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Fund trading divergence and performance contribution

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ABSTRACT

Considering that the most distinct trading decisions are crucial to evaluate the ability of fund managers to add value, this paper aims to examine the trading divergence level among mutual funds and to capture its determinants and its performance consequences. We propose a measure that is more informative than the traditional overlap metrics, providing evidence of a positive and significant trend of fund trading divergence over time, especially after the Global Financial Crisis (GFC) of 2008. Our results also show a negative influence of market stress on the trading divergence level. Interestingly, we find greater contribution to subsequent fund performance in the divergent portions of trading decisions.

1. Introduction

Mutual fund research has focused on the skills and added value of managers, showing that on average, active funds do not outperform benchmarks (Fama & French, 2010). However, some studies document a positive relationship between the value created and trading activity (Wermers, 2000; Dahlquist, Engström, & Söderlind, 2000; Engström & Westerberg, 2004; Pástor, Stambaugh, & Taylor, 2015). Along this line, Cremers and Petajisto (2009) find that portfolio holdings that differ from the benchmark weights show a higher performance. Furthermore, Fulkerson (2013) develops a new measure of the value of active mutual fund management and reveals that most of the skill documented by previous literature arises from correctly trading stocks within industries. Jiang, Verbeek, and Wang (2014) also find that in actively managed funds, overweighted stocks perform substantially better than underweighted stocks.

An important economic principle extended to research on mutual fund managers is that financial agents can obtain excess returns if and only if they manage to stand out from other funds, showing that management skills provide a competitive advantage (Berk & Van Binsbergen, 2015). In this line, Khorana and Servaes (2007) document that product differentiation strategies are effective in obtaining market share, and thus, the market share is higher in families in which the new fund is more differentiated than the existing offerings. Furthermore, a greater level of difference among funds has a significantly positive influence not only on the family share in the market but also on the financial system. Getmansky, Girardi, Hanley, Nikolova, and Pelizzon (2016), Guo, Minca, and Wang (2016) and Delpini, Battiston, Caldarelli, and Riccaboni (2018, 2019) document that a significant similarity among funds plays an important role in the transmission of financial difficulties and can make the financial system more fragile. In addition, Choi and Sias (2009), Kremer and Nautz (2013) and Dewan and Dharni (2019) argue that the convergence in the trading decisions among funds may destabilise stock prices, and thus, impair the functioning of financial markets.

Previous literature has focused on the comparison of the portfolio management among different funds from the trading convergence (herding) and portfolio holding similarity (overlap) perspectives. Regarding the herding perspective, previous studies examine to what extent funds imitate the behaviour of others as well as its causes and economic consequences. There are herding metrics that rely on the changes in portfolio holdings (Dewan & Dharni, 2019; Kremer & Nautz, 2013; Lakonishok, Shleifer, & Vishny, 1992; Popescu & Xu, 2018; Sias, 2004) and metrics that rely on the changes and dispersion of the prices and returns of the stocks (BenSaïda, 2017; Blasco, Corredor, & Ferreruela, 2012; Chang, Cheng, & Khorana, 2000; Christie & Huang, 1995; Hwang & Salmon, 2004). The initial herding measures have been improved over time, including the quantitative perspective and the sign of trading decisions, but they are not able to capture the level of spurious versus intentional herding as Spyrou (2013) and Dewan and Dharni (2019) note. With respect to the overlap perspective, previous literature examines the coordination in fund families, calculating the number of

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positive and negative changes in portfolio holdings by each stock for all funds within a family (Kacperczyk & Seru, 2012) and tests whether socially connected fund managers have more similar holdings and trades (Pool, Stoffman, & Yonker, 2015). However, little is known about the measurement of divergent trading decisions and their implications to fund performance.

In this study, we propose a methodology to capture the trading divergence of funds, that is, their distinct investment decisions that allows evaluating whether fund managers have the ability to make different decisions in a given month without observing the decisions of the rest. This new measure has some differences and advantages over the herding and overlap measures used in previous literature. First, our measure provides quantitative values of both divergent and convergent trading by any fund pair in any stock and period. Hence, we can compare both the contribution of divergence and convergence to fund performance. Second, our metric takes into account both the buying and selling decisions of funds, which allows us to capture in a single measure three different cases of divergence: (1) when both funds buy or sell but with different weights in a given stock; (2) when one fund buys stock and the other fund sells; and (3) when one fund buys (or sells) and another fund does not trade. Therefore, our measure captures not only the "active" divergence that occurs when the two compared funds trade in the same stock but also the "passive" divergence that occurs when one fund trades in a stock and the other fund does not. Third, our metric also considers the previous and final weights in the portfolio holdings in each month, providing results that are more accurate because we can capture the divergent portion among trading decisions of each fund pair that really lead to more similar weights between them. Additionally, we can control when a fund cannot sell in a given stock because it is not in the portfolio holdings. Previous studies (see, e.g., Wylie, 2005; Frey & Herbst, 2014 and Popescu & Xu, 2018) indicate that the findings about herding behaviour could be biased because they assume that all funds can sell all stocks.

Investors and the top-management within fund families evaluate the performance of fund managers, their investment style and, in general terms, their ability to add value to their portfolios. Hence, the aim of this study is to isolate the trading decisions that are distinct regarding those carried out by other funds, and to explore whether managers generate added value with their divergent trading decisions.

First, we examine the evolution of the trading divergence level among equity mutual funds from January 2000 to June 2020 in the Spanish industry, and we explore the main breakpoints in its evolution. We hypothesise that the trading divergence level among funds follows an increasing trend, especially within the same family, to reduce costs and to increase market share. We could also expect that managers will try to increase their divergence level to reach higher performance records and therefore, a greater efficiency in the fund industry.

Second, we study the determinants of the trading divergence among funds to explore under what market conditions and portfolio characteristics fund managers trade more divergently. Specifically, we examine the influence of previous holdings, market stress and stock characteristics. W e may expect that those fund pairs that have more similarity in their previous holdings also show a lower trading divergence level during the following period. Furthermore, we could also expect that market stress supposes a negative influence on the trading divergence level among funds. A high market stress level implies high levels of uncertainty about the fundamental value of financial assets and information asymmetry in the market (Hakkio & Keeton, 2009). Moreover, this information asymmetry is higher for riskier stocks (Aslan, Easley, Hvidkjaer, & O'Hara, 2011; Martins & Paulo, 2014) and non-domestic stocks (Barron & Ni, 2008), causing feelings like fear and panic in fund managers, which influence their financial decisions (Birâu, 2012). Therefore, fund managers may tend to hold less risky and more familiar stocks in their portfolio and may have more incentives to make decisions similar to those of others (Karunanayake, Valadkhani, & O'brien, 2010; Khan, Hassairi, & Viviani, 2011, ; Zheng, Tang, Liu, & Guo, 2021). In addition, we study whether the trading divergence level is driven by certain stocks. The stock characteristics that have attracted greater attention in the literature are the size, the previous volatility and return, and the information level available in the market about them.

Finally, we study the consequences of trading divergence on subsequent fund performance and thus on industry efficiency. Although

Table 1
Summary statistics of the sample.

		March 2000	March 2005	March 2010	March 2015	March 2020
#Funds		159	166	151	95	90
#Families		76	68	66	47	52
#Familiesmore than one fund		35	31	34	25	23
Fund_size Mean		95,182	59,947	34,442	94,234	59,343
	Q1	115,824	74,558	33,549	140,799	65,782
	Q5	8442	6049	5119	18,572	8753
Fund_age Mean		4	8	11	16	18
	Q1	8	11	16	21	25
	Q5	1	4	7	11	11
Fund_fees Mean		0.17%	0.15%	0.16%	0.19%	0.14%
	Q1	0.21%	0.19%	0.19%	0.20%	0.17%
	Q5	0.12%	0.12%	0.13%	0.15%	0.11%
Fund_return Mean		−0.33%	−0.87%	6.51%	3.41%	0.14%
	Q1	2.06%	−0.09%	8.03%	4.04%	1.21%
	Q5	−2.95%	−1.49%	4.69%	2.76%	−1.30%
Fund_moneyflows Mean		5.04%	5.93%	−0.46%	0.78%	−0.83%
	Q1	11.46%	3.53%	0.31%	3.33%	1.50%
	Q5	−1.02%	−1.96%	−3.28%	−2.92%	−3.26%
Fund_#stocks Mean		52	44	39	40	41
	Q1	67	55	50	49	49
	Q5	34	31	27	31	30
Fund_#tradingdecisions Mean		40	28	29	26	30
	Q1	52	40	44	38	37
	Q5	24	16	15	12	13

This table shows summary statistics for our sample at five date points: March 2000, March 2005, March 2010, March 2015 and March 2020. Specifically, this table includes the mean, quintile 1 value (Q1), and quintile 5 value (Q5) of each fund characteristic. *#Funds* is the number of funds in our sample; *#Families* is the number of fund families in our sample; *#Families with more than one fund* is the number of fund families that manage more than one fund in our sample; *Fund_size* is the monthly TNA of funds in million euros; *Fund_age* is the age of funds in years, and we obtain the fund's age from its inception date; *Fund_fees* is the funds' monthly management and deposit fees; *Fund_return* is the funds' annual past gross return; *Fund_moneyflows* is the funds' monthly relative money flows; *Fund_#stocks* is the number of distinct stocks held by the funds' monthly portfolio holdings, and *Fund_#tradingdecisions* is the number of trading decisions made by funds.

previous literature has argued the inability of the active fund to outperform the benchmark, Cremers and Petajisto (2009), Cohen, Polk, and Silli (2010), Jiang et al. (2014) and Chen, Huang, and Jiang (2019) document that fund managers generate added value through some decisions. We hypothesise that the divergent portions in trading decisions have a higher contribution to fund performance than convergent portions.

Our paper is related to the literature that examines the funds' trading decisions, especially the growing literature that examines the herding behaviour of fund managers and the similarity level among trading decisions. However, we contribute methodologically to the literature in several aspects. First, we focus on the trading divergence level among funds by proposing a measure that simultaneously takes into account both buying and selling decisions. Furthermore, we compare the trading decisions among fund pairs quantitatively and contemporaneously. Second, we obtain the trading divergence level at the stock level in order to study the influence of the stock characteristics on this phenomenon. Third, we distinguish between the contribution of divergent and convergent trading decisions to fund performance.

The findings of the study have several implications for fund managers, families and industry regulators. Due to the significantly positive effect of trading divergence on fund performance, top management within families may be interested in motivating managers to seek investment opportunities. Brown and Wu (2016) document that on average; good family performance has a positive effect on the fund flows of its member funds. Managers may also be interested in searching for investment opportunities in order to differentiate themselves from the rest because their reputation and remuneration depend on their performance records (Mason, Agyei-Ampomah, & Skinner, 2016). Finally, a higher trading divergence level has a positive influence on the efficiency of the industry and might reduce the fragility of the financial system (see, Delpini et al., 2018, 2019).

The rest of the paper is organised as follows. Section 2 describes the data and methodology. Section 3 studies the evolution of trading divergence among funds. Section 4 focuses on the determinants of this phenomenon. Section 5 focuses on performance and efficiency consequences, and Section 6 is the conclusion.

2. Data and methodology

2.1. Data

We analyse the trading divergence among fund pairs in the Spanish equity mutual fund industry from January 2000 to June 2020. Our sample includes funds classified by the Spanish Securities Exchange Commission (*CNMV*) as Euro equity funds, which invest at least 75% of their portfolio holdings in equity assets with a minimum of 60% of the equity allocation in Euro zone domiciled companies. The sample is free of survivorship bias, including both surviving and dead funds. ETFs, index funds and funds with less than 2 years of data were excluded. This leads to a final sample of 315 Euro equity mutual funds managed by 114 fund families.

The *CNMV* database includes monthly portfolio holdings from December 1999 to December 2006 and quarterly holdings from March 2007 to June 2020. The quarterly holdings from December 2006 of *CNMV* are completed with monthly portfolios when this information is available in Morningstar.[1] We use the ISIN codes of both the funds and the portfolio holdings for the merger of the two datasets.

[1] The Spanish fund industry is examined due to its importance in the Euro Zone in terms of both, the total net assets (subsequently TNA) and number of funds. This industry also deserves research attention because of the higher concentration of TNA in few fund families and the higher dependence of banking sector in comparison with other European markets as shown by Ferreira and Ramos (2009), Ferreira et al. (2013) and Cambon and Losada (2014).

The monthly portfolio holding information[2] allows us to determine the trading decisions made by the funds more accurately than in other Euro zone fund industries in which only semi-annual or quarterly portfolio holdings are available. According to Elton et al. (2011) monthly holdings capture roundtrip trades missed by semi-annual (34.2%) and quarterly data (18.5%). The *CNMV* database also includes information about the fund TNA defined as the fund size, the family to which each fund belongs, the fund inception date, the management and deposit fees, and the net asset value (NAV).

Stock information is obtained from DataStream, which provides information about the prices, return and the market capitalization of stocks and considers the main capital operations, such as splits and the payment of dividends.

Table 1 reports the summary statistics of the sample. This table shows that due to the severe merging process caused by the strong reorganization of the banking system in the Spanish market during the last decade, both the number of funds (*#Funds*) and the number of fund families (*#Families*) decrease over time. Regarding fund size, Table 1 shows that the average fund size (*Fund_size*) decreases after the GFC of 2008 and then recovers, reaching a higher value than before the crisis. However, the average fund size in March 2020 is similar to that in March 2005 because of the significant decline produced in 2020.

Table 1 also shows that in March 2015, the fund fees (*Fund_fees*) are higher than the rest of the data points. However, the value of the fees has decreased in recent years, reaching the smallest value in March 2020. In addition, we observe that both fund returns (*Fund_returns*) and fund flows (*Fund_flows*) have shown a negative trend during recent years, showing negative values in March 2020. Finally, we find that the number of stocks within the portfolio (*Fund_#stocks*) decreases slightly over time. This decrease is consistent with the decrease in the number of trading decisions by fund (*Fund_#tradingdecisions*). Table 1 shows that the mean number of trading decisions by fund goes from 40 in March 2000 to 30 in March 2020.

2.2. Methodology

We capture each fund trading decision examining the change in the number of shares as suggested by Alexander, Cici, and Gibson (2007). This approach, as opposed, to the analysis of portfolio weight changes is not biased by passive changes in portfolio weights due to price changes during the trading period (Jiang, Yao, & Yu, 2007). For each stock s, we first measure the change in the number of this stock's shares held by mutual fund i in period t. Second, we calculate the amount of each trading decision by multiplying the change in the number of shares by the average market price of stock s in month t.

Once we know the amount of each trading decision of each fund for each stock in each month, we calculate the weight of each trading decision on the fund's TNA. Subsequently, we compare these trading weights on each stock for each fund pair to obtain the level of trading divergence among them.

We calculate the trading divergence level for each fund pair (i and j) in each month t as the actual trading divergence with respect to their maximum possible divergence among both funds. The actual trading divergence (numerator of Eq. 1) is the sum of all trading comparisons between both funds and the maximum possible divergence (denominator of Eq. 1) is the sum of the maximum divergence between them considering both buying and selling decisions. If both funds buy (or sell), the maximum is given by the fund with a higher trading weight in absolute value. If one fund buys and the other sells, the maximum possible divergence is given by the sum of both trading weights in absolute value. Finally, we exclude the sum of excess trading of one fund that cannot be made by the other fund due to its previous portfolio holdings ($ExcTD_{i,s,t}$ and $ExcTD_{j,s,t}$) from both the numerator and denominator. This

[2] We control approximately 85% of the monthly portfolios of the sample.

exclusion is important because a fund cannot sell a stock with lacking previous holding.

Specifically, the trading divergence level among funds *i* and *j* for each month *t* is computed as follows[3]:

$$\mathrm{TD}_{i,j,t} = \frac{\sum_s \left| t_{i,s,t-} \; t_{j,s,t} \right| - \sum_s \mathrm{ExcTD}_{i,s,t} - \sum_s \mathrm{ExcTD}_{j,s,t}}{\sum_s \left(Max\, |B_{i,j,s,t}| + Max\, |S_{i,j,s,t}| \right) - \sum_s \mathrm{ExcTD}_{i,s,t} - \sum_s \mathrm{ExcTD}_{j,s,t}} \quad (1)$$

where $TD_{i,j,t}$ is the trading divergence level between funds *i* and *j* in month *t*. This measure ranges from zero to one given that the actual trading divergence (numerator) is relativised by the maximum possible divergence (denominator).

$t_{i,s,t}$ and $t_{j,s,t}$ is the trading weight of fund *i* and fund *j*, respectively, for the stock *s* in the month *t*. This is positive when the fund buys and negative when the fund sells.

$Max\ |B_{i,j,s,t}| = Max\ (|B_{i,s,t}|\ ,\ |B_{j,s,t}|)$ is the higher weight of the buying decisions between fund *i* and fund *j* for the stock *s* in the month *t*.

$$|B_{i,s,t}| = t_{i,s,t} \text{ if } \quad t_{i,s,t} > 0, \text{or } |B_{i,s,t}| = 0 \text{ if } \quad t_{i,s,t} < 0$$

$$|B_{j,s,t}| = t_{j,s,t} \text{ if } \quad t_{j,s,t} > 0, \text{or } |B_{j,s,t}| = 0 \text{ if } \quad t_{j,s,t} < 0$$

$Max\ |S_{i,j,s,t}| = Max(|S_{i,s,t}|, |S_{j,s,t}|)$ is the higher weight in absolute value of selling decisions between fund *i* and fund *j* for the stock *s* in the month *t*.

$$|S_{i,s,t}| = t_{i,s,t} \text{ if } \quad t_{i,s,t} < 0, \text{or } |S_{i,s,t}| = 0 \text{ if } \quad t_{i,s,t} > 0$$

$$|S_{j,s,t}| = t_{j,s,t} \text{ if } \quad t_{j,s,t} < 0, \text{or } |S_{j,s,t}| = 0 \text{ if } \quad t_{j,s,t} > 0$$

$ExcTD_{i,s,t}$ is the excess trading of fund *i* for stock *s* in the month *t*, which cannot be made by fund *j* due to its previous stock holding portfolio.

$$\mathrm{ExcTD}_{i,s,t} = |min\left(0\left(t_{i,s,t} + W_{j,s,t-1}\right)\right)| \text{if } t_{i,s,t} < 0$$

$$\mathrm{ExcTD}_{i,s,t} = 0 \qquad \text{if } t_{i,s,t} \geq 0$$

where $W_{j,s,t-1}$ is the portfolio weight of fund *j* for stock *s* in month *t-1*.

$ExcTD_{j,s,t}$ is the excess trading of fund *j* for stock *s* in the month *t*, which cannot be made by fund *i* due to its previous stock holding portfolio.

$$\mathrm{ExcTD}_{j,s,t} = |min\left(0\left(t_{j,s,t} + W_{i,s,t-1}\right)\right)| \text{if } t_{j,s,t} < 0$$

$$\mathrm{ExcTD}_{j,s,t} = 0 \qquad \text{if } t_{j,s,t} \geq 0$$

where $W_{i,s,t-1}$ is the portfolio weight of fund *i* for stock *s* in month *t-1*.

3. The evolution of trading divergence among mutual funds

In this section, our aim is to study whether the level of trading divergence is constant over time or not and whether it shows a given trend. We first obtain the trading divergence level among fund pairs from 2000 to 2020. Section A of Table 2 presents the average of the divergence level of all fund pairs over time as well as these averages split according to whether the fund pairs belong to the same fund family or not (Sections B and C). In addition, Section D reports that the trading divergence level is statistically significantly lower among fund pairs within the same family. This result is consistent with the findings of previous literature in the US market. Specifically, Chen, Hong, Huang, and Kubik (2004) and Elton, Gruber, and Green (2007), Elton, Gruber, Blake, Krasny and Ozelge, 2011 show a higher portfolio overlap among fund pairs within the same family than among fund pairs in different families. Previous literature (Cici, Dahm, & Kempf, 2018; Elton et al., 2007; Kacperczyk & Seru, 2012) has indicated that this lower trading divergence level among funds within a family can be explained by the influence of common factors on the manager trading decisions, the common access to the same information by each manager and by the existence of guidelines from the family top-management. On the other hand, this lower level of trading divergence among funds of a given family has important consequences to the investors. This fact reduces the potential diversification for those investors who decide to concentrate all investment funds within the same fund family as documented by Andreu, Gimeno, and Ortiz (2022).

The development of the mutual fund industry in recent decades has increased competition in the industry. Therefore, fund families could have more incentives to offer different funds to increase their market share (Gavazza, 2011). In addition, fund managers could be more motivated to generate added value in their funds. Specifically, Voronkova and Bohl (2005) find a lower level of herd behaviour among managers in mature markets. Similarly, Arjoon and Bhatnagar (2017) note that the financial markets in the initial phases of development with small market capitalization and limited investment culture and experience show a higher level of herding behaviour. Shantha (2019) also examines the evolution of herding and establishes that it could decline and disappear over time through the competition and the adaptation of managers to market environment. In addition, the GFC of 2008 is included in our sample period. This crisis caused an intense reorganization of the Spanish banking system (Montes, 2014), and this reorganization was also translated to fund and fund family mergers (Neal & García-Iglesias, 2013). In this line, Delpini et al. (2019) also conclude that the GFC stimulated the decrease in the similarity level among portfolios. Therefore, the consolidation of the fund industry and the GFC provided incentives to increase the trading divergence among funds in an attempt to achieve a higher fund diversification and a higher efficiency level in the mutual fund industry.[4] Hence, our first hypothesis in this study is as follows:

H1. *The trading divergence level among mutual fund pairs increases over time.*

To test this hypothesis, and to study the trend of this divergence during the sample period, we use a dynamic panel-data model. Specifically, we apply the generalized method of moments (GMM) method of Arellano and Bover (1995) and Blundell and Bond (1998) on a quarterly basis as follows[5]:

$$\begin{aligned}\mathrm{TD}_{i,j,t} = {} & \alpha_{i,j,t} + \gamma TD_{i,j,t-1} + \beta_1 \mathrm{Time}_t + \beta_2 \mathrm{Fund\_family}_{i,j,t} + \beta_3 \mathrm{Size}.\mathit{Difference}_{i,j,t} + \\ & \beta_4 \mathit{Age}.\mathit{Difference}_{i,j,t} + \beta_5 \mathrm{Fees}.\mathit{Difference}_{i,j,t} + \beta_6 \mathrm{Return}.\mathit{Difference}_{i,j,t} + \\ & + \beta_7 \#\mathrm{Stocks\_Difference}_{i,j,t} + \beta_8 \#\mathrm{MoneyFlows\_Difference}_{i,j,t} + \varepsilon_{i,j,t}\end{aligned} \quad (2)$$

where $TD_{i,j,t}$ and $TD_{i,j,t-1}$ are the average trading divergence between

[3] For illustrative purposes, Appendix I shows an example.

[4] According to DeYoung, Evanoff, and Molyneux (2009), the larger and more diversified financial services firms are more likely to come out of the restructuring periods in the financial market.

[5] In Equations 2 and 3, the dynamic model has also been carried out on a yearly basis. However, the dynamic model has not been applied on a monthly basis as a consequence of non-adequate degrees of freedom due to the relative relationship between the number of individuals (in our study, the number of fund pairs) and the number of time periods (Roodman, 2009). In this situation, previous literature proposed grouping data in longer periods of time (for example, the grouping of monthly data into quarterly data), reducing thus the number of time periods (Lee, Pesaran, & Pierse, 1990; Pesaran, Pierse, & Kumar, 1989). For robustness purposes, in Equations 2 and 3, we also apply the fixed effects (FE) model in monthly, quarterly, and annual computations. The results obtained are robust and are available upon request.

Table 2
Overall results of the trading divergence among fund pairs.

	Section A *All fund pairs*		*Section B* *Fund pairs in the same fund family*			*Section C* *Fund pairs in different fund families*			*Section D* *Difference (same-different family)*	
Year	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	#fund pairs	Mean TD	St. Dvt. TD	Mean TD	St. Dvt. TD
2000	95.64%	6.75%	325	80.71%	23.30%	13,879	95.97%	5.43%	−15.27%***	17.87%***
2001	96.49%	6.52%	478	82.62%	23.84%	16,282	96.89%	4.70%	−14.26%***	19.14%***
2002	96.69%	6.24%	363	83.36%	24.64%	14,475	96.99%	4.71%	−13.63%***	19.92%***
2003	96.78%	5.96%	340	84.20%	23.70%	14,622	97.05%	4.57%	−12.85%***	19.14%***
2004	96.61%	6.43%	337	83.52%	24.65%	13,672	96.94%	4.78%	−13.41%***	19.87%***
2005	96.65%	6.15%	391	84.66%	22.96%	14,613	96.98%	4.52%	−12.32%***	18.44%***
2006	96.36%	6.38%	432	84.03%	23.40%	15,352	96.70%	5.27%	−12.67%***	18.13%***
2007	94.88%	6.89%	465	83.19%	21.22%	16,529	95.32%	5.17%	−12.13%***	16.05%***
2008	94.35%	8.04%	476	84.31%	21.96%	16,244	94.81%	6.37%	−10.50%***	15.59%***
2009	95.28%	7.22%	436	84.52%	21.71%	14,492	95.68%	5.63%	−11.16%***	16.08%***
2010	96.37%	6.12%	267	86.64%	21.65%	11,458	96.68%	4.52%	−10.04%***	17.13%***
2011	96.73%	6.07%	239	86.71%	23.53%	9727	97.02%	4.30%	−10.31%***	19.23%***
2012	96.47%	6.49%	193	87.90%	22.72%	7764	96.72%	5.11%	−8.82%***	17.61%***
2013	96.82%	5.78%	167	88.75%	21.05%	6171	97.04%	4.53%	−8.29%***	16.52%***
2014	96.45%	5.92%	98	88.33%	22.12%	4625	96.63%	4.83%	−8.30%***	17.30%***
2015	96.88%	5.23%	104	90.61%	16.57%	4655	97.04%	4.48%	−6.43%***	12.08%***
2016	97.49%	4.46%	100	92.42%	13.49%	4909	97.60%	3.97%	−5.18%***	9.52%***
2017	97.74%	4.70%	89	91.98%	14.50%	4753	97.85%	4.19%	−5.88%***	10.31%***
2018	97.88%	4.37%	73	92.56%	13.43%	4732	97.97%	3.95%	−5.42%***	9.48%***
2019	97.70%	4.51%	60	93.33%	11.19%	4311	97.78%	4.25%	−4.45%***	6.94%***
2020	97.55%	4.19%	62	94.31%	8.62%	4077	97.61%	4.02%	−3.30%***	4.60%***
2000–2020	96.56%	6.37%	1190	87.08%	22.68%	35,521	96.82%	4.93%	−9.74%***	17.75%***

This table reports the results of the trading divergence (TD) among fund pairs for each year. Section A shows the mean and the standard deviation (St. Dvt.) of the trading divergence level among all fund pairs. Section B shows the number of fund pairs within the same family and the mean and the St. Dvt. of their trading divergence level. Section C shows the number of fund pairs in different fund families and the mean and the St. Dvt. of their trading divergence level. Section D shows the mean and the St. Dvt. difference between the value of fund pairs in the same family and the value of fund pairs in different families. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, in the mean difference test between both groups of fund pairs. Note that in this table, we present a yearly report of the number of fund pairs compared during each year, while Table 1 presents the total number of funds only at five specific points of the sample period.

funds i and j in quarter t and t-1. $Time_t$ ranges from 1 in the first quarter to 82 in the last quarter. The model also includes control variables of the differences among the family and fund characteristics in each fund pair. $Fund\_family_{i,j,t}$ is equal to 1 if funds i and j in quarter t belong to the same fund family. Pertaining to fund characteristics, $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$ and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences among the sizes, ages, fees, returns related to the last twelve months, number of stocks held in portfolios and the relative money flows of funds i and j in quarter t.

The inclusion of *Fund_family* variable is explained by the fact that, as we can observe in Table 2, the trading divergence level is lower among fund pairs within the same fund family than across families. As control variables, we also include the standard characteristics of mutual funds such as size, age, fees, prior year return, number of stocks within portfolios and money flows, because previous literature has documented that those characteristics influence the trading decisions (e.g., Evans, Prado, & Zambrana, 2020; Parida, 2018). The findings of previous studies lead us to presume that the greater the difference among fund characteristics is, the greater the probability that the trading divergence among them will be high.

Section A of Table 3 shows that the coefficient of the *Time* variable is significantly positive at the 5% level. Therefore, we find that the trading divergence increases over time as we can also observe in Fig. A.1 (Appendix II).[6] This result is consistent with the findings in the US market of Bekiros, Jlassi, Lucey, Naoui, and Uddin (2017) and Delpini et al. (2019) who find that the portfolio overlap and the herding behaviour tent to decrease over time, respectively. We also apply the Bai-Perron test to find structural breaks in the level of trading divergence, and we find that 2009 is the main breakpoint in the pattern of this phenomenon. According to this result, we split the whole sample period into two sub-periods. Sections B and C of Table 3 show that in the first sub-period 2000–2009, the trading divergence tends to decrease, while the sub-period 2010–2020 presents an increasing divergence evolution.

Regarding the control variables, overall, we find a lower trading divergence in fund pairs when the pairs are within the same family (as previously shown in Table 2), and when the difference in the numbers of stocks held in their portfolios and their sizes are low. However, the results show significant opposite results between the sub-periods for the rest of the control variables (age, past return and money flows), which does not allow clear conclusions about the influence of these variables. Finally, the difference in fund fees does not seem to show a significant influence on the trading divergence level among funds for either the whole period or the sub-periods.

4. Determinants of the trading divergence among mutual funds

This section aims to identify the determinants that may influence the trading divergence among mutual funds. Specifically, we study whether the trading divergence between two funds is influenced by their previous portfolio holdings and by the level of the market stress. We also study whether this phenomenon is driven by certain stock characteristics.[7]

4.1. Management and external market determinants

Previous studies have documented that similar investment objectives and common access to the same information and resources are the main causes of portfolio overlap among any fund pair (e.g., see Elton et al.,

[6] The values of the trading divergence level are high since the methodology of this paper not only captures the “active” divergence that occurs when both compared funds trade in a certain stock (both trade in the same direction or in the opposite directions) but also the “passive” divergence that occurs when a fund trades in a certain stock and the other fund does not trade in this stock.

[7] Appendix III includes the results of the influence of stocks characteristics on the trading divergence level.

Table 3
The evolution of the trading divergence and characteristics of mutual funds.[1, 2]

	Section A *Period 2000–2020*	*Section B* *Sub-period:2000–2009*	*Section C* *Sub-period:2010–2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.8693*** (0.000)	0.9406*** (0.000)	0.8626*** (0.000)
TD_{t-1}	0.0812*** (0.000)	0.0735*** (0.000)	0.0481*** (0.000)
Time	0.0001** (0.030)	−0.0012*** (0.000)	0.0006*** (0.000)
Fund family	−0.1204*** (0.000)	−0.1488*** (0.000)	−0.0380*** (0.000)
Size_Difference	−0.0002 (0.884)	0.0007*** (0.003)	0.0005** (0.036)
Age_Difference	0.0230*** (0.000)	−0.0460*** (0.000)	0.0566*** (0.000)
Fees_Difference	−0.0455 (0.844)	−0.7563 (0.178)	0.3631 (0.110)
Return_Difference	−0.0040*** (0.000)	0.0083*** (0.000)	−0.0098*** (0.000)
#Stocks_Difference	0.0002*** (0.000)	0.0002*** (0.000)	0.0001*** (0.002)
MoneyFlows_Difference	0.0009* (0.080)	0.0050*** (0.000)	−0.0062*** (0.000)
Wald	1,383.5*** (0.000)	2,419.5*** (0.000)	322.39*** (0.000)
VIF	1.02	1.03	1.03

This table shows the results obtained from Eq. 2 with the dynamic model on a quarterly basis. Section A shows the coefficients and *p*-values for the whole sample period (January 2000–June 2020). Section B shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section C shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$ is the trading divergence among funds *i* and *j* in quarter *t,* and the independent variables are the following: $TD_{i,j,t-1}$ is the trading divergence among funds *i* and *j* in quarter *t-1; $Time_t$* ranges from 1 in the first quarter of our sample period to 82 in the last quarter; $Fund\_family_{i,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* belong to the same fund family and it is equal to 0, otherwise; $Size\_Difference_{i,j,t}$, $Age\_Difference_{i,j,t}$, $Fees\_Difference_{i,j,t}$, $Return\_Difference_{i,j,t}$, $\#Stocks\_Difference_{i,j,t}$, and $MoneyFlows\_Difference_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of fund *i* and *j* in quarter *t*, respectively. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

[1] Model was estimated with Robust Standard Errors.
[2] Variance Inflation Factors (VIF) values are widely acceptable in the literature.

2007; Pool et al., 2015), the high correlation among their performance (Brown & Wu, 2016) and the herding behaviour among fund managers (Brown, Wei, & Wermers, 2014; Kremer & Nautz, 2013). We consider that funds that have a high (low) portfolio overlap in their previous holdings may show less (more) trading divergence in the subsequent period. Therefore, our second hypothesis is as follows:

H2. *Previous portfolio overlap negatively influences the level of trading divergence among mutual funds.*

The trading behaviour of fund managers may differ under different market conditions, as documented in the literature. Raddatz and Schmukler (2012) find that both investors and fund managers react to periods of market stress with substantial adjustments in their decisions and pro-cyclical behaviour, reducing their exposure in riskier countries. Furthermore, several studies argue that investment agents prefer to take risks on more visible stocks (Covrig, Lau, & Ng, 2006) and on more familiar stocks (Epstein & Schneider, 2008; Garlappi, Uppal, & Wang, 2007) and that this preference could be enhanced with a higher stress in the market. Therefore, moments of high stress in the market may incite fund managers to buy less risky and more familiar stocks and to sell risky stocks; thus, this common trading objective may result in a lower trading divergence level during these periods.

Similarly, previous studies find that financial market stress tends to generate contagion and herding behaviour among fund managers (Hwang & Salmon, 2004; Kodres & Pritsker, 2002). Social comparisons (Popescu & Xu, 2018) and the influence of the performance records of managers on their compensation (Casavecchia, 2016; Hedesström, Gärling, Andersson, & Biel, 2015; Kempf, Ruenzi, & Thiele, 2009; Maug & Naik, 2011) may cause a tendency to herd among fund managers, specially, in periods of high market stress. Recent papers like Clements, Hurn, and Shi (2017), Bekiros et al. (2017), BenSaïda (2017) and Ferreruela and Mallor (2021) show that herding tends to be intense under extreme market conditions and during financial crises and bubbles. Karunanayake et al. (2010) and Khan, Hassairi, & Viviani, 2011 also argue that the cost and time of processing information are higher in market stress periods, increasing the incentives of fund managers to make decisions similar to those made by others. Consequently, we could expect a significantly negative relationship between the trading divergence level and market stress. Our third hypothesis is as follows:

H3. *Market stress negatively influences the level of trading divergence among mutual funds.*

To examine the determinants of the level of trading divergence, we apply the dynamic GMM model of Arellano and Bover (1995) and Blundell and Bond (1998) on a quarterly basis as follows[8]:

$$\begin{aligned} TD_{i,j,t} = {} & \alpha_{i,j,t} + \gamma TD_{i,j,t-1} + \beta_1 Portfolio\_Overlap_{i,j,t-1} + \\ & \beta_2 \mathrm{MarketStress}_t + \beta_3 \mathrm{Fund\_Family}_{i,j,t} + \\ & \beta_4 Size\_Difference_{i,j,t} + \beta_5 Age\_Difference_{i,j,t} + \\ & \beta_6 Fees\_Difference_{i,j,t} + \beta_7 \#Return\_Difference_{i,j,t} + \\ & \beta_8 \#Stocks\_Difference_{i,j,t} + \\ & \beta_9 \#MoneyFlows\_Difference_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \tag{3}$$

where $Portfolio\ Overlap_{i,j,t}$ is the average portfolio overlap between funds *i* and *j* in quarter *t-1.*[9] *Market Stress$_t$* is the level of equity market stress measured with the Spanish Financial Market Stress Indicator (FMSI)[10] of CNMV. The rest of the control variables are defined in Eq. 2.

Table 4 presents the results of Eq. 3 for the 2000–2009 and the 2010–2020 sub-periods. The findings show that the previous portfolio overlap of a fund pair significantly influences its subsequent trading divergence and that the fund pairs with a higher (or lower) previous portfolio overlap show a lower (or higher) divergence level among their following trading decisions, as expected according to H2. In addition, the results show that the coefficient of the market stress variable is

[8] We apply Equation 3 to each sub-period (2000–2009 and 2010–2020) because we find different patterns in the trading divergence level between both periods, as documented in the previous section. In addition, we apply Equation 3 for monthly, quarterly and annual frequency, and we use both the dynamic and FE model, as in Equation 2.

[9] Following the methodology used by Elton et al. (2007) and Pool et al. (2015), we obtain the portfolio overlap.

[10] The FMSI was introduced by Cambón and Estévez (2016) and is used in several studies, such as Kremer (2016). FMSI is similar to the "Composite Indicator of Systemic Stress" that Holló, Kremer, and Lo Duca (2012) proposed for the Euro area as a whole. This indicator represents a real-time measure of systemic risk and tries to quantify stress in the Spanish financial system. Specifically, to capture the stress in the equity market, the index comprises three individual stress indicators, namely, volatility, liquidity and sudden asset price movements that are common in a period of financial crisis.

Table 4
Determinants of the trading divergence among mutual funds.[1, 2]

	Section A *Sub-period:2000–2009*	*Section B* *Sub-period:2010–2020*
	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9197*** (0.000)	0.9471*** (0.000)
TD_{t-1}	0.0584*** (0.000)	0.0316*** (0.000)
$Portfolio\_Overlap_{t-1}$	−0.1058*** (0.000)	-0.0196*** (0.000)
Market Strees	−0.0919*** (0.000)	-0.0010** (0.034)
Fund family	−0.1308*** (0.000)	−0.0376*** (0.000)
Size_Difference	0.0004** (0.039)	0.0001*** (0.000)
Age_Difference	0.0350*** (0.000)	−0.0139*** (0.000)
Fees_Difference	−0.3774 (0.480)	0.1866 (0.559)
Return_Difference	0.0005 (0.709)	−0.0093*** (0.000)
#Stocks_Difference	0.0001*** (0.000)	0.0001*** (0.000)
MoneyFlows_Difference	0.0028*** (0.000)	−0.0073*** (0.000)
Wald	3561.63*** (0.000)	503.71*** (0.000)
VIF	1.06	1.05

This table shows the results obtained from Eq. 3 with the dynamic model on a quarterly basis. Section A shows the coefficients and *p*-values for the sub-period comprising January 2000 to December 2009. Section B shows the coefficients and *p*-values for the sub-period comprising January 2010 to June 2020. The dependent variable, $TD_{i,j,t}$is the trading divergence among funds *i* and *j* in quarter *t* and the independent variables are as follows*:* $TD_{i,j,t-1}$is the trading divergence among funds *i* and *j* in quarter *t-1; Portfolio_Overlap*$_{i,j,t-1}$ is the portfolio overlap of funds *i* and *j* in quarter *t-1; Market Stress*$_t$ is the level of equity market and is measured with the Spanish Financial Market Stress Indicator (FMSI); *Fund_family*$_{i,j,t}$ is equal to 1 when funds *i* and *j* in quarter *t* are within the same fund family and it is equals to 0, otherwise; *Size_Difference*$_{i,j,t}$, *Age_Difference*$_{i,j,t}$, *Fees_Difference*$_{i,j,t}$, *Return_Difference*$_{i,j,t}$, *#Stocks_Difference*$_{i,j,t}$, and *MoneyFlows_Difference*$_{i,j,t}$ are the absolute values of the differences between the size, age, fees, yearly past return, number of stocks held in the portfolio and relative money flows of funds *i* and *j* in quarter *t*. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
[1] Equation was estimated with Robust Standard Errors.
[2] Variance Inflation Factors (VIF) values are widely acceptable in the literature.

significantly negative in both sub-periods, highlighting that market stress negatively influences the level of divergence among fund trading decisions. This finding is in line with the results obtained in the US market, which show that in periods of extreme market conditions, there is a higher likelihood of herding behaviour as well as a greater incentive for managers to make decisions similar to those of others (Bekiros et al., 2017; BenSaïda, 2017; Clements et al., 2017; Popescu & Xu, 2018; Stavroyiannis & Babalos, 2017), as stated in H3.

The findings of the control variables are consistent with the results obtained in Eq. 2, that is, there is a lower trading divergence among fund pairs that are within the same fund family, have a smaller difference in their size, and have a smaller difference in the number of stocks held in their portfolios.

4.2. Trading divergence considering the previous fund holdings

In Section 4.1, we find that trading divergence is affected by the previous holdings of the funds analysed. However, mutual funds with different initial positions for certain stocks could show different trading decisions captured as trading divergence to finally achieve a similar weight on these stocks to adjust the portfolio to the analysts' recommendations.[11] For that reason, the trading divergence obtained in Eq. 1 may be overvalued. In this section, we approach a more accurate trading divergence measure by excluding the contribution to divergence caused by trading decisions that led to similar final portfolio weights.

First, we determine the holding difference (HD) in the portfolio weight in each stock *s* for each fund pair in both the current period *t* and the previous period *t-1*.

$$\mathrm{HD}_{i,j,s,t} = |\mathrm{w}_{i,s,t} - \mathrm{w}_{j,s,t}| \tag{4}$$

$$\mathrm{HD}_{i,j,s,t-1} = |\mathrm{w}_{i,s,t-1} - \mathrm{w}_{j,s,t-1}| \tag{5}$$

where $w_{i,s,t}$ and $w_{i,s,t-1}$ are the portfolio weights in stock *s* for fund *i* in the current period *t* and the previous period *t-1*, respectively. $w_{j,s,t}$ and $w_{j,s,t-1}$ are the portfolio weights in stock *s* for fund *j* in the current period *t* and the previous period *t-1*, respectively.

Second, we compute the portion of false trading divergence (FTD) in each fund pair for each stock *s* in each month *t*.

$$\mathrm{FTD}_{i,j,s,t} = max\left(0, \mathrm{HD}_{i,j,s,t-1} - \mathrm{HD}_{i,j,s,t}\right) \tag{6}$$

Then, we calculate a new trading divergence measure (TD*) between funds *i* and *j* in each month *t* as follows:

$$\mathrm{TD}^*_{i,j,t} = \frac{\sum_s \left|\mathrm{t}_{i,s,t} - \mathrm{t}_{j,s,t}\right| - \sum_s \mathrm{ExcTD}_{i,s,t} - \sum_s \mathrm{ExcTD}_{j,s,t} - \sum_s \mathrm{FTD}_{i,j,s,t}}{\sum_s \left(Max\,|\mathrm{B}_{i,j,s,t}| + Max\,|\mathrm{S}_{i,j,s,t}|\right) - \sum_s \mathrm{ExcTD}_{i,s,t} - \sum_s \mathrm{ExcTD}_{j,s,t}} \tag{7}$$

Note that we conduct the following analyses in the paper with this new trading divergence measure (TD*).[12]

5. Performance consequences of the divergent trading

5.1. The influence of trading divergence on fund performance

In this section, we examine the performance consequences of the divergent trading following previous studies that demonstrate the superior performance for certain stocks and trading decisions. Specifically, previous research shows a higher performance for the overweighed stocks (Jiang et al., 2014); the best ideas of managers (Cohen et al., 2010) or the trading based on valuation criteria (Alexander et al., 2007; Andreu, Mateos, & Sarto, 2017). Furthermore, according to Jiang and Verardo (2018), funds that show a lower herding level make better investment decisions. Similarly, Koch (2017) finds that leader funds exhibit a higher subsequent performance due to their ability to value stocks. We hypothesise that the most divergent decisions of a fund manager with respect to the remaining funds are based on valuation criteria since their reputation and compensation depend on the fund's performance records (Mason et al., 2016). Therefore, we could expect a significantly positive relationship between the trading divergence level and the subsequent fund performance, and our hypothesis is as follows:

H4. *The trading divergence level positively influences subsequent fund performance.*

To test this hypothesis, we first obtain the average divergence level of each fund *i* in each month *t* with respect to the rest of the funds.

[11] The impact of the analysts' recommendations on the trading decisions of fund managers has been documented by many studies. Franck and Kert (2013) show that fund managers attribute high information value to consensus forecast revisions and that thus, mutual funds significantly increase (decrease) their holdings in stocks when any of the consensus forecast measures increases (decreases) within the quarter prior to the observation period.

[12] For robustness proposes, we run Equations 2 and 3 with the new divergence measure (TD*). We find robust results for the evolution of this phenomenon and for the influence of market stress; the findings are not reported for the sake of brevity. However, the use of TD* leads to the loss of significance of the Fund_family variable, which means that there are no significant differences among the fund pairs in the same family and those in different families. This could be explained by the fact that the probability that trading decisions will lead to similar positions in portfolios is greater among funds that belong to different families, since, as previously documented, mutual funds in the same family already show a higher previous holding overlap.

$$\mathrm{TD}^{*}{}_{\mathrm{i,t}} = \overline{\mathrm{TD}^{*}{}_{\mathrm{i,j,t}}} \tag{8}$$

Then, we run the following FE model on a quarterly basis as follows:[13]

$$\begin{aligned}\text{Fund\_Performance}_{i,t+n} = \alpha_{i,t} + \beta_1 \mathrm{TD}^{*}{}_{\mathrm{i,t}} + \beta_2 \text{Fund\_size}_{i,t} + \beta_3 \text{Fund\_age}_{i,t} + \\ + \beta_4 \text{Fund\_fees}_{i,t} + \beta_5 \text{Fund\_\#stocks}_{i,t} + \beta_6 \text{Fund\_flows}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{9}$$

where *Fund_Performancei, t + n* represents the alpha of fund *i* in quarter $t + n$ and is measured through the capital asset pricing model (CAPM), the Fama and French three-factor model and the Carhart four-factor model, with $n \in \{3,6,12\}$ months. $TD^{*}_{i,t}$ is the average trading divergence level of fund *i* in quarter *t*, as defined in Eq. 8. *Fund_size, Fund_age, Fund_fees, Fund_#stocks, Fund_flows* are the size, age, fees, number of stocks held in portfolios and relative money flows of fund *i* in quarter *t*, respectively.

Table 5 shows a significantly positive relationship between the trading divergence level and the subsequent fund performance. Therefore, our results provide evidence that funds that make the most divergent trading decisions in the industry outperform their counterparts, even after controlling for their characteristics. This finding is consistent with previous studies in the US market that document a significantly negative influence of the herding behaviour on the subsequent fund performance (Bhattacharya & Sonaer, 2018; Jiang & Verardo, 2018; Koch, 2017).

Regarding the control variables, in general terms, we observe that fund age, fund fees and fund money flows have a significantly positive influence on fund performance. Our findings support previous evidence that documents a positive influence of the fund experience and that higher fees can result in higher gross returns (Ferreira, Keswani, Miguel, & Ramos, 2013) and reflect the investors' ability to predict future fund performance (i.e., the “smart money” effect). In addition, in line with the previous literature documenting that fund size erodes its performance (Kacperczyk & Seru, 2007; Pástor et al., 2015), Table 5 shows a significantly negative influence of the size variable. Finally, the number of stocks in portfolio holdings does not seem to have a significant influence on fund performance.

5.2. The contribution to fund performance of the divergent portions of trading decisions

In this section, we compare the contribution of the actual trading divergence and the contribution of the actual trading convergence of funds to their performance. Given that in Section 5.1 we find a positive and statistically significant impact of the trading divergence level on fund performance, we could expect a higher contribution of the divergent portions of trading decisions to fund performance. Then, our hypothesis is as follows:

H5. *The contribution of divergent portions of trading decisions to fund performance is significantly higher than that of convergent portions.*

First, we obtain the actual trading divergence (ATD*) and the actual trading convergence (ATC*) between fund *i* and fund *j* in each month *t* as follows:

$$ATD^{*}{}_{i,j,s,t} \begin{cases} = \sum_s \left(t_{i,s,t} - t_{j,s,t}\right) - \sum_s ExcTD_{i,s,t} - \sum_s ExcTD_{j,s,t} - \sum_s FTD_{i,j,s,t} \; if \\ \left(t_{i,s,t} - t_{j,s,t}\right) \rangle 0 \\ = \sum_s \left(t_{i,s,t} - t_{j,s,t}\right) + \sum_s ExcTD_{i,s,t} + \sum_s ExcTD_{j,s,t} + \sum_s FTD_{i,j,s,t} \; if \\ \left(t_{i,s,t} - t_{j,s,t}\right) \langle 0 \end{cases} \tag{10}$$

$$ATC^{*}{}_{i,j,s,t} = \min\left(PTD_{i,j,s,t} - ATD^{*}{}_{i,j,s,t}; t_{i,s,t}\right) \tag{11}$$

where $ATD^{*}_{i,j,s,t}$ is the numerator of Eq. 7 and represents the more accurate actual trading divergence between funds *i* and *j* in stock *s* and month *t*, controlling the sign of the trading divergence for each fund within each pair.[14] $ATC^{*}_{i,j,s,t}$ is calculated as the difference between the potential trading divergence (PTD) that is represented for the denominator in Eq. 7 and the ATD* for each fund pair in each stock *s*, controlling that this difference is not greater than the trading weight of fund *i* in stock *s*.

Second, for each fund pair in each month, we obtain the contribution of the actual trading divergence (C_ATD*) and the contribution of the actual trading convergence (C_ATC*) to the fund performance, multiplying the ATD* and the ATC* of the fund pair in each stock by the stock alpha. Then, we sum all of these multiplications (see Eqs. 12 and 13).

$$\mathrm{C\_ATD}^{*}{}_{\mathrm{i,j,t+n}} = \sum_{\mathrm{s}} \left(\mathrm{ATD}^{*}_{\mathrm{i,j,s,t}}.\alpha_{\mathrm{s,t+n}}\right) \qquad \forall \mathrm{j} \neq \mathrm{i} \tag{12}$$

$$\mathrm{C\_ATC}^{*}{}_{\mathrm{i,j,t+n}} = \sum_{\mathrm{s}} \left(\mathrm{ATC}^{*}_{\mathrm{i,j,s,t}}.\alpha_{\mathrm{s,t+n}}\right) \forall \mathrm{j} \neq \mathrm{i} \tag{13}$$

where $C\_ATD^{*}_{i,t+n}$ is the contribution of the actual trading divergence between funds *i* and *j* in month $t + n$. $C\_ATC^{*}_{i,t}$ is the contribution of the actual trading convergence between funds *i* and *j* in month $t + n$. $\alpha_{s,\,t+n}$ is the subsequent alpha of stock *s* in month $t + n$.[15]

Third, for each fund in each month, we obtain the average contribution of the actual trading divergence (C_ATD*) and the average contribution of the actual trading convergence (C_ATC*) of a given fund *i* with the rest of the funds in month $t + n$ as follows:

$$\mathrm{C\_ATD}^{*}{}_{\mathrm{i,t+n}} = \overline{\mathrm{C\_ATD}^{*}_{\mathrm{i,j,t+n}}} \tag{14}$$

$$\mathrm{C\_ATC}^{*}{}_{\mathrm{i,t+n}} = \overline{\mathrm{C\_ATC}^{*}_{\mathrm{i,j,t+n}}} \tag{15}$$

Finally, we compare the values of C_ATD* and C_ATC* through the mean difference test. Table 6 shows that the contribution of trading divergence to fund performance is significantly higher than the contribution of trading convergence, as stated in H5. The results show a significantly positive difference of up to 0.15% in the annual performance. This outstanding conclusion provides evidence that fund managers who seek distinct trading strategies are more prone to offer added value to their investors.

5.3. Robustness test of the performance consequences of trading divergence

In this section, we compare the performance of two subsets of portfolios: funds with the highest and funds with the lowest trading divergence as a robustness test of the findings obtained in the previous

[13] The selection of the model is supported by the Hausman test, which suggests the use of FE instead of RE. Robust standard errors are used in the estimation. For robustness purposes, we also apply the FE model in monthly and annual computations. The results obtained are robust and are available upon request.

[14] Note that in a fund pair, one fund could buy in a certain stock, while the other fund could sell in this stock. Whether the subsequent performance of this stock is positive, the contribution of this trading divergence to the performance will be positive for the buying fund and negative for the selling fund.

[15] For robustness purposes, similarly to Equation 11, in this analysis, we also consider the alpha with the CAPM, the Fama and French three-factor model, and the Carhart four-factor model, with $n \in \{3,6,12\}$ months.

Table 5
The trading divergence and the subsequent fund performance.

	Fund_Performance$_{i,\ t}$								
	Section A: CAPM			*Section B: 3Factors*			*Section C: 4Factors*		
	t + 3	*t + 6*	*t + 12*	*t + 3*	*t + 6*	*t + 12*	*t + 3*	*t + 6*	*t + 12*
Constant	−0.0009***	−0.0007***	−0.0005***	−0.0006***	−0.0007***	−0.0007***	−0.0005***	−0.0007***	−0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
*TD**	0.0008***	0.0006***	0.0005***	0.0004***	0.0005***	0.0006***	0.0003***	0.0005***	0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund_size	−0.0001***	−0.0001***	−0.0001**	−0.0001***	−0.0001**	−0.0001	−0.0001***	−0.0001**	−0.0001
	(0.002)	(0.004)	(0.028)	(0.006)	(0.024)	(0.230)	(0.003)	(0.027)	(0.261)
Fund_age	0.0001	0.0001*	0.0001**	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0001**
	(0.107)	(0.054)	(0.017)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.019)
Fund_fees	0.0542**	0.0453**	0.0026	0.0346*	0.0305*	0.0105	0.0337*	0.0267*	0.0021
	(0.020)	(0.022)	(0.880)	(0.067)	(0.054)	(0.540)	(0.072)	(0.093)	(0.903)
Fund_#stocks	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.244)	(0.913)	(0.515)	(0.628)	(0.445)	(0.226)	(0.617)	(0.312)	(0.155)
Fund_flows	0.001	0.0001**	0.0001***	0.0001	0.0001***	0.0001**	0.0001	0.0001**	0.0001***
	(0.167)	(0.010)	(0.003)	(0.316)	(0.003)	(0.010)	(0.275)	(0.010)	(0.005)
F	19.20***	14.01***	12.11***	9.11***	13.52***	13.79***	6.86***	13.15***	13.19***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	1.41%	1.85%	2.61%	1.52%	2.20%	3.09%	2.24%	2.07%	3.01%
Hausman test	17.19***	43.01***	81.18***	54.08***	13.52***	52.26***	60.81***	58.75***	49.44***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

This table shows the results obtained from Eq. 9 on a quarterly basis. Section A shows the results obtained with the fund alpha of the CAPM. Section B shows the results obtained with the fund alpha of the Fama and French three-factor model. Section C shows the results obtained with the fund alpha of the Carhart four-factor model. We estimate the alphas by using rolling windows of 60 ($t+3$), 120 ($t+6$) and 240 ($t+12$) daily data. The dependent variable is the subsequent performance of the fund i in quarter t, and the independent variables are as follows: $TD^*_{i,t}$ is the average of the trading divergence level of fund i in quarter t; $Fund\_size_{i,t}$ is the average of the relativised size of fund i in quarter t; $Fund\_age_{i,t}$ is the average of the relativised age of fund i in quarter t; $Fund\_fees_{i,t}$ is the average fees of fund i in quarter t; $Fund\_\#stocks_{i,t}$ is the average number of stocks held by fund i in quarter t; and $Fund\_flows_{i,t}$ is the average relative money flows of fund i in the year t. The p-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
The contribution of trading divergence and trading convergence levels to the fund performance.

Panel A: CAPM	*t + 3*	*t + 6*	*t + 12*
*C_ATD**	0.0216%	0.0168%	0.0102%
*C_ATC**	−0.0075%	−0.0694%	−0.0089%
C_ATD– C_ATC**	0.0291%** (0.023)	0.0862%*** (0.000)	0.0192%*** (0.003)
Panel B: 3Factors	*t + 3*	*t + 6*	*t + 12*
*C_ATD**	0.0370%	0.0136%	0.0083%
*C_ATC**	−0.1161%	−0.0022%	−0.0094%
C_ATD– C_ATC**	0.1531%** (0.000)	0.0158%*** (0.000)	0.0177%*** (0.002)
Panel C: 4Factors	*t + 3*	*t + 6*	*t + 12*
*C_ATD**	0.0126%	0.0086%	0.0136%
*C_ATC**	−0.1120%	−0.0197%	−0.0020%
C_ATD– C_ATC**	0.1245%*** (0.000)	0.0283%*** (0.000)	0.0155%** (0.012)

This table reports the results of the average contribution of the actual trading divergence level (*C_ATD**) and the average of the contribution of the actual trading convergence level (*C_ATC**) to the fund performance in annual computation and the difference between both values *(C_ATD*– C_ATC*)*. Panel A shows the results obtained with the stock alpha of the capital asset pricing model (CAPM). Panel B shows the results obtained with the alpha of the Fama and French three-factor model. Panel C shows the results obtained with the stock alpha of the Carhart four-factor model. We estimate the alphas by using rolling windows of 60 ($t+3$), 120 ($t+6$) and 240 ($t+12$) daily data. The p-value of the mean difference test is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

analyses. Given the previous results, we could expect significantly higher levels of average performance in the top-quintile funds than in those funds included in the bottom quintile. Then, our hypothesis is as follows:

H6. *The performance of funds in the top quintile is significantly higher than the performance of funds in the bottom quintile.*

We divide the fund sample into quintiles according to the level of trading divergence in each month or quarter, depending on the analysis. Then, we compare the performance in the top quintile (Q1) and in the bottom quintile (Q5), thorough the mean-difference test. Table 7 indicates that the performance of funds in the top quintile is significantly higher than the performance of funds in the bottom quintile as stated in H6.[16] The result is robust regardless of the frequency of rebalancing the portfolios, regardless of the performance metric used and regardless of the subsequent time horizon considered to obtain the fund performance. Therefore, we conclude that the most divergent funds outperform the funds with less trading divergence, providing robustness to previous results of the economic consequences of this phenomenon.

6. Conclusions

In this paper, we link the strand of the literature that analyses the ability of fund managers to add value to their shareholders and the literature that compares managers' trading decisions. Specifically, we capture to what extent the trading of a fund differs with respect to that for the rest of the funds in any period and how the divergent portions of decisions contribute to fund performance, considering that this distinct trading may be an important source of the value added by fund managers.

We find that funds that belong to the same family present lower levels of divergent trading. The higher similarity among funds of the same family documented by the previous research and our evidence of a lower trading divergence among funds with a higher previous portfolio overlap lead us to control the potential influence of the previous holdings, obtaining thus a more accurate value of the trading divergence

[16] The results are robust when using terciles instead of quintiles. The results using terciles are available upon request.

Table 7
Performance differences of portfolios based on their level of trading divergence.

Panel A: CAPM	Monthly			Quartely		
	t + 3	t + 6	t + 12	t + 3	t + 6	t + 12
*TD*_Q1*	0.0276%	0.0222%	0.0175%	0.0692%	0.0521%	0.0385%
*TD*_Q5*	0.0128%	0.0005%	0.0001%	0.0001%	0.0008%	0.0001%
*(TD*_Q1-TD*_Q5)*	0.0148%***	0.0217%***	0.0174%***	0.0691%***	0.0513%***	0.0384%***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)
Panel B: 3Factors	*Monthly*			*Quartely*		
	t + 3	*t + 6*	*t + 12*	*t + 3*	*t + 6*	*t + 12*
*TD*_Q1*	0.0221%	0.0152%	0.0105%	0.0520%	0.0332%	0.0222%
*TD*_Q5*	0.0099%	−0.0039%	−0.0058%	−0.0017%	−0.0028%	−0.0056%
*(TD*_Q1-TD*_Q5)*	0.0122%***	0.0191%***	0.0163%***	0.0537%***	0.0360%***	0.0278%***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.001)
Panel C: 4Factors	*Monthly*			*Quartely*		
	t + 3	*t + 6*	*t + 12*	*t + 3*	*t + 6*	*t + 12*
*TD*_Q1*	0.0214%	0.0145%	0.0096%	0.0522%	0.0290%	0.0171%
*TD*_Q5*	0.0102%	−0.0043%	−0.0061%	−0.0012%	−0.0031%	−0.0058%
*(TD*_Q1-TD*_Q5)*	0.0112%***	0.0188%***	0.0157%***	0.0534%***	0.0321%***	0.0229%***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.002)

This table reports the results of the average performance of funds with the highest level of trading divergence *(TD*_Q1)* and the average performance of funds with the lowest level of trading divergence *(TD*_Q5)* and the difference between both values *(TD*_Q1-TD*_Q5)* in monthly and quarterly basis. Panel A shows the results obtained with the stock alpha of the capital asset pricing model (CAPM). Panel B shows the results obtained with the alpha of the Fama and French three-factor model. Panel C shows the results obtained with the stock alpha of the Carhart four-factor model. We estimate the alphas by using rolling windows of 60 (*t + 3*), 120 (*t + 6*) and 240 (*t + 12*) daily data. The *p*-value of the mean difference test is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

level. Even when controlling this effect, we find an increase in distinct trading among funds over time, especially after the GFC of 2008. Previous literature documents that the fragility of the fund industry and the potential shock propagation depend on the correlation among trading decisions. Hence, the divergence level among portfolios could be a key element to reduce the systemic risk within fund industry. In addition, previous studies indicate that the convergence in the trading decisions among funds may destabilise stock prices, impairing the functioning of financial markets. Therefore, the increasing evolution of the trading divergence level found in this study could lead to a higher level of efficiency in the mutual fund industry. Our analyses also reveal that the level of trading divergence is lower in periods with high market stress. This finding is in line with previous studies indicating that managers tend to reduce risk and invest in popular stocks in critical situations.

Finally, our study shows that funds with higher levels of trading divergence obtain significantly higher performance. This noteworthy evidence is confirmed when we compare the divergent and convergent portions of trading decisions, revealing that managers generate added value with their distinct decisions. These results could encourage the active portfolio management due to the investments skills of managers to add value through their divergent trading decisions. Therefore, these findings are interesting for fund families and managers and should increase their willingness to seek new investment opportunities to add value in portfolio management.

Further research should examine the trading divergence level in a different market such as the US due to its higher level of development and its lower level of concentration and dependence to the banking sector which leads to a higher competition. Additionally, the remuneration system of US fund managers is more linked to the performance records obtained than in less developed markets. Hence, US fund managers could have more incentives to make divergent decisions to differentiate from the rest and add value to their funds. The high levels of divergence obtained in our application to the Spanish market allow us to confirm the robustness of our results because we could expect similar or slightly higher divergence values in the US market.

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Author statement

All authors discussed the results and commented on the manuscript.

CRediT authorship contribution statement

Ruth Gimeno: Conceptualization, Formal analysis, Writing – original draft. **Laura Andreu:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **José Luis Sarto:** Conceptualization, Methodology, Formal analysis, Supervision.

Declaration of Competing Interest

None.

Appendix I. Example of trading divergence calculation

For illustrative purposes, we calculate the level of trading divergence between fund *i* and fund *j* in month *t*. Table A.1 reports the weight of the holding in each stock *s* at the end of the previous month *t-1* ($w_{i,s,t-1}$ and $w_{j,s,t-1}$) and the weight of the trading decision in each stock *s* for fund *i* and fund *j* in month *t* ($t_{i,s,t}$ and $t_{j,s,t}$), indicating the type of trading (buying, B and selling, S). Fund *i* buys shares of stock 2, 3, 4, 7 and 11, and sells shares of stocks 5, 6, 10, 12, 13. Fund *j* buys shares of stock 1, 3, 4, 8 and 12, and sells shares of stocks 5, 6, 9, 10, 11 and 14.

Table A.1
Illustration of the trading divergence measure.

Stock	Fund *i*			Fund *j*			a)	b)	c)	d)	e)	f) The actual divergence *a)-d)-e)*	g) The maximum potential divergence *b) + c)-d)-e)*	h) $FTD_{i,j,s,t}$	i) *f)-h)*
	$w_{i,s,t-1}$	$t_{i,s,t}$	Type of trading	$w_{j,s,t-1}$	$t_{j,s,t}$	Type of trading	$\lvert t_{i,s,t} - t_{j,s,t}\rvert$	*Max* $\lvert B_{i,j,s,t}\rvert$	*Max* $\lvert S_{i,j,s,t}\rvert$	$ExcTD_{i,s,t}$	$ExcTD_{j,s,t}$				
Stock 1				0.47%	1.85%	B	1.85%	1.85%				1.85%	1.85%		1.85%
Stock 2		2.33%	B				2.33%	2.33%				2.33%	2.33%		2.33%
Stock 3	1.54%	0.28%	B	2.42%	0.53%	B	0.25%	0.53%				0.25%	0.53%		0.25%
Stock 4	2.50%	0.50%	B	1.50%	1.50%	B	1.00%	1.50%				1.00%	1.50%	1.00%	0.00%
Stock 5	3.55%	−0.34%	S	1.74%	−0.50%	S	0.16%		0.50%			0.16%	0.50%		0.16%
Stock 6	4.75%	−1.25%	S	3.15%	−0.40%	S	0.85%		1.25%			0.85%	1.25%	0.85%	0.00%
Stock 7	3.10%	2.20%	B	2.90%			2.20%	2.20%				2.20%	2.20%		2.20%
Stock 8	4.50%			2.53%	1.85%	B	1.85%	1.85%				1.85%	1.85%	1.85%	0.00%
Stock 9	4.30%			6.90%	−1.20%	S	1.20%		1.20%			1.20%	1.20%	1.20%	0.00%
Stock 10	3.65%	−0.50%	S	2.37%	−0.80%	S	0.30%		0.80%			0.30%	0.80%		0.30%
Stock 11	4.35%	0.40%	B	3.45%	−0.25%	S	0.65%	0.40%	0.25%			0.65%	0.65%		0.65%
Stock 12	5.80%	−1.50%	S	2.94%	1.15%	B	2.65%	1.15%	1.50%			2.65%	2.65%	2.65%	0.00%
Stock 13	2.50%	−1.20%	S				1.20%		1.20%	1.20%		0.00%	0.00%		0.00%
Stock 14				5.60%	−1.90%	S	1.90%		1.90%		1.90%	0.00%	0.00%		0.00%
$\sum$ Stocks							18.39%	11.81%	8.60%	1.20%	1.90%	15.29%	17.31%	7.55%	7.74%

a) $|t_{i,s,t} - t_{j,s,t}|$ is the difference in absolute value of the trading weights between fund *i* and fund *j* for each stock *s* in month *t*.

This calculation allows us to capture three different cases of divergence:
Case 1: when both funds buy or sell but with different weights in a given stock (see, e.g., stocks 3, 4, 5, 6 and 10).
Case 2: when one fund buys and the other fund sells (see, e.g., stocks 11 and 12).
Case 3: when one fund buys (or sells) and another fund does not trade (see, e.g., stocks 1, 2, 7, 8, 9, 13 and 14).

b) Max $|B_{i,j,s,t}|$
in case 1 is the higher weight of the buying decisions between funds *i* and *j* when both funds buy (see, e.g., stocks 3 and 4) and zero when both funds sell (see, e.g., stocks 5, 6 and 10).
In case 2 is the trading weight of the fund that buys. For stocks 11 and 12 is the weight of the buying decision of fund *i,* and fund *j*, respectively.
In case 3 is the weight of the buying decisions (see, e.g., stocks 1, 2, 7 and 8) and zero if the trading fund sells (see, e.g., stocks 9, 13 and 14).

c) Max $|S_{i,j,s,t}|$
in case 1 is the higher weight in absolute value of the selling decisions between funds *i* and *j* when both funds sell (see, e.g., stocks 5, 6 and 10) and zero when both funds buy (see, e.g., stock 3 and 4).
In case 2 is the trading weight of the fund that sells (in absolute value). For stocks 11 and 12 is the weight of the selling decision of fund *j,* and fund *i*, respectively.
In case 3 is the absolute value of the weight of the selling decisions (see, e.g., stocks 9, 13 and 14) and zero if the trading fund buys (see, e.g., stocks 1, 2, 7 and 8).

In addition, the methodology allows us to control when a fund cannot sell a stock with lacking previous holding:

d) $ExcTD_{i,s,t}$ is the trading weight of fund *i* which cannot be made by fund *j* due to its lacking previous holding (see, stock 13).
e) $ExcTD_{j,s,t}$ is the trading weight of fund *j* which cannot be made by fund *i* due to its lacking previous holding (see, stock 14).

Then, we obtain $TD_{i,j,t}$ as the sum of all trading comparisons (the actual divergence) with respect to the sum of all maximum divergence values (the maximum possible divergence) between them, excluding the values of excess trading:

$$\mathrm{TD}_{i,j,t} = \frac{f)}{g)} = \frac{\sum_{s}\left|t_{i,s,t-}\ t_{j,s,t}\right| - \sum_{s}\mathrm{ExcTD}_{i,s,t} - \sum_{s}\mathrm{ExcTD}_{j,s,t}}{\sum_{s}\left(Max\ |B_{i,j,s,t}|+Max\ |S_{i,j,s,t}|\right) - \sum_{s}\mathrm{ExcTD}_{i,s,t} - \sum_{s}\mathrm{ExcTD}_{j,s,t}} = \frac{15.29\%}{17.31\%} = 88.33\%$$

Then, we detect whether there is false trading divergence, obtaining the holding difference at the end of month *t-1* and at the end of month *t* between both funds in each stock *s*. If the holding difference (*HD*) decreases, the trading decisions lead to more similar portfolio weights and thus, there is false trading divergence (see, e.g., stocks 4, 6, 8, 9 and 12). For instance, the trading weights of funds *i* and *j* for stock 4 are equal to 0.5% and 1.5%, respectively. However, the holding difference between both funds in this stock goes from 1% at the end of month *t-1* to zero at the end of month *t.* Therefore, what initially was considered as actual trading divergence is false trading divergence.

h) $\mathsf{FTD}_{i,j,s,t} = max\left(0, \mathsf{HD}_{i,j,s,t-1} - \mathsf{HD}_{i,j,s,t}\right)$

Finally, we calculate a more accurate trading divergence measure ($TD^*_{i,j,t}$) by excluding the false trading divergence ($FTD_{i,j,t}$):

$$TD^{*}{}_{i,j,t} = \frac{i)}{g)} = \frac{\sum_{s}\left|t_{i,s,t-}\ t_{j,s,t}\right| - \sum_{s}ExcTD_{i,s,t} - \sum_{s}ExcTD_{j,s,t} - FTD_{i,j,t}}{\sum_{s}\left(Max\ |B_{i,j,s,t}| + Max\ |S_{i,j,s,t}|\right) - \sum_{s}ExcTD_{i,s,t} - \sum_{s}ExcTD_{j,s,t}} = \frac{15.29\% - 7.55\%}{17.31\%} = 44.71\%$$

Appendix II. Evolution of the trading divergence level

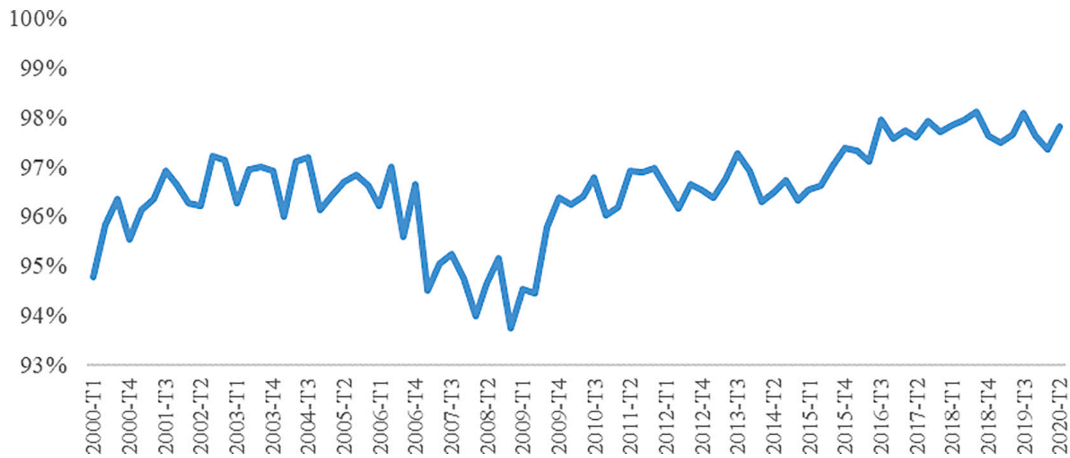

Fig. A.1. Evolution of the trading divergence level for all fund pairs.

This figure represents the evolution of the trading divergence level for all fund pairs from January 2000 to June 2020. The value is computed quarterly based on the average of their months.

Appendix III. The influence of stock characteristics on the trading divergence at the stock level

We examine whether the trading divergence level is driven by stock characteristics. Some studies suggest that institutional investors tend to converge in buying large stocks because these investors follow common market signals (Lin & Swanson, 2003; Lu, Fang, & Nieh, 2012; Sias, 2004). However, other studies indicate that convergence is more pronounced in small stocks because fund managers may receive lower and bounded information from these stocks (Huang, Liu, Rhee, & Zhang, 2010; Liao, Huang, & Wu, 2011). In addition, previous literature shows that mutual fund managers have also preference for certain stocks according to the size, volatility, past return, and information available for these stocks (Aggarwal, Klapper, & Wysocki, 2005; Brands, Gallagher, & Looi, 2006; Covrig et al., 2006; Gompers & Metrick, 2001; Otten & Bams, 2002).

Firstly, we aggregate the trading divergence of all fund pairs by each stock s in each month t as shown in Eq. A.1:

$$TD^{*}{}_{s,t} = \frac{\sum_{i,j|i<j}\left(\sum_{s}|t_{i,s,t-}\ t_{j,s,t}| - \sum_{s}ExcTD_{i,s,t} - \sum_{s}ExcTD_{j,s,t} - FTD_{i,j,s,t}\right)}{\sum_{i,j|i<j}\left(\left(\sum_{s}(Max\ |B_{i,j,s,t}| + Max\ |S_{i,j,s,t}|\right) - \sum_{s}ExcTD_{i,s,t} - \sum_{s}ExcTD_{j,s,t}\right)} \tag{A.1}$$

Secondly, to examine the stock characteristics that influence the level of trading divergence at the stock level, we apply the FE model on a quarterly basis as follows: [17]

$$TD^{*}{}_{s,t} = \alpha_{s,t} + \beta_1 Stock\_return_{s,t} + \beta_2 Stock\_volatility_{s,t} + \beta_3 Stock\_size_{s,t} + \beta_4 Stock\_popularity_{s,t} + \varepsilon_{s,t} \tag{A.2}$$

where $TD^{*}{}_{s,t}$ is the average trading divergence level among funds for stock s in quarter t and the independent variables are as follows: $Stock\_return_{s,t}$ is the return of stock s in quarter t related to the last twelve months in absolute value. $Stock\_volatility_{s,t}$ is the volatility of stock s in quarter t and is measured as the standard deviation of its return during the last twelve months. $Stock\_size_{s,t}$ is the market capitalization of stock s in quarter t. $Stock\_popularity_{s,t}$ is the popularity level of stock s in quarter t and is measured with the relation between the number of funds that trade the stock and the number of funds existing in that quarter in the sample.

Table A.2 shows the influence of the stock characteristics on the trading divergence level at the stock level. The influence of the previous return is not statistically significant when considering all fund pairs. However, if we focus on within (or across) families, we observe a lower (or higher) divergence level in the stocks with an extreme previous performance (both very positive and very negative previous performance). This result suggests that within a family, the top management who influences managers' trading decisions may have a common opinion about stocks with outstanding

[17] The selection of the model is supported by the Hausman test, which suggests the use of FE instead of Random effects (RE). Robust standard errors are used in the estimation. For robustness purposes, we also apply the FE model in monthly and annual computations. The results obtained are robust and are available upon request. The dynamic model has not been applied in Equation 9 because the test of Sargan (1958) shows over-identifying restrictions. Note that to be overidentified just means that there are more instruments than endogenous variables. In this case, the literature recommends the use of static panel data models.

performance, which results in similar trading decisions in these stocks among their funds. However, across families, the existence of extreme positive (or negative) performance leads to a higher divergence because each family can see investment opportunities in different stocks. On the other hand, most managers could have the same interest in the remaining undistinguished stocks regardless of the fund family to which the funds belong.

Stock volatility has a negative influence on the trading divergence level, but this effect is only statistically significant for fund pairs belonging to the same family. This finding provides evidence about the internal control of the risk management level within families and how this internal control results in a lower divergence trading level in the more volatile stocks among their funds.

In the analysis of all fund pairs or of the fund pairs in different families, we also find a lower trading divergence level in larger stocks, which could be explained by the fact that the information available on these stocks is greater (Lin & Swanson, 2003; Lu et al., 2012; Sias, 2004). However, we find a lower level of trading divergence in small stocks within families, shedding light on the fact that fund managers could have a greater autonomy to make decisions about large companies, while the trading decisions for small companies are more influenced by the guidelines from the family's top management.

Finally, we find a lower level of trading divergence in stocks with a higher level of popularity in the market, regardless of whether analysing funds from the same family or from different families.

Table A.2
Stock characteristics and trading divergence among mutual funds.

	Section A *All fund pairs*	*Section B* *Fund pairs in the same fund family*	*Section C* *Fund pairs in different fund families*
	Coefficient (*p*-value)	Coefficient (*p*-value)	Coefficient (*p*-value)
Constant	0.9459*** (0.000)	0.9358*** (0.000)	0.9537*** (0.000)
Stock_return	0.0022 (0.406)	−0.0029** (0.039)	0.0038** (0.015)
Stock_volatility	−0.0234 (0.231)	−0.0846*** (0.002)	−0.0036 (0.812)
Stock_Size	−0.0029*** (0.001)	0.0059* (0.084)	−0.0035*** (0.000)
Stock_popularity	−0.4469*** (0.000)	-0.8770*** (0.000)	−0.4223*** (0.000)
F	162.7*** (0.000)	111.37*** (0.000)	143.75*** (0.000)
R^2	12.03%	15.30%	22.59%
Hauman Test	243.48*** (0.000)	13.43*** (0.009)	731.17*** (0.000)

This table shows the results obtained from Eq. A.2 with the FE model on a quarterly basis. Section A shows the results for all fund pairs. Section B shows the results for fund pairs within the same family. Section C shows the results for fund pairs in different fund families. The dependent variable, $TD^*_{s,t}$ is the trading divergence level among funds for stock *s* in quarter *t,* and the independent variables are as follows*: Stock_returns*,*t* is the absolute value of the yearly past return of stock *s* in quarter *t; Stock_volatilitys*, *t* is the volatility of stock *s* in quarter *t* and is measured as the standard deviation of its return during the last year; *Stock_sizes*, *t* is the market capitalization of stock *s* in quarter *t*; and *Stock_popularitys*, *t* is the popularity level of stock *s* in quarter *t* and is measured with the percentage of funds that trade in the stock *s* within our sample. The *p*-value is reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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