Herding Behavior – New Evidence From Portuguese Mutual Funds (2006 – 2013)

By

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Master in Finance - Dissertation

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Autobiographical Note

Daniel José Ferreira Barroso Martins Pacheco born on the 22nd of May 1990, got his graduation in Economics, in the year 2014, by the Catholic University of Portugal. In September of that same year, he started the Master in Finance course at the Faculty of Economics of the University of Oporto.

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Abstract

The objective of this study is to analyze the herding behavior in the financial markets. The main aim is to see if there is evidence from herding by the portuguese mutual funds and, to achieve that, a comprehensive analysis on herding behavior is going to be done using as sample the selected mutual funds portfolio over the period 2006 to 2013.

The scientific relevance of this dissertation is related to the fact that the study of the level of herding by institutional investors can contribute to a better understanding of the market by helping to enlight the knowledge on different phenomena such as excess volatility, price momentum, speculative bubbles, etc. And that can be important to the current debates on market efficiency and on the validity of the traditional asset pricing models.

To answer the reserch question, we selected the data about the variation of the institutional investors portfolio, from the Portuguese Securities Market Comission (CMVM), and we used both the Lakonishok et al. (LSV) (1992) and Sias (2004) methodology.

We found evidence that both measures reveal high overall herding levels, confirming previous studies also conducted in Portugal on this subject. We also got the confirmation that, for the LSV measure, the herding levels for subgroups is much lower than the one found in the overall sample, and the levels found in Portugal are much higher than the ones found in more mature markets like the US or the UK markets.

Key-words: Herding behavior; Mutual funds

JEL Codes: D7; G23

Resumo

O objetivo deste estudo é analisar o efeito de rebanho (ou *Herding*) nos mercados financeiros. A intenção principal é ver se há evidências deste fenómeno nos fundos de investimento portugueses e, para conseguir isso, uma análise abrangente sobre o efeito de rebanho foi feita usando como amostra a variação da carteira dos fundos de investimento seleccionado para o período de 2006 a 2013.

A relevância científica desta dissertação está relacionada com o fato de que o estudo deste tópico (efeito de rebanho) nos investidores institucionais, pode contribuir para uma melhor compreensão do mercado, ajudando a esclarecer o conhecimento sobre diferentes fenómenos, tais como o excesso de volatilidade, a dinâmica de preços, as bolhas especulativas, entre outros, e isso pode ser importante para os debates actuais sobre a eficiência do mercado e para a validação dos modelos de precificação de ativos tradicionais.

De maneira a atingir o objectivo proposto, foram selecionados os dados sobre a variação das carteiras de investidores institucionais, a partir do site da Comissão do Mercado de Valores Mobiliários (CMVM), e usamos tanto a metodologia de Lakonishok et al. (LSV) (1992) como a de Sias (2004).

Nesta dissertação descobrimos que ambas as medidas revelam elevados níveis de efeito de rebanho, confirmando estudos anteriores, também realizados em Portugal sobre este assunto. Tivemos ainda a confirmação de que, para a medida de LSV, os níveis de efeito de rebanho para os subgrupos estudados forma sempre muito menores do que os encontrados na amostra global, e de que os níveis encontrados em Portugal são muito mais elevados do que os encontrados em mercados mais maduros, como é o caso do mercados dos Estados Unidos ou do Reino Unido.

Palavras-chave: Efeito de rebanho; Fundos de Investimento

Códigos JEL: D7; G23

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1. Introduction

Herding behavior can be defined as the correlation in trades that result from interactions between investors. That type of behavior can lead to errors and misvaluation of assets contributing to the inefficiency of the market, (Nagel *et al.*, 2004; Griffin *et al.*, 2011). So, the study of this type of behavior is of extreme value not only for researchers but also for investors, traders and regulators. The answer to the question "Why do investors herd?" has normaly two types of approach: The first suggests that herding is irrational and is caused by "herd instinct"; the second claims that the herding phenomena may be entirely rational and that is where several theories like the informational cascades, the agency reputation risk and the information inefficiencies came from. In relation to the extent of herding there is no consensus in the studies realized in the US market, but in Portugal, the studies conducted by Lobão and Serra (2007) and Holmes *et al.* (2013) tell us that, there was and apparently still is a strong evidence of herding by portuguese mutual funds in the portuguese market.

If previous studies show that there was evidence of herding in Portugal and if herding can be the source of market inefficiency that is the main motivation to see what was the evolution and what is the current level of herding in Portugal.

The main contribution of the study comes from the objective of, through the monthly analysis of the selected mutual funds portfolio, for the period of 2006 to 2013, see, with the help of both LSV and Sias methodologies, what is not only the overall level of herding but also what is the relation of the fund specific characteristics (market capitalization, portfolio holdings, rebalancing frequency) and the market conditions (stock market returns and volatility) with herding. Something that has never been done before in Portugal, and that can help to get a more complete and solid study about herding in a period never analyzed before.

The aim of the dissertation is to see if there is herding evidence from the portuguese mutual funds and the main questions that the study intends to answer are:

1. What was the evolution of portuguese mutual funds?
2. What was the evolution of herding in the portuguese mutual funds?
3. Is the maturity/state of the market relevant?
4. Are the characteristics of the mutual funds relevant?

To achieve the objective we propose, we will analyze the monthly portfolio holdings for the selected portuguese equity mutual funds and then we will use both the LSV (1992) and Sias (2004) measure.

After the monthly analysis and the use of the methodologies, we found very high overall herding levels, much higher than the ones found in more developed markets for the LSV measure, but similar to the ones found in previous studies conducted in Portugal.

The structure of the dissertation will be the following: In Chapter 2 we will do the literature review of the relevant studies on the subject, show the relevant definitions and do a critical review of the studies presented. In Chapter 3 we will present the data and methodologies used. In Chapter 4 the empirical results will be disclosed and in Chapter 5 the main conclusion will be exposed and future research ideas about the topic will be suggested.

2. Literature review

This chapter presents a literature review in order to clarify the relevant definitions of the topic, to present the main theories and models, to show the main results and contributions of the similiar studies and to make a critical analysis of them.

2.1. Relevant definitions

According to literature, there are two polar views of herding, the irrational and rational.

The irrational view centers on investor psychology and suggests that individuals are irrational when they behave. One example, is the tendency for people in group to think and behave similarly which seems to suggest some kind of irrationality such as loyalty-induced psychological motivation to be in agreement with the group members. (Shiller, 1995).

The rational view, tell us that individuals are rational when they behave, and several theories have been developed to help explaining why rational investors trade together: Informational cascades, agency reputation based models and information inefficiencies.

Informational cascades are the more common explanation for herding. The observation of prior investors' trades can be so informative that investors are better-off disregarding their private information and trading in the same direction (Bikhchandani *et al.*, 1992; Hirshleifer and Hong Teoh, 2003). An alternative explanation for herding is reputational risk: under certain circumstances, asset managers (Scharfstein and Stein, 1990) or security analysts (Hong et al., 2000) have incentives not to act differently from other competing managers, regardless of their own signals (see also Boyson, 2010). Finally, herding could result from the way investors deal with information: investors may find attractive to use only private information shared by other investors, and disregard any other private unique information they have. Resource allocation regarding information acquisition is inefficient in this setting (Froot *et al.* 1992; Hirshleifer *et al.*, 1994).

2.2. Similar studies

The study conducted by Lakonishok *et al.* (1992) examined 769 US pension funds, managed by 341 different portfolio managers, between 1985 and 1989. They found no solid evidence that institutional investors destabilize prices of individual stocks concluding that the level of herding was not significant in the US market.

Grinblatt *et al.* (1995) analyzed trading data for 274 mutual funds in the US over the period of 1974-1984 and found that the average level of herding was statistically significant, but not particularly large.

Wermers (1999) investigated herding over a 20-year period using quarterly portfolio holdings for all mutual funds based in the US from 1975 to 1994. He found a low level of herding among mutual funds but a stronger herding effects among growth-oriented mutual funds and in small and winner stocks.

Sias (2004) used his own methodology and the data of all US based mutual funds between the period of 1983-1997 to reach the conclusion that mutual funds herding levels were relevant.

Wylie (2005) examined data on 268 UK equity mutual funds from 1986 to 1993 and found that the level of herding is similar to the herding found for US mutual funds and pension fund managers.

Theriou *et al.* (2011) examined data from 31 Greek mutual funds between 2001 and 2006. They found that mutual fund managers undoubtedly herd, mainly in large capitalisation stocks.

Lobão and Serra (2007) studied the quarterly portfolio holdings for 32 portuguese equity mutual funds between 1998 and 2000. The overall level of herding was very significant, and higher than that found in previous studies conducted in the US and UK. It was also found in this study that when the market provided higher returns and when it was more volatile the levels of herding were lower.

Holmes et al. (2013) used the data of 45 portuguese mutual funds between the period of 1998-2005 and the methodology developed by Sias (2004) to reach the conclusion that the overall herding level was relevant in Portugal. Here, unlike the previous studies, the data used was monthly instead of either quarterly or semi-annual.

Kremer et al. (2013) used daily data from all German institutions, except the ones trading exclusively for the purpose of market making and institutions that were formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock, trought the period of 2006 to 2009 to show that herding occurs on a daily basis. The values were statistically significant, high for the Sias measure but quite low for the LSV.

2.3. Critical review of the literature

In the literature review presented, there are mainly two type of limitations: methodological and sample related.

In relation to the methodology, the model developed by Lakonishok *et al.*, still used today as in the case of Theriou *et al.* (2011) and Brown *et al.* (2013), has important limitations. The first is that, as Wylie (2005) mentioned, it is subject to biases due to making three implicit assumptions which are not upheld in real data: It implicitly assumes that all fund managers may not short sell all stocks[1], the ex-ante probability of a manager buying rather than selling a stock (the propensity to buy) is assumed to depend only on the degree of herding[2] and the error in estimating the managers' propensity to buy, in any particular period, can be ignored in finite datasets[3]. The second, as Sias (2004) points out, is that the LSV measure only indirectly tests for cross-sectional temporal dependence in institutional demand, which is not the most robust way to test whether institutional investors follow each other's trades over the time. The third, comes from the fact that it is not possible to disentangle institutions which follow their own trades from those that follow the trades of others when using the LSV measure. The fourth and final limitation of the model is that it doesn't take in consideration whether the correlation trades results from imitation or merely reflect the use of the same information.

One way to minimize these limitations would be to do like Kremer *et al.* (2013) and, instead of using only the LSV measure, use the LSV measure associated with the Sias (2004) measure. The LSV herding measure is a static measure that detects contemporaneous buying or selling within the same time period. In contrast, the dynamic approach proposed by Sias (2004) explores whether the buying tendency of traders

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[1] If short selling is prohibited the measure tends to overestimates the true herding value (Wylie, 2005; Oehler and Chao, 2000).

[2] Not considering either the initial weight of the stock in the manager's portfolio or the amount of new money that the manager must invest because of investment flows.

[3] The herding level is calculated using an expected proportion of buyers based on the sample rather than in its population counterpart. LSV ignore this effect because estimation error is very small in their large dataset. However, this bias brings into question the suitability of the Lakonishok *et al*. measure on small datasets or small subsets of data from large datasets.

persists from one period to the other. The focus of the Sias herding measure is on whether institutional investors follow each others trades by examining the correlation between institutional trades over time. This measure allows to solve the majority of the LSV limitations because Sias (2004) directly tests for herding without being sensitive to biases in its estimates and it differentiates the herding of institutions following their own trades and following the trades of other institutions. The "strength" of the results between both measures is that the correlation (Sias measure) focuses on whether those stocks that had the greatest institutional demand (or supply) last quarter have the greatest demand (or supply) this quarter and, in contrast, the LSV measure evaluates the average herding across every industry every quarter. Both measures are complementary to one another.

The second limitation is related to the sample data used. The majority of the studies here presented use quarterly or semi-annual data. According to Kremer et al. (2013) which used daily data of all transactions made by financial institutions in the German stock market, herding behavior occurs on a daily basis. Quarterly data provide only a crude basis for inferring trades and this frequency might be too low in a rapidly changing stock market environment.

The study realized by Kremer et al. (2013) is the most well conducted study done so far in the herding subject to the extent of my knowladge and the objective of this dissertation is to conduct a similar study, in Portugal, which has never been done.

3. Data and methodology

3.1. Data

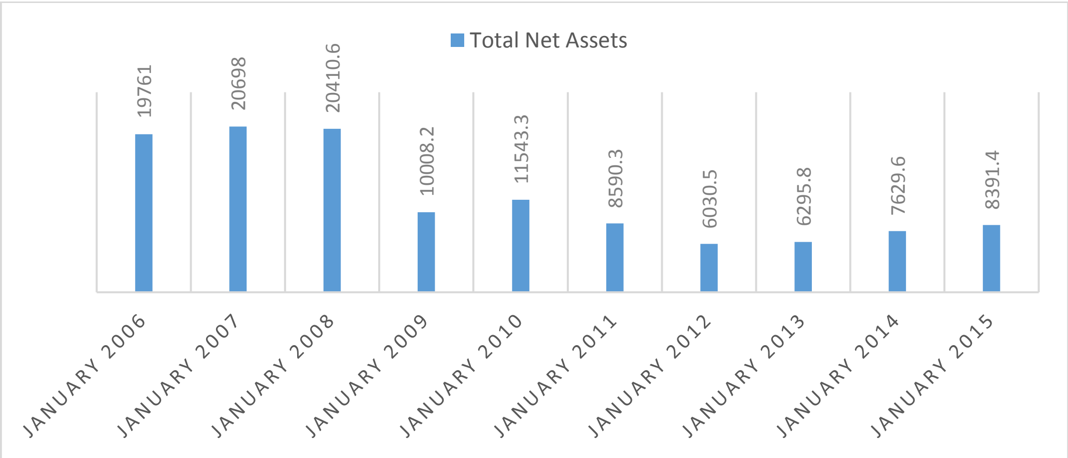
3.1.1. The evolution of the mutual fund industry in Portugal

The first registration of a domestic investment fund was made in June 1964. This type of activity stopped in 1975, and only recommenced in 1986 with the entrance of the *Invest fund*, followed in 1987, by the entrance of four additional mutual funds.

To demonstrate the fast growth of the industry in Portugal, in 1986 there was only one investment fund, as previously said, whose value amounted to just 51 million euros and, by the end of 2009, there were 194 funds and 18 management companies who ran a total of 11.653 million euros (representing 6.8% of GDP).

Despite the decline that we see after 2008, apparently due to the subprime crisis [1], where the net assets under management declined from 20.410 million euros in 2008 to 6.030 million in 2012, which can translate in a lower impact in prices due to herding between mutual funds, the tendency observed is of recovery as we can see by the data where we register 6.295 millions in 2013 to 8.391,4 millions in 2015. Meaning that, in the future, the herding subject can be more relevant than it is now.

Figure 1 - The evolution of portuguese mutual funds



[1] The subprime crisis was a nationwide banking emergency that coincided with the U.S. recession of December 2007 – June 2009. It was triggered by a large decline in home prices after the collapse of a housing bubble, leading to mortgage delinquencies and foreclosures and the devaluation of housing-related securities.

3.1.2. Sample

The database used for this study consists of all securities mutual funds (shares, flexible, alternative, etc.) available in the CMVM site, as existing in the portuguese capital market (even though its objective of activity is linked to other countries not only Portugal), and as having at least 10% of portuguese shares in the composition of its portfolio.

The first criteria is that the funds have to have those 10% invested in portuguese shares in January 2006 (the beginning of the database) and are not excluded from the sample even if they lower this bar, imposing no minimum survival period requirement for a fund to be included in the sample[2]. The second criteria is to analyze the following years (from January 2007 to September 2013) to check when some other fund, which already existed or was created, shall meet the requirements and can be added to the database.

In total, the funds analyzed were 37. It is a very close number, but still lower than the 45 funds analyzed by Holmes *et al.* (2013), which analyzed all the portuguese mutual funds (even those in which the percentage of portuguese shares in the portfolio is very close to 0%), but is identical to the study by Lobão and Serra (2007) where 32 portuguese mutual funds were analyzed and where the criteria in this case was that the portfolio had to have at least 75% of the net asset value invested in equities.

In order to analyze the "herd effect" on domestic equity market, by mutual funds present in the portuguese capital market, I think the proposed database can be as representative as the ones proposed in previous studies.

3.2. Methodology

The methodology used in this dissertation are the two herding measures predominantly applied in the literature, the LSV and the Sias measure.

3.2.1. The LSV measure

The first herding measure had been introduced by Lakonishok et al. (1992). According to the LSV measure, herding is defined as the tendency of traders to accumulate on the

[2] See, for example, Grinblatt et al. (1995) and Wermers (1999). Previous research has shown that the impact of survival bias on performance (Grinblatt and Titman, 1989; Brown and Goetzmann, 1995) and herding (Wermers, 1999; Wylie, 2005) is trivial.

same side of the market in a specific stock and at the same time, relative to what would be expected if they traded independently.

The LSV herding statistic is given by:

$$H(i,t) = \left| p(i,t) - p(t) \right| - AF(i,t)$$

Equation 3. 1

where

$$p(i,t) = \frac{B(i,t)}{B(i,t) + S(i,t)}$$

Equation 3. 2

and

$$p(t) = \frac{\sum_{i=1}^{n} p(i,t)}{n}$$

Equation 3. 3

B(i,t) [S(i,t)] is the number of funds that buy (sell) the stock *i* during quarter *t*, *p(i,t)* is the proportion of funds trading stock *i* that were buyers and *p(t)* is a proxy for the expected proportion of buyers under the null of independently trading by funds, *E(p(i,t))*, and is given by the proportion of all stock trades by funds that were purchases during that quarter *t*. *p(t)* is constant for all stocks during a quarter but varies over time. The adjustment factor *AF(i,t)* is given by:

$$AF(i,t) = E\left[\left| p(i,t) - E(p(i,t)) \right|\right].$$

Equation 3. 4

This factor allows to capture the random variation of *p(i,t)* around its expected proportion of buyers, under the null hypothesis of independent trading and assuming *B(i,t)* has a binomial distribution with parameter $p = p(t)$.

The null hypothesis states that if herding does not exist, the proportion of buyers (and sellers) has the same expected value for all stocks in a given period and is constant equal to *p(t) [1− p(t)]*. Under the null, *H(i,t)* = 0. Deviations from *p(t)*, above the expected *AF(i,t)*, signal herding.

As *N(i,t)=B(i,t)+S(i,t)* becomes larger then, under the null, *AF(i,t)* will be close to zero. The main reason for including the adjustment factor is to account for bias that would occur if stocks were illiquid and traded only by a few investors.

3.2.2. The Sias measure

The LSV herding measure is a static measure that detects contemporaneous buying or selling within the same time period. In contrast, the dynamic approach proposed by Sias (2004) explores whether the buying tendency of traders persists over time. The focus of the Sias herding measure is on whether institutional investors follow each others' trades by examining the correlation between institutional trades over time. Similarly to the LSV measure, the starting point of the Sias measure is the number of buyers as a fraction of all traders. According to Sias (2004), the ratio is standardized to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})}$$

Equation 3. 5

$\sigma(br_{it})$ is the cross sectional standard deviation of buyer ratios across *i* stocks at time *t*. The Sias herding measure is defined as the correlation between the standardized buyer ratios in consecutive periods:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}$$

Equation 3. 6

The cross-sectional regression is estimated for each day t and then the time-series average of the coefficients is calculated:

$$\beta = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$$

Equation 3. 7

A high buyer ratio would usually result in a higher LSV measure (if higher than on average) but not necessarily to a higher Sias measure as this depends on the ratio at the next trading day.

The Sias methodology further diferentiates between investors who follow the trades of others (i.e., true herding according to Sias (2004)) and those who follow their own trades. For this purpose, the correlation is decomposed into two components:

$$\beta = \rho(\Delta_{it}, \Delta_{i,t-1}) = \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right] + \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \sum_{m=1, m\neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right]$$

Equation 3. 8

Where N_{it} is the number of institutions trading stock *i* at time *t* and *I* is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,\,t-1}$ is a dummy variable that equals one if trader *m* (who is different from trader *n*) is a buyer at day *t-1*. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent days. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent days. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as first evidence for informational cascades.

4. Empirical Results

4.1. LSV measure

4.1.1. Overall levels of herding

In table 1, the overall levels of herding for the period studied (2006 - 2013) are presented.

Tabela 1 - Herding results

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds. The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)|, where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. n is the number of funds required to trade a stock in each quarter used to compute the Lakonishok et al. (1992) herding measure. The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
n=>1	15.13[a]	13.80[a]	15.06[a]	13.67[a]	12.5[a]	12.77[a]	11.35[a]	13.30[a]	**13.45**[a]
n=>2	17.65[a]	15.75[a]	16.75[a]	15.50[a]	14.38[a]	13.99[a]	13.95[a]	14.62[a]	**14.61**[a]
n=>5	19.32[a]	17.12[a]	18.23[a]	17.13[a]	17.09[a]	16.32[a]	18.37[a]	18.56[a]	**15.16**[a]
n=>10	17.78[a]	17.11[a]	19.10[a]	18.48[a]	17.26[a]	17.38[a]	18.34[a]	18.38[a]	**18.48**[a]
n=>15	18.35[a]	17.34[a]	21.84[a]	17.29[a]	15.63[a]	16.95[a]	17.86[a]	14.10[a]	**19.20**[a]

The herding measure of 13.45% shown (in table 1) can be interpreted as, if 100 funds trade a given stock then, approximately thirteen more funds trade on one side of the market than would be expected if there was no positive feedback trading between funds. In other words, if the number of changes in holdings was, a priori, equally balanced between positive and negative changes, 63.45% (50%+13.45%) of the funds traded in one direction and the remaining 36.55% (50%-13.45%) traded in the opposite direction.

The average herding measure does not vary much across the seven years in sample, the lowest level being observed in 2012 (H=11.35%) and the highest level being observed in 2006 (H=15.13%).

The overall level of herding we find is much higher than that reported in previous studies conducted in Germany, UK and US but, is close to the values found by Lobão and Serra (2007), by Choe *et al.* (1999) for their study on the herding behavior of foreign individual investors in the Korean stock market and Voronkova *et al.* (2005) in their study about institutional herding and positive feedback trading of pension fund investors on the Polish stock market (See table 2).

Tabela 2 – Different maturity market comparison

Below the herding level obtained by different studies in different market are presented in percentage terms, using the LSV measure, for different number of stocks traded in each stock-quarter (from 1 or more to 15 or more).

Study (Date)	Country	n=>1	n=>2	n=>5	n=>10	n=>15
Lakonishok et al. (1992)	USA	2.7	-	-	2.0	-
Wermers (1999)	USA	-	-	3.4	3.61	-
Wylie (2005)	UK	-	2.6	2.5	3.3	4.3
Walter et al. (2006)	Germany	2.67	5.11	5.59	5.59	-
Voronkova et al. (2005)	Poland	14.6	-	10.90	11.50	16.5
Lobão and Serra (2002)	Portugal	11.38	12.44	13.54	13.96	13.60
Current Paper	Portugal	13.45	14.61	15.16	18.48	19.20

This higher average level of herding for less mature stock markets is consistent with arguments that rely on informational cascades or information inefficiencies arguments. Stock markets that exhibit poorer aggregation of information and where the precision of the public pool of information is lower tend to form herds more often. An implication of these results should be that as stock markets become more mature, the level of herding decreases. Agency models would not predict different levels of herding across stock markets in different stages of maturity.

Here, as in previous studies, the expectation that a larger number of funds trading a given stock in a certain quarter would decrease the herding measure (given that stocks that are traded by many funds usually have more public information and, as such, the herding effect should be lower) does not hold (see table 1 and table 2).

4.1.2. Buy-herding *vs* sell-herding

After computed the average buy-herding (See table 3) and sell-herding (See table 4) measures for all period and for each individual year we are able to see that the level of herding is significant in either side of the market and, over time, the value of the statistic changes and so does the side of the market where herding is predominant. Despiste that, the most predominant herd side is the buy side.

Tabela 3 - Buy herding

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by purchases and sales. The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)| ,where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. Buy herding stock-quarters are those where p(i,t) > p(t), that is, the proportion of buyers was greater than the expected proportion of buyers. n is the number of funds required to trade a stock in each quarter used to compute the Lakonishok et al. (1992) herding measure; The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
n>=1	14.10 [a]	14.15 [a]	15.75 [a]	13.38 [a]	13.86 [a]	11.95 [a]	16.57 [a]	17.99 [a]	**14.61** [a]
n>=2	16.57 [a]	15.17 [a]	15.92 [a]	13.58 [a]	13.81 [a]	12.01 [a]	16.81 [a]	18.12 [a]	**15.16** [a]
n>=5	18.94 [a]	18.19 [a]	19.62 [a]	17.69 [a]	18.69 [a]	16.72 [a]	19.51 [a]	18.53 [a]	**18.48** [a]
n>=10	19.03 [a]	17.17 [a]	20.13 [a]	19.52 [a]	17.69 [a]	19.00 [a]	18.70 [a]	20.04 [a]	**18.87** [a]
n>=15	20.39 [a]	18.83 [a]	24.16 [a]	17.34 [a]	16.74 [a]	21.25 [a]	18.26 [a]	14.11 [a]	**19.20** [a]

Tabela 4 - Sell herding

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by purchases and sales. The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)| ,where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. Sell stock-quarters are those where p(i,t) < p(t) meaning the proportion of sellers was greater than the expected proportion of sellers. n is the number of funds required to trade a stock in each quarter used to compute the Lakonishok et al. (1992) herding measure; The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
n>=1	16.95 [a]	13.46 [a]	14.78 [a]	14.24 [a]	10.91 [a]	13.57 [a]	7.23 [a]	9.26 [a]	**12.66** [a]
n>=2	18.92 [a]	16.65 [a]	17.79 [a]	17.66 [a]	14.98 [a]	16.07 [a]	11.92 [a]	11.83 [a]	**15.85** [a]
n>=5	20.21 [a]	16.67 [a]	17.30 [a]	17.68 [a]	15.96 [a]	16.12 [a]	18.37 [a]	19.16 [a]	**17.64** [a]
n>=10	17.02 [a]	17.39 [a]	19.09 [a]	18.22 [a]	17.29 [a]	16.85 [a]	19.46 [a]	18.15 [a]	**17.93** [a]
n>=15	18.47 [a]	17.25 [a]	21.42 [a]	17.99 [a]	15.46 [a]	14.85 [a]	20.93 [a]	18.67 [a]	**18.10** [a]

The evidence in our study is similar to the one reported by previous studies like Wylie (2005), Lobão and Serra (2007) and Haigh *et al.* (2006) who report a stronger herding effect on the buy.

4.1.3. Herding and the market conditions

a) Market stock return

Informational cascades predict that when markets are doing well, investors are more confident and that may increase the likelihood of using their private signals and deviating from others. We should expect then to find lower levels of herding when markets are doing well.

Differently, agency models suggest that when the market is doing very well or very badly, the signals are more precise, it is easier to detect a good from a bad manager and therefore bad managers will try to mimic good managers more often to fool their clients. Thus we should expect higher levels of herding when markets are doing very well or very bad.

Despite the lack of relevant connection between the level of market return and the herding levels for when there is a lower number of funds trading a given stock in a given quarter it seems that, if there is a larger number of funds trading a given stock in a given quarter, when markets are doing good there is less herding and when markets are doing bad there is more herding (See table 5). This might suggest a confirmation of the informational cascade theory. This result is also supported by both Holmes et al. (2013) and Lobão and Serra (2007).

Tabela 5 - Market stock return

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by market volatility. Subgroups are formed on the basis of the portuguese Stock Index (PSI20) daily returns standard deviation in each quarter (low volatility, medium volatility, high volatility). The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)|, where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. n is the number of funds required to trade a stock in each quarter used to compute the Lakonishok et al. (1992) herding measure. The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	Low Return	Medium Return	High Return
n>=1	13.31 [a]	13.45 [a]	13.45 [a]
n>=2	14.97 [a]	15.93 [a]	15.05 [a]
n>=5	17.37 [a]	18.14 [a]	17.68 [a]
n>=10	18.55 [a]	17.80 [a]	17.49 [a]
n>=15	18.34 [a]	17.98 [a]	16.44 [a]

b) Market volatility

Some theories predict higher levels of herding when markets are more volatile. One example is that higher uncertainty may result in that public information becomes less precise and reliable and therefore cascades are more likely to occur. Higher uncertainty in private information may result in that cascades start sooner. Therefore, we should observe higher levels of herding for periods when market volatility is high.

Other theories predict a negative relation between volatility and the level of herding. The argument is that if investors are not ex-ante identical, the arrival of an individual with deviant information or of very unexpected public information, can dislodge the cascade. Therefore, we could also observe lower levels of herding for periods when market volatility is high.

In this specific case, according to our results, there seems to be no relation between the level of volatiliy in the market and the level of herding (See table 6), once the medium volatility group is always the one with higher herding levels.

Tabela 6 - Market volatility

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by market volatility. Subgroups are formed on the basis of the portuguese Stock Index (PSI20) daily returns standard deviation in each quarter (low volatility, medium volatility, high volatility). The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)|, where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. n is the number of funds required to trade a stock in each quarter used to compute the Lakonishok et al. (1992) herding measure. The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	Low volatility	Medium volatility	High volatility
n>=1	13.36 [a]	14.13 [a]	12.85 [a]
n>=2	15.49 [a]	15.87 [a]	14.76 [a]
n>=5	17.76 [a]	18.20 [a]	17.26 [a]
n>=10	16.96 [a]	19.04 [a]	17.83 [a]
n>=15	16.97 [a]	18.27 [a]	17.52 [a]

4.1.4. Herding and the fund specific characteristics

a) Market size

Table 7 presents the herding measures averaged over stock-quarters segregated by fund size.

Taking off the extreme negative values as happened with Theriou *et al*. (2011), which come from the fact that, as previously said, the model used is not based on absolutely realistic assumption, we find that the levels of herding computed for these subgroups of funds are much smaller than that observed for the overall sample.

This results are consistent with cascade or information inefficiency based explanations. The implication of the reputational explanation for the levels of herding across different subgroups is not borne out by the data because, if the behavior of funds were driven by reputation concerns, funds would herd within their group to preserve their status quo.

We have then two alternatives left, the idea that funds within the same size-class would show less herding because the imitation would occur across different size groups. In particular, small funds would follow large, presumably more informed funds. And the potential reason that instead of size, style might be the central characteristic when choosing the fund to imitate.

Lakonishok *et al.* (1992) and Lobão and Serra (2007) report similar results: size subgroups of funds exhibit lower levels of herding than that observed for the overall sample.

Tabela 7 - Market size

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by fund size. Size is measured by total assets under management. Each quintile is formed on the basis of the size of the fund during the quarter prior to the herding measure quarter. Quintiles are recalculated every year. The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)| , where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding. The herding measures |p(i,t)-p(t)|-E|p(i,t)-p(t)| are averaged separately over stock-quarters belonging to diferente fund size quintiles. In each stock-period the funds of the sample were divided R times into 5 with a remainder of S. Then the qth quintile contains R observations, except the third quintile which contains R+S observations. We impose no minimum requirement on the number of funds trading a stock in each period. The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. Q1 is the quintile with the lowest size funds and Q5 the quintile with the biggest size funds. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
Q1	-7.98 [b]	-15.71 [a]	-10.37 [a]	-9.92 [b]	-14.00 [b]	-22.07 [a]	-15.25 [a]	-56.46 [a]	**-17.76** [a]
Q2	-6.52	3.32	-9.29 [b]	-0.40	6.54 [a]	-0.04	1.83	0.48	**-0.54**
Q3	5.86 [a]	9.68 [a]	9.45 [a]	7.22 [a]	-10.34 [a]	-0.90	-3.73	-7.94 [a]	**1.46**
Q4	0.42	2.21	11.13 [a]	6.62 [a]	5.71 [b]	5.46 [b]	-5.18	5.68	**3.95** [a]
Q5	10.48 [a]	9.66 [a]	8.48 [a]	9.61 [a]	-8.29 [b]	-2.10	-5.19	-2.72	**2.66** [b]

b) Portfolio rebalancing

To study the relation between the style or the investment horizon (assuming that this correspond to funds that trade less or more frequently) and the herding levels, we divided the sample in quintiles formed on the basis of the degree of portfolio rebalancing. To proxy the degree of rebalancing, we computed for the period analized the most frequent and least frequent rebalancing mutual funds.

Once again taking off the extreme negative values as happened with Theriou *et al*. (2011), we find that the levels of herding computed for subgroups of funds are again smaller than that observed for the overall sample, suggesting that the level of herding is lower among funds with similar trading patterns. Despite that, the results shown in table 8, suggests a relation between the level of herding and the degree of rebalancing: herds seem to be formed with funds with the same trading strategies, at least in relation to the more frequent portfolio rebalancing. The evidence presented here apparently supports an informational inefficiency based explanation, that would predict that funds with lower investment horizons, exhibit higher levels of herding.

Tabela 8 - Portfolio rebalancing

The table reports the Lakonishok et al. (1992) herding measure in percentage terms for a sample of 37 portuguese mutual funds segregated by portfolio rebalancing. Portfolio rebalancing is measured by total variation of assets under management and each quintile is formed on the basis of the total variation of assets during the analized period. The herding statistic for a given stock-quarter is defined as |p(i,t)-p(t)|-E|p(i,t)-p(t)| , where p(i,t) is the proportion of funds trading stock i during quarter t that are buyers and p(t) is the average of p(i,t) over all stocks i in quarter t. E|p(i,t)-p(t)| is the adjustment factor calculated using a binomial distribution under the hypothesis of no herding.The herding measures |p(i,t)-p(t)|-E|p(i,t)-p(t)| are averaged separately over stock-quarters belonging to diferente portfolio rebalancing quintiles. The funds of the sample were divided R times into 5 with a remainder of S. Then the qth quintile contains R observations, except the third quintile which contains R+S observations. We impose no minimum requirement on the number of funds trading a stock in each period. The herding measures are computed in each stock-quarter and then averaged over the constituents of each group. Q1 is the quintile composed by the funds with less frequent portfolio rebalacing and Q5 is the quintile composed by the funds with more frequent portfolio rebalancing. [a] indicates statistically significance at the 1 percent level; [b] indicates statistically significant at the significance of 5 percent level.

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
Q1	-72.69[a]	-82.22[a]	-90.40[a]	-64.65[a]	-62.22[a]	-43.31[a]	-35.45[b]	-41.51[a]	**-62**[a]
Q2	-54.16[a]	-50.99[a]	-20.89[b]	-18.69[b]	-19.43[a]	-9.29[b]	-22.59[b]	-61.11[a]	**-31.99**[a]
Q3	-1.00	-8.77[b]	-12.42[a]	-3.74	3.38	-3.20	3.19	0.79	**-2.86**[b]
Q4	9.52[a]	14.25[a]	8.07[a]	11.32[a]	5.45[b]	-1.15	-2.88	-0.55	**5.94**[a]
Q5	14.84[a]	16.27[a]	16.92[a]	16.06[a]	11.40[a]	12.71[a]	7.17[a]	9.46[a]	**13.39**[a]

4.2. Sias measure

Despite the impossibility to distinguish between traders that follow their own trades and traders that follow the trades of other mutual funds, we were able to see that the overall level o herding using the Sias measure is higher than the LSV measure, being 20.05% (See table 9). This difference between methodologies is consistent with the results found by Kremer *et al.* (2013), where he also found higher levels of herding using the Sias measure, when compared to the LSV measure.

The result is different from the one obtained in the study conducted by Holmes *et al.* (2013) where the levels of herding was 4.24% but is similar to the results obtained with both daily (18.01%) and quarterly (20.32%) data in the study conducted by Kremer *et al.* (2013) and to the results obtained by Puckett *et al.* (2008), 40.4%, when he analyzed the existence and impact of short-term institutional herding in the US market between 1994 to 2004, using weekly data.

The difference in the results from the studies conducted in the portuguese market might come from the fact that the data used by Holmes *et al.* (2013) is from the period between 1998 - 2005, before the subprime crisis, and the data used in this study is between 2006 - 2013, including the period during and after the crisis.

Tabela 9 - Sias measure

This table reports the results, in percentage terms, from the equation:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}$$

For each security and month between January 2006 and September 2013 we calculate the fraction of funds that changed their position in a certain security. All data are standardised (i.e. rescaled to zero mean, unit variance) each month. We estimate monthly cross-sectional regressions of institutional demand on lagged institutional demand. Because there is a single independent variable in each regression and the data are standardised, these regression coefficients are also the cross-sectional correlations between institutional demand and lagged institutional demand. [a] *indicates statistically significance at the 1 percent level;* [b] *indicates statistically significant at the significance of 5 percent level.*

	2006	2007	2008	2009	2010	2011	2012	2013	**2006-2013**
Average Coefficient (β)	19.19 [b]	18.70 [a]	5.58	11.96	19.05 [a]	21.76 [a]	32.57 [a]	35.36 [a]	**20.05** [a]

5. Conclusion

In this dissertation we investigate herding in the portuguese stock market, between the period of 2006 - 2013, using monthly data from the portuguese mutual funds portfolio holdings. We find clear evidence of herding taking place during the period analyzed.

The growth of the portuguese mutual funds was huge until 2008, period when the value of the net assets under management (NAUM) suffered a big decline (20.410 million euros to 6.030 million in 2012). Nevertheless, from that period of decline forward, the tendency has been of growth, with the NAUM increasing from 6.030 million in 2012 to 8.391,4 millions in 2015. This means that the influence of the mutal funds is again increasingly important, which is a central aspect because if mutual funds are not influent, the herding between them will not have the ability to destabilize price and to contribute to the inefficiencies of the market.

Trought the observation of the overall level of herding we can see that the levels are high and, when compared with previous studies in the portuguese market like Lobão and Serra (2007) and Holmes *et al.* (2013), we can say that the herding level have increased. This result is confirmed by both Sias and LSV methodologies.

The maturity of the market seems to be relevant once when using the LSV measure, the herding levels in smaller, more concentrated markets like the portuguese (Lobão and Serra, 2007), the Polish market (Voronkova *et al.*, 2005) and the Finnish market (Do *et al.,* 2006) are significantly higher than in more mature markets like in the German (Walter *et al.*, 2006), in the French (Arouri *et al.*, 2013), in the US (Lakonishok *et al.*, 1992 and Wermers, 1999) and in the UK market (Wylie (2005)).

In this study the relation between market return and herding was nonexistent for less traded stocks in each quarter but, we could say that, for the most traded stocks in each quarter, when markets are doing good there seems to be less herding and when markets are doing bad there seems to be more herding which might suggest a connection to the informational cascade theory.

In relation to volatility, this study can’t establish any connection either for the less traded or for the most traded stocks in each quarter, once the medium volatility subgroup is always the one with higher herding levels. This information suggest that volatility might not be an important factor when related to herding. Holmes *et al*. (2013) reached a similar conclusion.

In relation to the characteristics of the mutual funds and their relation to the herding levels, despite the fragilities of the methodology, it was not established a relevant connection between the level of herding and the market size. Regarding the portfolio rebalancing, herds seem to be formed with funds with the same trading strategies, at least in relation to the more frequent portfolio rebalancing.

The difference in the levels of herding between markets with different maturity levels, the fact that herds seem to be formed with funds of different size, the fact that when markets are doing good there is less herding and when markets are doing bad there is more herding for the most traded stocks in each period, as a whole, our results are consistent with the implications of the informational cascades theory. The herding between funds with similar trading strategies might also suggest an informational inefficiency based explanation.

Solved in this dissertation the time restraint present in the majority of the previous studies where the data used was almost always quarterly or semi-annual, for future research dissertations in this topic I would suggest to complete the Sias measure for the overall level of herding, by distinguishing between the funds who follow their own trades and the funds who follow the trades of others. I would also recommend to use the Sias measure to analyse the relation between herding and the market conditions and the fund specific characteristics. This way, a more complete analysis would be conducted, and that would allow to surpass the limitations of the LSV measure that influenced some of the results here presented, thing that I was not able to do due to time restraints.

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Appendix

Appendix 1 - Funds in the sample

Fund	Asset Management Company
ALVES RIBEIRO - MÉDIAS EMPRESAS PORTUGAL - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES	Invest Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BANIF ACÇÕES PORTUGAL - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES NACIONAIS	Banif Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BANIF IBÉRIA - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO FLEXÍVEL	Banif Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BANIF PPA - FUNDO DE POUPANÇA EM ACÇÕES	Banif Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BPI ALTERNATIVE FUND: IBERIAN EQUITIES LONG/SHORT FUND - FUNDO ESPECIAL DE INVESTIMENTO ABERTO	BPI Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BPI IBÉRIA - FUNDO DE INVESTIMENTO ABERTO DE ACÇÕES	BPI Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BPI PORTUGAL - FUNDO DE INVESTIMENTO ABERTO DE ACÇÕES	BPI Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
BPI POUPANÇA ACÇÕES (PPA) - FUNDO DE INVESTIMENTO ABERTO	BPI Gestão de Activos - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
CAIXAGEST ACÇÕES PORTUGAL - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES	Caixagest - Técnicas de Gestão de Fundos, SA
CAIXAGEST PPA - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE POUPANÇA EM ACÇÕES	Caixagest - Técnicas de Gestão de Fundos, SA
CARREGOSA TECHNICAL TRADING - FUNDO ESPECIAL DE INVESTIMENTO ABERTO NÃO HARMONIZADO	Optimize Investment Partners - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
ESPÍRITO SANTO RENDIMENTO DINÂMICO - FUNDO ESPECIAL DE INVESTIMENTO ABERTO	GNB - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO BARCLAYS FPA	Barclays Wealth Managers Portugal - SGFIM, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO BARCLAYS PREMIER ACÇÕES PORTUGAL	Barclays Wealth Managers Portugal - SGFIM, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO BBVA PPA ÍNDICE PSI20	BBVA Fundos - Sociedade Gestora de Fundos de Pensões, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO OREY ACÇÕES EUROPA	Orey Financial - Instituição Financeira de Crédito, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO POUPANÇA ACÇÕES SANTANDER PPA	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO RAIZ POUPANÇA ACÇÕES	Crédito Agrícola Gest - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO SANTANDER ACÇÕES EUROPA	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA
FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO SANTANDER ACÇÕES PORTUGAL	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA
IMGA ACÇÕES PORTUGAL - FUNDO DE INVESTIMENTO ABERTO DE ACÇÕES NACIONAIS	IM Gestão de Ativos - Sociedade Gestora de Fundos de Investimento, SA
MILLENNIUM PPA - FUNDO DE INVESTIMENTO ABERTO POUPANÇA EM ACÇÕES	IM Gestão de Ativos - Sociedade Gestora de Fundos de Investimento, SA
MONTEPIO ACÇÕES - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
MONTEPIO CAPITAL - FUNDO DE INVESTIMENTO ABERTO DE ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
MONTEPIO EURO ENERGY - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
MONTEPIO EURO TELCOS - FUNDO DE INVESTIMENTO MOBILIÁRIO EM ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
MONTEPIO EURO UTILITIES - FUNDO DE INVESTIMENTO MOBILIÁRIO EM ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
NB PLANO DINÂMICO - FUNDO DE INVESTIMENTO ABERTO FLEXÍVEL	GNB - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
NB PREMIUM - FUNDO ESPECIAL DE INVESTIMENTO ABERTO	GNB - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
NOVO BANCO ACÇÕES - PPA - FUNDO DE INVESTIMENTO ABERTO DE POUPANÇA ACÇÕES	GNB - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
NOVO BANCO PORTUGAL ACÇÕES - FUNDO DE INVESTIMENTO ABERTO DE ACÇÕES NACIONAIS	GNB - Sociedade Gestora de Fundos de Investimento Mobiliário, SA
POPULAR PPA - POUPANÇA ACÇÕES, FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO	Popular Gestão de Activos - Sociedade Gestora Fundos Investimento, SA
POSTAL ACÇÕES - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO DE ACÇÕES	Caixagest - Técnicas de Gestão de Fundos, SA
PPA MONTEPIO - FUNDO DE POUPANÇA EM ACÇÕES	Montepio Gestão de Activos - Sociedade Gestora de Fundos de Investimento, SA
SANTANDER GESTÃO PREMIUM VALOR ACÇÕES - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO HARMONIZADO MISTO DE ACÇÕES	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA
SANTANDER GESTÃO PRIVATE ACÇÕES - FUNDO DE INVESTIMENTO MOBILIÁRIO ABERTO HARMONIZADO MISTO DE ACÇÕES	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA
SANTANDER SELECÇÃO ACÇÕES - FUNDO ESPECIAL DE INVESTIMENTO ABERTO	Santander Asset Management - Sociedade Gestora Fundos Investimento Mobiliário, SA