089***
	(<0.0001)	(0.002)	(<0.0001)
Denmark	0.163***	−0.002	0.105***
	(0.001)	(0.904)	(<0.0001)
Finland	0.007	−0.051***	0.327***
	(0.900)	(<0.0001)	(<0.0001)
Germany	0.272***	−0.066***	0.042***
	(<0.0001)	(<0.0001)	(<0.0001)
Ireland	0.120***	−0.033***	−0.091***
	(0.001)	(<0.0001)	(<0.0001)
Italy	0.064***	−0.088***	−0.091***
	(0.009)	(<0.0001)	(<0.0001)
Netherlands	0.334***	−0.058***	0.040***
	(0.001)	(0.001)	(0.006)
Spain	0.013	−0.104***	−0.053***
	(0.502)	(<0.0001)	(<0.0001)
Sweden	0.190***	−0.018*	0.066***
	(<0.0001)	(0.058)	(<0.0001)
Switzerland	0.265***	−0.025**	−0.103***
	(<0.0001)	(0.014)	(<0.0001)
United Kingdom	0.058	−0.015	0.012**
	(0.253)	(0.109)	(0.032)

is the largest and most developed equity market in the world, can influence other financial markets. Information from the US equity market (e.g., investor optimism and pessimism) can transfer to other markets. The time series plots of all the sentiment indexes used are shown in Figure 1. The regression results for this analysis are shown in Table 9.

The results in Table 9 are consistent with the previous ones reported in Table 7, using the CCI to measure investor sentiment. All four alternative sentiment indices show a strong negative relation with fund performance, while fund management selectivity remains positively and significantly correlated with fund performance.

3.3 | Effect of country-level variables on fund selectivity profitability

In this section, we use a two-step regression procedure, as described in section 2.4, to investigate whether country-level characteristics influence the profitability of fund managers' selectivity ability.

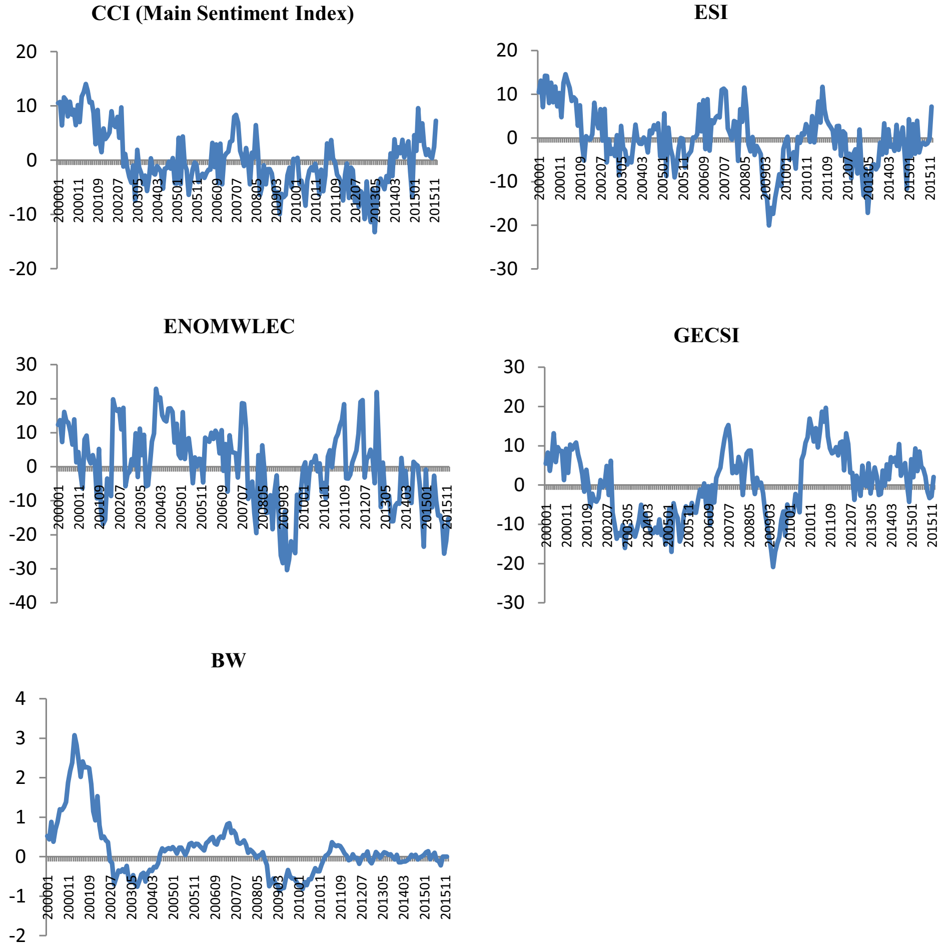

FIGURE 1 Time series plot of each sentiment measure (free of macroeconomic influences) from January 2000 to December 2015

Unlike the previous literature, which focuses on the direct influence of those variables on fund performance, we treat the country characteristics as moderating variables. The results of regressing the selectivity coefficient on a list of country-level variables are reported in Table 10.

The results in Table 10 confirm our hypothesis that country-level characteristics work as mediators and affect the relation between fund selectivity and fund performance. First, we find no evidence that a country's GDP per capita can influence the profitability of mutual fund managers' selectivity ability. Consistent with Ferreira et al. (2013), we argue that, after incorporating other country-level variables, the effect of this broad economic indicator is diluted. However, we find a strong relation between fund selectivity profitability and Internet usage, as we expected. We conclude that higher Internet usage proxies for better-educated investors in the equity markets, which consequently increases the information quality and benefits skilled fund managers.

Both variables capturing the quality of a country's legal system show a positive and significant relation with selectivity profitability. This result confirms our hypothesis that the strength of the legal system limits insider trading and market noise, which help make fund managerial analytical ability more valuable.

TABLE 9 The effect of market sentiment on fund performance, using alternative European sentiment measures

This table reports the results of regressing fund *alpha* on manager's selectivity and different market sentiment measures, controlling for other fund characteristics. The dependent variable is fund *alpha*, which is the difference between fund excess return (over risk-free rate) in month t and the expected excess return of the same month. The expected excess return for each fund in month t is calculated by multiplying the FFC model factor loadings from the 24-month preceding estimation period ($t-24$ to $t-1$) by the FFC model factors in the current month. The process repeats by moving the estimation and test period 1 month at a time. The main independent variables are fund selectivity, which is the logistic transformed value of $(1-R^2_{t-1})$, and market sentiment. We use four alternatives to measure market sentiment: ESI, which is the Economic Sentiment Indicator calculated from the European Commission's Business and Consumer Surveys; ENOMWLEC, which comes from surveys of business conditions in Germany; GECSI, which is the German Consumer Confidence Indicator, and BW, which is the Baker and Wurgler sentiment index (BW sentiment index, available at Jeffrey Wurgler's website). All the sentiment indexes are free of macroeconomic influences. Fund-level control variables contain fund $alpha_{t-1}$, expense ratio, log value of fund age, value of total net assets (TNA), and squared log value of TNA. Sample period covers from January 2000 through September 2015. ***, **, *Significance at the 1%, 5%, or 10% level.

	Fund *alpha*			
Intercept	−0.105	−0.068	−0.263***	−0.081
	(0.138)	(0.339)	(0.000)	(0.258)
Fund Selectivity	0.113***	0.089***	0.076***	0.114***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
ESI	−0.044***			
	(<0.0001)			
ENOMWLEC		−0.002**		
		(0.016)		
GECSI			−0.025***	
			(<0.0001)	
BW				−0.392***
				(<0.0001)
$Alpha_{t-1}$	0.131***	0.102***	0.162***	0.122***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Expense Ratio	−0.009	−0.008	−0.011	−0.006
	(0.340)	(0.416)	(0.269)	(0.553)
Log(Age)	0.104***	0.116***	0.162***	0.096***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Log(TNA)	0.063***	0.055***	0.043**	0.070***
	(0.003)	(0.010)	(0.044)	(0.001)
$Log(TNA)^2$	−0.005**	−0.005**	−0.004*	−0.006**
	(0.039)	(0.039)	(0.086)	(0.022)
Strategy Control	YES	YES	YES	YES
Adj. R^2	0.005	0.002	0.004	0.002

TABLE 10 The effect of country-level variables on the relationship between fund performance and selectivity

This table presents the regression results from the two-step procedure. First, we calculate the annual data of correlation between fund selectivity and fund performance by regressing fund *alpha* on fund selectivity, controlling for other fund-level control variables using monthly data of current year and 1 year prior (24 months). Only funds with full 24 months' data within the current year and the previous year are included. Second, we regress each coefficient (selectivity profitability) on eight country-level variables. The country-level variables consist of GDP per capita, percentage of Internet users, total size of equity market, equity share turnover, dummy variable for common law (common law is set equal to 1, otherwise 0), securities regulation, mutual fund industry age, and mutual fund industry proportion within equity market. We also show adjusted R^2- and p-values. ***, **, *Significance at the 1%, 5%, or 10% level.

	Selectivity profitability	
Intercept	−34.117***	−53.177***
	(<0.0001)	(<0.0001)
GDP per Capita ($ million)	−0.059	0.135
	(0.660)	(0.309)
Internet (%)	0.877***	1.209***
	(<0.0001)	(<0.0001)
Common Law	9.636***	
	(0.001)	
Securities Regulation		4.367***
		(<0.0001)
Equity Market Size ($ billion)	−0.003***	−0.001***
	(<0.0001)	(0.005)
Share Turnover (%)	0.061***	0.030***
	(<0.0001)	(<0.0001)
Mutual Fund Industry Age (years)	−0.607***	−0.930***
	(<0.0001)	(<0.0001)
Mutual Fund Industry Proportion	−0.107	−0.064
	(0.788)	(0.858)
Adj. R^2	15.20%	16.50%

Market liquidity, measured by the share turnover ratio, has a strong positive relation with selectivity profitability. The results, in line with our expectation, indicate that fund managers' skill delivers greater value when the fund's strategy is quickly adjusted to incorporate new information. On the other hand, we find a significant negative relation between equity market size and fund selectivity profitability. This could be caused by the presence of noisier information in larger equity markets.

Finally, we find that fund managers' selectivity ability is more profitable if the country's mutual fund industry is young. Since the older the mutual fund industry is, the more competitive it is, it is harder for fund managers to achieve superior performance by competing with one another. In addition, the mutual fund industry proportion of the equity market shows no evidence of affecting the relation between fund selectivity and fund performance.

In sum, the results provide strong evidence that, at the same fund management skill level, mutual funds from countries with better economic development and legal protection, a less developed mutual fund industry, a smaller equity market, and greater equity market liquidity generate higher returns.

Thus, country-level characteristics work as mediators between fund selectivity and fund performance and allow fund managers' selectivity ability to be more profitable.

4 | CONCLUSION

This study investigates the predictive power of fund selectivity on fund performance (i.e., fund *alpha*) in the context of the European mutual fund industry, using a unique sample of actively managed domestic equity mutual funds from 11 European countries. Our empirical evidence reveals that, as in the US mutual fund industry, fund management selectivity is a valid skill measure in the European context, implying that mutual fund managers with higher levels of selectivity ability generate superior risk-adjusted excess returns. While mutual fund performance can be influenced by financial market conditions, such as market sentiment and market dispersion, the positive relation between fund management selectivity and fund performance remains robust after controlling for these effects. Furthermore, we find that country-level characteristics serve as moderating factors between fund management selectivity and fund performance, and with the same level of fund management skill, funds from a country with better economic development, stronger legal protection, a less developed mutual fund industry, a smaller equity market, and greater equity market liquidity generate higher returns.

The practical implication of our results is that mutual fund management skill, in the context of the European mutual fund industry, guides portfolio selection to realize superior fund performance and, therefore, cannot be ignored in deciding in which funds to invest. Consistent superior fund performance (*alpha*), the outcome of superior fund selectivity skill, should attract the attention and capital of investors aiming to realize higher returns. More importantly, the effect of fund management skill on mutual fund *alpha* is not mitigated by investor sentiment or market dispersion conditions, suggesting that skilled fund managers' *alpha*-generating ability comes through their superior insight and analytical skill in identifying stocks with the greatest potential to outperform the market. Finally, the consistency between the European and the US mutual fund industry suggests that the power of fund management skill to predict profitability holds across markets.

REFERENCES

Abinzano, I., Muga, L., & Santamaria, R. (2010). Do managerial skills vary across fund managers? Results using European mutual funds. *Journal of Financial Services Research*, *38*, 41–67.

Amihud, Y., & Goyenko, R. (2013). Mutual fund's R^2 as predictor of performance. *Review of Financial Studies*, *26*, 667–694.

Amromin, G., & Sharpe, S. A. (2009). Expectations of risk and return among household investors: Are their Sharpe ratios countercyclical? Available at SSRN 1327134.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2015). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*, 347–367.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*, 1645–1680.

Banegas, A., Gillen, B., Timmermann, A., & Wermers, R. (2013). The cross section of conditional mutual fund performance in European stock markets. *Journal of Financial Economics*, *108*, 699–726.

Berk, J. B., & Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*, 1269–1295.

Berk, J. B., & van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*, *118*, 1–20.

Blake, D., & Timmermann, A. (1998). Mutual fund performance: Evidence from the UK. *European Finance Review*, *2*, 57–77.

Brands, S., Brown, S. J., & Gallagher, D. R. (2005). Portfolio concentration and investment manager performance. *International Review of Finance*, *5*, 149–174.

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

Cesari, R., & Panetta, F. (2002). The performance of Italian equity funds. *Journal of Banking & Finance*, *26*, 99–126.

Cohen, L., Frazzini, A., & Malloy, C. (2007). *The small world of investing: Board connections and mutual fund returns*. Cambridge, MA: National Bureau of Economic Research.

Cremers, K. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, *22*, 3329–3365.

Cremers, M., Ferreira, M. A., Matos, P. P., & Starks, L. T. (2016). Indexing and active fund management: International evidence. *Journal of Financial Economics*, *120*, 539–560.

Cuthbertson, K., Nitzsche, D., & O'Sullivan, N. (2008). UK mutual fund performance: Skill or luck? *Journal of Empirical Finance*, *15*, 613–634.

Dahlquist, M., Engström, S., & Söderlind, P. (2000). Performance and characteristics of Swedish mutual funds. *Journal of Financial and Quantitative Analysis*, *35*, 409–423.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, *52*, 1035–1058.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, *53*, 1839–1885.

Dermine, J., & Röller, L. H. (1992). Economies of scale and scope in French mutual funds. *Journal of Financial Intermediation*, *2*, 83–93.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2013). The determinants of mutual fund performance: A cross-country study. *Review of Finance*, *17*, 483–525.

Franck, A., & Kerl, A. (2013). Analyst forecasts and European mutual fund trading. *Journal of Banking & Finance*, *37*, 2677–2692.

Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The Journal of Finance*, *51*, 783–810.

Grünbichler, A., & Pleschiutschnig, U. H. (1999). *Performance persistence: Evidence for the European mutual funds market* (Working Paper).

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*, 2143–2184.

Investment Company Institute (US). (2015). Investment Company Fact Book. Investment Company Institute.

Kacperczyk, M., Sialm, C., & Zheng, L. (2015). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, *60*, 1983–2011.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2011). *Rational attention allocation over the business cycle* (Working Paper). New York, NY: New York University.

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2006). What works in securities laws? *The Journal of Finance*, *61*, 1–32.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (1999). The quality of government. *Journal of Law, Economics, and Organization*, *15*, 222–279.

Malkiel, B. G. (1995). Returns from investing in equity mutual funds 1971 to 1991. *The Journal of Finance*, *50*, 549–572.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, *58*, 215–260.

Otten, R., & Bams, D. (2002). European mutual fund performance. *European Financial Management*, *8*, 75–101.

Petajisto, A. (2013). Active share and mutual fund performance. *Financial Analysts Journal*, *69*, 73–93.

Shukla, R. K., & van Inwegen, G. B. (1995). Do locals perform better than foreigners?: An analysis of UK and US mutual fund managers. *Journal of Economics and Business*, *47*, 241–254.

von Reibnitz, A. H. (2013). When opportunity knocks: Cross-sectional return dispersion and active fund performance. Paper presented at the 26th Australasian Finance and Banking Conference.

Zheng, L. (1999). Is money smart? A study of mutual fund investors' fund selection ability. *The Journal of Finance*, *54*, 901–933.

How to cite this article: Dong F, Doukas JA. The payback of mutual fund selectivity in European markets. *Eur Financ Manag*. 2017;1–21. https://doi.org/10.1111/eufm.12160

APPENDIX

Country-Level Variable Description and Data Resource

Variable name	Variable group	Description	Data type	Data resource
GDP per Capita (million)	Economic development	Gross domestic product divided by midyear population. Data are in constant 2010 US dollars	Time series	World Development Indicators (WDI) database
Internet	Economic development	Percentage of individuals who have used the Internet (from any location) in the last 12 months. Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV, etc.	Time series	World Development Indicators (WDI) database
Equity Market Size	Equity market development	The total number of shares traded, both domestic and foreign, multiplied by their respective matching prices. Data are end of year values converted to US dollars using corresponding year-end foreign exchange rates	Time series	World Development Indicators (WDI) database
Share Turnover	Equity market development	The value of domestic shares traded divided by their market capitalization. The value is annualized by multiplying the monthly average by 12	Time series	World Development Indicators (WDI) database
Common Law	Investor protection and legal strength	1 if the legal origin is common law and 0 if the legal origin is civil law	Dummy	La Porta et al. (1999)
Securities Regulation	Investor protection and legal strength	Combination of disclosure requirements, liability standards, and public enforcement	Cross sectional	La Porta et al. (2006)
Mutual Fund Industry Age (years)	Mutual fund industry development	Number of years since the first open-ended fund was sold in the country	Time series	Ferreira et al. (2013)
Mutual Fund Industry Proportion	Mutual fund industry development	Relative mutual fund industry size, which is total equity assets under management divided by equity market size	Time series	World Development Indicators (WDI) database; EFAMA Asset Management Report