



# **Herding around the world: Do cultural differences influence investors' behavior?**

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## **Biographic Note**

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## **Abstract**

Over the last years, there has been an increase of interest in exploring the behavioral field of finance, in order to understand better investors' decisions in the market. This happens because models currently used are not very accurate to predict and explain investors' decisions.

More recently, researchers started to consider cultural factors in the explanation of some decision-making processes of different agents, including investors. There are studies that explain momentum, M&A and other financial phenomena through a cultural approach. However, the number of existing studies regarding the subject is really small.

In our work we intend to test the impact of cultural differences on herding in 39 countries between 2001-2013, using the measure proposed by Chang *et al.* (2000) and Hofstede's (2001) five cultural dimensions. The purpose is to give a further insight on the relevance of culture in financial decision-making, pursuing a cultural approach to explain differences in the intensity of herding in distinct financial markets, since there is not, of our knowledge, any study that relates herd behavior with culture.

Our results show that cultural dimensions have influence on the imitative investors' behavior, finding that masculinity and power distance have an inverse relationship with herd behavior. The results for individualism and uncertainty avoidance are only significant when we use a less stringent method for standard deviations and they suggest a negative relationship between individualism and herding and a positive relationship between uncertainty avoidance and herding. Long-term orientation is not statistically significant. For the dimensions that were significant, our results for masculinity corresponded to what we expected. Regarding power distance, our expectation was ambiguous, being the results coincident with an association of power distance with cooperation and harmony values. Furthermore, we conclude that the contribution of each cultural dimension to the decision to act in a crowd is different if we consider the period before the crisis and the period of crisis.

**JEL Codes:** D70; G02; G14; G15; Z10

**Keywords:** Herding; Cultural dimensions; Cross-country analysis

## **Resumo**

Ao longo dos últimos anos tem-se verificado um interesse crescente pela área das Finanças Comportamentais, no sentido de perceber melhor como os investidores tomam efetivamente as suas decisões. Isto ocorre porque os modelos utilizados atualmente não conseguem explicar os comportamentos adotados pelos investidores.

Mais recentemente, é possível encontrar estudos que incorporam os fatores culturais nos processos de tomada de decisão, focando-se essencialmente na explicação do momentum, de fusões e aquisições e outros fenómenos financeiros. No entanto, o número de estudos existentes referentes a este tema é ainda muito escasso.

Com o nosso trabalho, pretendemos testar o impacto das diferenças culturais no comportamento de herding em 39 países no período de 2001-2013, utilizando a medida de Chang *et al.* (2000) e as cinco dimensões culturais de Hofstede (2001). O objetivo é destacar a influência das diferenças culturais no processo de tomada de decisão, utilizando uma abordagem cultural para explicar a existência e diferentes intensidades de herding nos vários mercados, já que não existe nenhum estudo, que seja do nosso conhecimento, que inclua uma análise cultural no comportamento de herding.

Os nossos resultados sugerem que a cultura é relevante para perceber o fenómeno do herding, tendo as dimensões da masculinidade e da distância hierárquica uma relação inversa com o herding. Os resultados para o individualismo e controlo pela incerteza apenas são significativos quando utilizamos um método menos restrito ao nível dos desvios-padrão, sendo que a primeira dimensão apresenta uma relação positiva com o herding, enquanto que a segunda apresenta uma relação negativa. Os resultados para a dimensão da orientação de longo-prazo não são estatisticamente significativos.

Concluimos também que a análise do impacto da cultura no comportamento de herding varia consoante o período analisado (antes da crise e durante a crise).

**Códigos JEL:** D70; G02; G14; G15; Z10

**Palavras-chave:** Herding; Dimensões culturais; Análise cross-country



## 1. Introduction

The relevance of studying investors' behavior has increased over the last few decades, concerning especially the when and how behavioral patterns impact stock prices (Blasco *et al.*, 2012). This happens because sometimes the models currently used fail to explain some phenomena in financial markets (e.g. bubbles), leading us to the need of considering the contributions of behavioral finance to try to understand how investors really make their decisions and the impact of those decisions on stock prices.

In fact, the 90's were marked by several financial crises worldwide that warned economists for the fragility of the financial system and the behavioral component that may be associated with such episodes. Empirical studies argue that, although fundamentals help to predict the occurrence of crises, the fact is that it is possible for a country with solid macroeconomic indicators to be hit by a crisis or for a country with weak fundamentals never to suffer from a crisis (Cipriani and Guarino, 2008). This idea was also explored by Fenz and Pelzman (2012), highlighting that traditional theories are not able to fully explain or predict trends in financial markets and, since economy is a social science, we have to consider both social and psychological forces underlying investors' behavior. This clearly prompts the question if financial decisions are made in accordance with traditional models, or if investors suffer from psychological biases and are prone to social interactions that make behavioral considerations relevant.

The behavioral component of decision-making process is easily understandable if we think of our daily life. Every day we make decisions that we can hardly classify as entirely of our own. For example, when we want to choose a restaurant, we are probably influenced by others' opinion (e.g. through friends that already visited the restaurant or customer reviews) or tend to choose the restaurant that everybody goes. Indeed, we are prone to psychological biases and social interactions that may lead us to adopt a different choice from what is deemed "rational". In the same way, we can say that an investor does not make decisions based on his information exclusively and what would be his optimal choice, but also considers what other investors are doing in the market.

In fact, according to Fenz and Pelzmann (2012), we can see that investors buy and sell stocks in reaction to the buy and sell decisions made by other investors and

their recommendations. This is reinforced in the studies of Shiller and Pound (1989), Hong *et al.* (2004) and Hong *et al.* (2005) that conclude investors find a market to be more attractive if their peers also participate. The idea that social interaction influences investors' decisions is shown in Hong *et al.* (2004), who concluded that market participation is related to the word-of-mouth phenomenon and the enjoyment people get from conversations with friends about market movements. Also, Hong *et al.* (2005) realized that investors from the same city tend to trade the same stocks rather than those traded by managers from a different city, since they are more prone to direct contact with one another, leading them to exchange ideas among them. Finally, Shiller and Pound (1989) analysed individual and institutional investors through a survey and reached the conclusion that both of them get interested in a stock because they are stimulated by another person and not by reading about the stock alone.

Since individuals take into account others' opinion, it is important to analyse a collective behavior, called herding, that may emerge in financial markets. The relevance of this phenomenon, where people act in a crowd, is related to the ability it has to explain variability in the returns, due to price alterations that imply prices to deviate from fundamentals (Christie and Huang, 1995).

On the other hand, it is important to notice that investors' behavior and their social interactions are also dependent on the country they live in, because they have different cultural backgrounds that impact their view of the reality. In that sense, Stulz and Williamson (2003) alerted that if individuals are prone to psychological biases that influence their financial decisions, it is almost inevitable that their views of the world, as determined by culture, play a role in how they act in financial markets. Chang and Noorbaksh (2009) noted as well that recent literature has been paying more attention to social and cultural environments to study effectively economic phenomena.

Consequently, although investors' decisions should reflect capital market theories and optimal portfolio allocation that are globally uniform, we have to consider country-specific differences that may be related with cultural influences on individuals' behavior (Beckmann *et al.*, 2008).

Even with the recognition that culture can potentially impact investors' decisions we cannot find many studies incorporating culture in finance and, there is not any of our knowledge that explains herding through cultural differences among countries. So, we

try to fill this gap in literature, testing if the herd behavior observed in financial markets varies with cultural dimensions.

Hence, our main purpose is to understand the behavioral differences in financial markets across the globe, focusing on the influence of culture on herd behavior, analysing this phenomenon in 39 countries. For that we use the measure of herding proposed by Chang *et al.* (2000), perceiving that way how investors really make their decisions in financial markets and not focusing on what they should ideally do. Also, we confront the existence and intensity of herding with cultural differences, applying Hofstede's five cultural dimensions (2001) to observe if national culture affects investors' behavior and in what way. We will essentially focus on the cultural approach since there is already a vast literature regarding herd behavior.

The dissertation is structured as follows. In section 2 we have a brief literature review concerning herding and culture, where we summarize the main previous empirical studies on herd behavior, capturing different countries, periods and measures of herding, and present the cultural dimensions we use, as well as its criticisms. Also, we expose some of the empirical studies made so far that relate financial phenomena with cultural differences. We proceed in section 3 with the formulation of hypothesis regarding the impact cultural dimensions may have on herd behavior, as well as data concerning stock market, cultural dimensions and determinants of herding. We also present in this section the methodology employed to measure herding and to test the influence of the cultural dimensions on herding. The results are shown in section 4, where we discuss the impact that the determinants of herding and, most importantly, cultural dimensions have on herd behavior. Also, we give some insight of the consequences the results obtained can have in management, political decisions and financial markets. In section 5 we conclude, pointing some limitations of our study and suggesting further research on the subject.

## 2. Literature Review

Nowadays, the capital market theory about risk and return studied by Fama (1970) and the theory of having a diversified portfolio studied by Markowitz (1952) are worldwide taught, however, if we look at the anomalies that occur in financial markets, we can observe that their magnitude and frequency are too significant to be ignored. For instance, Jegadeesh and Titman (1993, 2001) realized that momentum profits are around 12% a year in the United States and Rouwenhorst (1998) reached the same conclusion when analysed 12 European countries. Also, De Bondt and Thaler (1985) noticed that on the long-run tends to exist a mean-reversion effect, concluding that a losing portfolio outperforms a winner portfolio by approximately 8% per year. Both momentum and mean-reversion effects (as well as other phenomena observable in financial markets) are unlikely to be explained only by traditional risk-based theories.

In fact, we can recently observe an increase in behavioral finance literature concerning the anomalies that happen in financial markets and the reasons behind them, focusing on psychological forces that make individuals to act differently from what traditional models predict. This makes sense because, like Baruch (1957) (*cfr* Mohacsy and Lefer, 2007) referred, “above all...stock market is people. It is people trying to read the future”, so we have to consider in our studies about financial markets the human component that reflects conflicting judgments made by investors.

In particular, in this behavioral literature we can find several studies related to herd behavior, which is the phenomenon we want to analyse, since it may explain bubbles and similar extreme situations. However, available literature focus more in the existence of herding in one particular market (e.g. Christie and Huang, 1995; Lobão and Serra, 2006; Goodfellow *et al.*, 2009; Tessaromatis and Thomas, 2009; Patro and Kanagaraj, 2012) or, in a fewer number, even in the comparison between markets around the world (e.g. Chang *et al.*, 2000; Chiang and Zheng, 2010; Economou *et al.*, 2011; Lindhe, 2012), but without a cross-country analysis focusing on country-specific factors, like culture, that can impact investors' decision-making.

We begin our literature review with the definition of herding and the possible causes for that phenomenon (both rational and irrational). Then, we present some existing empirical studies on herd behavior covering different markets, methodologies and

periods. We proceed with the definition of culture and explanation of the cultural dimensions to be employed in this study, as well as the main criticisms around them. We finish our literature review with the empirical studies made so far that include culture in financial decision-making.

## **2.1 Herding**

During a crisis, “herd behavior” has a negative connotation in financial lexicon, being associated with a type of behavior that exacerbates volatility, destabilizes markets and increases the fragility of the financial system (Bikhchandani and Sharma, 2001).

Considering this, we should first of all clarify the meaning of herding. Herd behavior consists in investors’ mutual imitation and, according to Christie and Huang (1995), implies individuals to suppress their own beliefs and follow what others are doing, basing their investment decisions on collective actions of the market, even when they disagree with its predictions. This suggests that investors are attracted to market consensus and individual returns tend to approach market return. In the words of Banerjee (1992), herding simply consists in “everybody doing what everyone else is doing even when their private information suggests doing something else”, which leads to a convergence of action in the market.

One of the most claimed examples of herding is given by Keynes (1936), that compared investors’ behavior in financial markets to the behavior of judges in a beauty contest, where the decision of a judge is based on what he expects others will choose and not on who he actually thinks is the most beautiful. Shiller (2005) stated that the explanation for people to act in the same way is partly related with their reaction to the same public available information, but he also admitted that this cannot be the only reason. Taking this into account, we may be led to think of herding as an irrational behavior where an investor simply follows the others in the market blindly. However, as mentioned by Tversky and Kahnemann (1986), reactions induced by psychological and behavioral traits can also be consistent with rational decision-making. Thus, it is important to understand the reasons behind such behavior.

According to Devenow and Welch (1996), there are two polar views of herding: irrational and rational. The irrational view is related to psychology, implying investors

to follow one another blindly and the rational view is related to optimal decision-making being distorted by information difficulties or incentive issues.

Considering the rational view, one of the explanations is the information-based herding, which was initially developed by Banerjee (1992), Bikhchandani *et al.* (1992) and Welch (1992). According to this explanation, the decisions are made sequentially, so an investor observes the actions made by other investors and infer that they have relevant information, thus incorporating that information in his decision-making. This is more prone to happen when costs of acquiring information in the market are high, because in this case people tend to not incur in such costs and trust other's decisions, assuming that they have more information. Bikhchandani and Sharma (2001) demonstrated this situation through a sequential game, where the investor that is currently deciding has access to his own information and he is able to observe the actions that the other investors in the market made before. Although he is not able to see the private information that other investors have, he believes that their actions reflect some relevant information. So, if the number of predecessors who made a certain decision is higher by two or more than the number of predecessors that made the opposite one, he will ignore his private information and decide according to his predecessors. This will cause a formation of what is called an informational cascade, where the actions observed do not reflect private information anymore, leading all investors that decide after to act in accordance with their predecessors. Consequently, if the number of investors choosing the same action is high, the following investors will not reflect their private information in their decisions and will imitate their predecessors.

Another explanation for this phenomenon has to do with principal-agent relationship. Usually the manager and the owner of a fund are different people, so the manager has an incentive to gain or maintain his reputation in order to have a good evaluation. According to Bikhchandani and Sharma (2001), if the manager is not sure about his ability, he prefers to follow what others are doing in the market in order to maintain his reputation. The authors argued that is safer for the manager to have this behavior because if their decision turns out to be the right one, he will be seen as a good manager, and if their decision proves to be the wrong one, he will not lose his reputation since that outcome is attributed to bad luck (and not to the fact of being a bad manager,

because it is almost impossible that nobody got the right information). Keynes (1936) summarized reputational incentives to herd affirming that “it is better for reputation to fail conventionally than to succeed unconventionally”. Ohlson (2010) also followed the same idea referring that investors have an incentive to stand out from the crowd doing the opposite thing that others are doing, however the benefit they will obtain for being the only ones to be right is not as great as the risk of being the only ones to be wrong.

The first reputational model of herding was developed by Scharfstein and Stein (1990). In their model they considered two different kinds of managers (the “smart” ones that receive informative signals and the “dumb” ones that only receive noise signals), where the manager with lower aptitude (“dumb”) mimics the manager with higher aptitude (“smart”), regardless of his own signal, in order to be seen as a high ability manager. But their results predicted that even “smart” managers would have incentive to herd. That happens because a bad investment decision only reveals the manager’s poor quality if the rest of the managers make a different investment (if everyone made the same bad decision it is suggested that it was due to a poor investment climate). Then, if enough “dumb” managers herd on a bad decision, even “smart” managers would prefer to herd instead of taking the risk with an investment they believe to be superior.

The last cause of rational herding is related to the compensation that the investor will get. If his compensation is related to the comparison made between his performance and the performance of the market, he will have incentives to imitate other investors (Bikhchandani and Sharma, 2001).

Although we can find theoretical grounding to justify the existence of herding, to prove it empirically is a difficult task because it consists in correlations in investors’ behavior. Since we cannot access their private information, when we observe investors trading in the same direction, we do not know if they are imitating others or if they just had access to the same information (this is known as “spurious herding”) However, if the decision that everyone made in the market turned out to be the wrong one, we can say that investors imitated each other, because it does not seem very plausible that no one received the correct signal (Effinger and Polborn, 2001).

## 2.2. Prior empirical studies of herding

Empirically, we can find several studies concerning herd behavior that span different periods and markets from diverse geographical areas and with different development levels. The authors that analysed this phenomenon opted to employ different measures of herding, being the measures of Lakonishok *et al.* (1992), of Christie and Huang (1995) and of Chang *et al.* (2000) the most used ones.

The measure of Lakonishok *et al.* (1992) explores whether managers tend to end up trading in the same side of the market in a given stock, observing if there is a disproportionate number of managers buying or selling a specific stock. The measure of Christie and Huang (1995) consists on the cross-sectional standard deviation of returns (CSSD). The measure of Chang *et al.* (2000) is a variant of Christie and Huang's (1995) measure, but instead it considers the cross-sectional absolute deviation of returns (CSAD).

We expose the empirical studies presenting, in first place, the studies that consider a single market and, in second place, the studies that cover multiple markets. In each division, the studies are shown chronologically.

Among the authors that studied a single market are Lakonishok *et al.* (1992), who analysed the institutional investors in the United States from 1985 to 1989, but did not find any evidence of herding. Grinblatt *et al.* (1995), on the other hand, studied the existence of herd behavior in mutual funds in the United States from 1975 to 1984, using the measure proposed by Lakonishok *et al.* (1992), and found evidence of herding. Another authors that analysed the United States market were Christie and Huang (1995), that tested the existence of the phenomenon from 1925 to 1988 and found that there was no evidence of herding, being the empirical results consistent with the predictions from rational models. Also, Nofsinger and Sias (1999) found evidence of herding in the United States between 1977 and 1996, using a measure that captures the relation between changes in institutional ownership and returns over the herding interval (period of time where a group of investors buy or sell the same stock).

Although the US market is the most analysed one, we can find examples of studies from other countries around the world. For instance, Caparelli *et al.* (2004) found evidence of herding in Italian market from 1988 to 2001, using the measure



proposed by Christie and Huang (1995). Also, Lobão and Serra (2006) tested the presence of herd behavior in Portuguese mutual funds from 1998 to 2000 and used the measure from Lakonishok *et al.* (1992). They found a strong evidence of herding that is 4 or 5 times higher than the evidence found in more mature markets. Kallinterakis and Ferreira (2006) studied Portuguese market as well but did not focus on mutual funds. They used the data available from PSI-20 and the measure proposed by Hwang and Salmon (2004) to test the existence of herding in the period 1993-2005 and found higher evidence from 1996 to 1999.

Besides the works already mentioned, we can also refer to the one of Demirer and Kutan (2006), that tested the existence of herding in the Chinese market, applying the measure of Christie and Huang (1995) to the data from individual firms (1999-2002), Shanghai Stock Exchange (1993-2001) and Shenze Stock Exchange (1994-2001). They did not find evidence of herding, suggesting that the Chinese investors make rational decisions. Also, Manganaro and Von Martens (2007) studied herding for mutual funds in Sweden between 2000 and 2007, using the measure from Lakonishok *et al.* (1992). They found that there was a strong evidence of herd behavior when compared to more mature markets (e.g. United States and United Kingdom) but less evidence than that of we could verify in emerging markets. In their empirical results, if 100 funds trade a given stock, approximately 7 more funds trade on the same side of the market than what should be expected if their choice was made independently.

Furthermore, Goodfellow *et al.* (2009) studied the existence of herding in Poland during the period from 1996 and 2000 and found evidence of this behavior only for individual investors (and not for institutional investors). Tessaromatis and Thomas (2009) tested if herding was present in the Greek market between 1985 and 2004. For that they relied on the measure from Christie and Huang (1995), but did not find evidence of this behavior when they considered the period as a whole. However, when they considered the sub period from 1998 to 2003 the existence of herding began to gain relevance. Ohlson (2010) studied the herd behavior in Swedish market using the measures proposed by Christie and Huang (1995) and Chang *et al.* (2000). He found evidence of herding from 1998 to 2009, being this behavior more intense during the bullish market of 2005 and 2007. He concluded that there is a tendency of increasing levels of herding over the measured period, which can be attributed to the increase of

institutional investors that tend to be less experienced and are thus more prone to herd. Finally, Patro and Kanagaraj (2012) proved the existence of herd behavior in Indian mutual funds between 2009 and 2011, applying the measure proposed by Lakonishok *et al.* (1992).

Despite the existing studies focus more in a single market, we can find some studies that test this phenomenon for more than one market. For example, Chang *et al.* (2000) verified if herding was observable in the United States, Hong Kong, Japan, South Korea and Taiwan from 1963 to 1997. They found evidence of herd behavior for South Korea and Taiwan, partial evidence for Japan and no evidence for the United States and Hong Kong. Furthermore, Economou *et al.* (2011) used daily data from 1998 to 2008 to analyse if herding was observable in Portugal, Italy, Greece and Spain, employing the measure proposed by Chang *et al.* (2000). Their results showed evidence of herding for Greece and Italy, being this behavior stronger in bull markets. As for Portugal, they were able to find some evidence of herd behavior only for bear markets and the results obtained for Spain showed that Spanish investors behave consistently with the predictions from rational models. When the authors analysed only the period of the financial crisis (2008), they could find herding in Portugal exclusively. Also, Khan *et al.* (2011) tested the presence of herding in four European markets (France, Germany, Italy and United Kingdom) from 2003 to 2008. They resorted to the measure proposed by Hwang and Salmon (2004) and found evidence of herd behavior for all of them. Finally, Lindhe (2012) studied herd behavior in four Nordic countries (Denmark, Finland, Norway and Sweden) during the period 2001-2012, using the measure of Chiang and Zheng (2010), which is based on the measure of Chang *et al.* (2000). She only found evidence of herding in Finland. Although she was not able to find evidence of herding in the other countries in their own market, she showed that Finland and Sweden herd around the US market and all of them herd around the European market and around each other.

We can observe that, empirically, there is mixed evidence whether herding is detected in financial markets or not. Some authors found evidence (some of them a strong evidence) of herding and some authors did not find evidence at all. In sum, there is no consensus regarding the presence of herding in financial markets around the world since we can find evidence that supports its existence and evidence that contradicts it.

However, it seems to be observable that less mature markets tend to exhibit more herding than mature markets and, according to Ohlson (2010), this may be due to the increase of mutual funds in those countries being pretty recent when compared to more developed markets, which implies the managers of those funds to be more inexperienced and thus, have more tendency to follow the actions of other market participants (they are more afraid of being the only ones making the wrong investment decision than they value outperforming others).

The studies made so far about herding that we have just referred are summarized in Table 1, presented below.

**Table 1-** Summary of empirical studies on herding

ONE MARKET				
Author	Country analysed	Period analysed	Measure of herding	Evidence of herding
Lakonishok <i>et al.</i> (1992)	United States	1985-1989	Lakonishok <i>et al.</i> (1992)	No
Grinblatt <i>et al.</i> (1995)	United States	1975-1984	Lakonishok <i>et al.</i> (1992)	Yes
Christie and Huang (1995)	United States	1925-1988	Christie and Huang (1995)	No
Nofsinger and Sias (1999)	United States	1977-1996	Nofsinger and Sias (1999)	Yes
Caparelli <i>et al.</i> (2004)	Italy	1988-2001	Christie and Huang (1995)	Yes
Lobão and Serra (2006)	Portugal	1998-2000	Lakonishok <i>et al.</i> (1992)	Yes
Kallinterakis and Ferreira (2006)	Portugal	1993-2005	Hwang and Salmon (2004)	Yes
Demirer and Kutan (2006)	China	1993-2002	Christie and Huang (1995)	No
Manganaro and Von Martens (2007)	Sweden	2000-2007	Lakonishok <i>et al.</i> (1992)	Yes
Goodfellow <i>et al.</i> (2009)	Poland	1996-2000	Chang <i>et al.</i> (2000)	Yes
Ohlson (2010)	Sweden	1998-2009	Christie and Huang (1995) Chang <i>et al.</i> (2000)	Yes
Patro and Kanagaraj (2012)	India	2009-2011	Lakonishok <i>et al.</i> (1992)	Yes

MULTIPLE MARKETS				
Author	Countries analysed	Period analysed	Measure of herding	Evidence of herding
Chang <i>et al.</i> (2000)	United States, Hong Kong, South Korea and Japan	1963-1997	Chang <i>et al.</i> (2000)	Yes: South Korea, Taiwan and Japan No: United States and Hong Kong
Economou <i>et al.</i> (2011)	Portugal, Italy, Greece and Spain	1998-2008	Chang <i>et al.</i> (2000)	Yes: Greece, Italy and Portugal No: Spain
Khan <i>et al.</i> (2011)	France, Germany, Italy and United Kingdom	2003-2008	Hwang and Salmon (2004)	Yes
Lindhe (2012)	Denmark, Finland, Norway and Sweden	2001-2012	Chiang and Zheng (2010)	Yes: Finland No: Denmark, Norway and Sweden

### 2.3. Culture and Hofstede's cultural dimensions

From our point of view, if we want to study a phenomenon involving different countries, we must consider culture, because it influences every aspects in our life and all the theories we are able to develop to explain our practises. As Hofstede (1991) referred, nothing in our life escapes the influence of culture.

So, being the objective of our study to test the influence of cultural differences on herding, we begin by giving a definition of culture. There are several available ways in the literature to define this concept, but in our study we give more emphasis to Hofstede's (2001) definition, where he considered culture as a collective programming of the mind which is manifested in values and norms and reflected in rituals and symbols, referring to this as a "software of the mind" that is stable over time and imply people to consistently behave the same way when facing similar situations. Hsu *et al.* (2013) also stated that culture represents values acting in concert rather than individual

factors that affect behavior. In fact, interactions with individuals in society determine cultural values more than value differences attributed to personal characteristics, existing a societal value system shared by the dominant groups that allows the perseverance of institutions with persistent structures (e.g. family, school and law). These institutions reinforce this value system in a way that a member that not follows it will be rejected by society (Hofstede, 2001). Indeed, culture may not just impose constraints, but has the ability to structure and encourage certain behaviors (Di Maggio, 1997).

Considering the definition of culture, it seems to be an abstract concept difficult to quantify. However, over the years we can find some attempts to measure culture through a dimensionalist approach, where numerical scales and dimensions are developed to distinguish nations' cultures. They consist in large-scale surveys containing value-statements collected from individuals, being then averaged by country and formed quantitative cultural characteristics (Reuter, 2011).

The main dimensionalist approaches on culture are the ones of Schwartz (1994), Inglehart (1997), Hofstede (2001) and House *et al.* (2004), being Schwartz's and Hofstede's dimensions the most widely used in empirical studies. We will explain briefly each one of them.

Schwartz (1994) conducted a survey to students and teachers, in 38 countries, from 1988 to 1992. He reached three dimensions: mastery vs. harmony, egalitarianism vs. hierarchy and conservatism vs. autonomy. Inglehart (1997) used data from World Values Survey to study 43 countries from 1989 to 1991 and reached the conclusion that the major two dimensions capable of explaining cross-cultural variation were survival vs. self-expression and traditional vs. secular-rational. House *et al.* (2004) created the worldwide known Project GLOBE and their surveys were made to 17300 managers from 931 different organizations, in 62 countries, from 1994 to 1997. They reached the following nine dimensions: future orientation, gender equality, assertiveness, human orientation, in-group collectivism, institutional collectivism, performance orientation, power distance and uncertainty avoidance.

We next refer to Hofstede's (2001) dimensions in more detail, since these are the ones to employ in our study.

### *2.3.1. Hofstede's cultural dimensions*

In our study we use the dimensions proposed by Hofstede (2001). He worked as a psychologist for IBM, where he inquired employees in 50 different countries from 1965 to 1971, reaching five cultural dimensions.

The first dimension opposes individualism to collectivism, reflecting the degree to which a society emphasizes the role of the individual as opposed to that of the group. He argued that in individualistic societies the bonds between individuals are weak, while in collectivistic societies individuals tend to be integrated in strong and cohesive groups. So, he observed that people from countries characterized by individualism tend to be more autonomous and independent, usually give more weight to their individual opinion compared to the opinion of the group and value differences of opinion. According to Hirshleifer and Thakor (1992), in this kind of societies the priority of the agents is to care of their own interests, focusing on their own attributes and abilities to differentiate themselves from others. On the contrary, people from countries characterized by collectivism tend to be more dependent on the group and group opinions prevail to personal opinions. As Markus and Kitayama (1991, p. 227) noted, in collectivistic cultures individuals tend to view themselves “not as separate from the social context but as more connected and less differentiated from others”. In conclusion, the dichotomy on this dimension focuses on the degree of reinforcement of individual or collective achievements and interpersonal relationships.

The second dimension confronts masculinity and femininity and is linked to the social role that is attributed to each gender in a certain culture. The author realized that men are usually associated with values such as firmness, competitiveness and toughness, so they tend to be more ambitious, self-confident and like to be recognized by their own merit. On the other hand, women are normally associated with tender roles and values such as protection, generosity and concern with human relations, so they tend to be more cooperative and solidary.

The third dimension contrasts countries with high and low uncertainty avoidance, referring to the extent to which people are uncomfortable with uncertain and unknown situations. In order not to feel threatened by ambiguous situations, cultures characterized with high uncertainty avoidance try to minimize their occurrence having strict rules and safety measures, thus increasing predictability. On the contrary,

according to Park and Lemaire (2011), in countries scoring low on uncertainty avoidance, individuals tend to feel naturally secure, tolerate different behaviors and opinions more easily and avoid excessive regulation.

The fourth dimension compares countries with high and low power distance. This has to do with the acceptance degree of an unequal power distribution within a society, by those who have less power. The author argued that countries with high power distance tend to be more obedient and respectful for an authority, so in these societies independence is not encouraged and own initiative is not supported. On the opposite side, in countries with low power distance, he observed that individuals tend to have control of their own actions, make decisions by themselves, they are independent and are encouraged to have own initiative.

The fifth dimension confronts long-term orientation with short-term orientation. Countries long-term oriented value thrift, perseverance and adapting to changing circumstances, since they give more importance to future outcomes. That way, countries with long-term orientation promote stability (discourage initiative, risk-seeking and change) and perseverance towards late outcomes, while countries short-term oriented give more weight to immediate results, valuing more the past and present, such as traditions and fulfilling social obligations. According to Fernandez *et al.* (1997) this dimension appeared after Hofstede's work with Michael Bond (1988) and was created to overcome the need of having a new dimension that emanated from oriental culture rather than being a measure developed in occidental countries and applied elsewhere.

#### **2.4. Criticisms to Hofstede's dimensions and comparison with other dimensions**

In this subsection we present briefly the main cultural dimensions used in empirical studies, as well as the major criticisms pointed to Hofstede's dimensions. We also establish the parallel between Hofstede's cultural dimensions and other existing dimensions, then justifying the advantage of choosing the first ones.

#### 2.4.1. Criticisms to Hofstede's cultural dimensions

Everything in life has its pros and cons, so Hofstede's (2001) dimensions also have their supporters and their opponents. In that sense, before we apply his dimensions we have to be aware of the criticisms made to them.

Kirkman *et al.* (2006) considered, in the first place, that it is impossible to reduce something as complex as culture only to five dimensions. Besides that, they argued that a sample of a single multinational company is not representative of a whole nation, so the study is a bit limitative in that issue. McSweeney (2002) also focused on the unrepresentativeness of the sample, arguing that IBM workers face a selective recruitment by the company and cannot be illustrative of a national culture.

Kirkman *et al.* (2006) continued their criticisms affirming that Hofstede does not take into account heterogeneity within a country, not giving relevance to subcultures that may exist. In fact, his dimensions attempt to reflect the culture of a nation as if the individuals of a particular country were homogeneous and shared the same values.

Another criticism has to do with the way Hofstede's dimensions are derived. House *et al.* (2004) affirmed that the dimensions are empirically-driven, in which scales are determined only after the results of the survey. This technique has the problem of being biased by the influence of empirical results. On the other hand, the dimensions developed by these authors are theoretically-driven, thus not suffering from biases related to the person that interprets the results.

Finally, the authors criticized the fact that the study was made in 1960's and 1970's and does not consider cultural changes that may have occurred over the years, due to globalization, economic growth or migration. This criticism gained preponderance with McSweeney (2002) and Craig and Douglas (2006), who emphasized that the original culture of a nation changes as a result of globalization and the advance in communication technologies, since people travel to countries with different cultural backgrounds and interact with individuals that live in those countries, "contaminating" and modifying their culture. This phenomenon is known as acculturation (interactions between different cultures lead a society to absorb some cultural aspects from another society) and it seems very plausible to make some alterations in cultural variables. McDonagh (1999) also claimed that modernisation makes people more individualistic and Ralston *et al.* (1999) exemplified cultural change with Chinese managers, observing



that the new generation tends to be more individualistic and to work more independently.

Despite the criticism, Kirkman *et al.* (2006) and McSweeney (2002) recognized that Hofstede's dimensions continue to be the most used ones due to its clarity, simplicity and applicability. Also, Steenkamp (2001) acknowledged that, although there is no consensus upon the choice of the most appropriate dimensions to conceptualize and operationalize culture, Hofstede's framework is the most widely used in several fields of study (e.g. sociology, marketing and management). This is reinforced by Lynn and Gelb (1996), who argued that his dimensions have received extensive support because they are effectively able to capture cross-country differences.

Regarding cultural change that may occur over time, Kirkman *et al.* (2006) also admitted it is a slow process, so it is not very likely that drastic changes were observed since Hofstede's study. That happens because, according to Becker (1996) (*cf* Guiso *et al.*, 2006) individuals do not have much control over their culture, so it is considered has "given" to them, which leads to a great difficulty in changing culture. In fact, since the original study by Hofstede, there were other authors that tried to replicate his study in other contexts and in more recent years (e.g. Merrit, 2000) and supported Hofstede's results, indicating that his conclusions are still relevant nowadays. Hofstede (2011) affirmed that there were six major attempts of replicating and updating his dimensions (using at least 14 countries) from 1990 to 2002, in which were used managers and workers from other organizations besides IBM, pilots and consumers, and the results showed no weakening of the correlations. That does not mean that there were no cultural changes throughout the years, but these studies reveal that in case that happened, the countries suffered alterations in the same direction, so their relative position did not change (Hofstede, 2011).

As an example, we can consider Beugelsdijk and Frijns' (2010) study related to international asset allocation, in which they performed a robustness test where they tried to update Hofstede's dimensions through the proposal of Tang and Koveos (2008), reaching the conclusion that this update did not have any impact on their results.

Regarding the plausibility of the acculturation phenomenon, Hsu *et al.* (2013) argued that there is no empirical evidence capable of confirming this issue.

As for the criticism concerning the representativeness of the sample, Hofstede (2001) noted that there are more 140 studies using non-IBM data that validated his cultural indexes. Hofstede himself, after his IBM study, decided to survey 400 managers (non-IBM workers) from 30 different countries and concluded that there were high correlations between the answers of those workers and the ones given by IBM-workers, so it is possible to extrapolate the results obtained in the IBM study to other contexts (Hofstede, 2011). Also, studying a single organization allows him to isolate the cultural effect, being the only variable that differs from country to country.

Furthermore, considering the criticism related to Hofstede's dimensions being empirically-driven, House *et al.* (2004) argued that this kind of studies are only possible with a large sample and Hofstede's study (2001) actually fulfilled this request.

Finally, Arosa *et al.* (2014) observed that, even subject to criticism, Hofstede's cultural dimensions are widely used and accepted and no other existing study was able to develop a model that equals or exceeds the one of Hofstede in terms of sample size, methodology or degree of acceptance among academics.

In conclusion, although there are some criticisms around Hofstede's dimensions that we must take into account, our choice for his dimensions are justified by the widely acceptance and maintenance of countries' relative position proved in recent studies. Also, according to Soares *et al.* (2007), they are useful when we want to formulate hypothesis for comparative cross-cultural studies.

#### *2.4.2. Comparison with other cultural dimensions*

As we already mentioned, Hofstede's dimensions are not the only existing ones, but alongside with Schwartz's (1994) cultural dimensions, they are the most known. In our study we decided to use Hofstede's dimensions (choice that was already justified), however we still have to consider that there may be some similarities between Hofstede's dimensions and other cultural dimensions, so we need to make a comparison between them and evaluate if in fact, these are preferable or not.

According to Hsu *et al.* (2013) we can find some resemblances between Hofstede's dimensions and Schwartz's dimensions. First, power distance is similar to egalitarianism/hierarchy since both of them relate to authority orientation. Second, individualism/collectivism coincides with autonomy/conservatism because both of them

focus on the relationship between the individual and the group. Third, masculinity/femininity overlaps harmony/mastery in that it concerns the relationship between people and the social environment. Li *et al.* (2013) also highlight the existing high degree of correlations between Hofstede's and Schwartz's measures and Schwartz (2004) agreed that such similarities exist, but they only verify at some extent. In Steenkamp's (2001) opinion, there also appears to be some overlap between Hofstede's and Schwartz's values, however the ones from the last author include elements of culture that are not captured by Hofstede, being thus able to explain greater cultural variation. On the other hand, Ng *et al.* (2007) affirmed that the dimensions proposed by Hofstede and Schwartz are not coincident and it is preferable to use Schwartz's dimensions when we are considering international trade.

Although the dimensions developed by the two aforementioned authors are the most widely used, there are also other dimensions available and we will also establish a comparison with those dimensions.

Regarding Inglehart's (1997) dimensions, Hsu *et al.* (2013) noted that power distance is similar to traditional/secular and individualism/collectivism is coincident with survival/self-expression. House *et al.* (2004) also compared their own dimensions from Project GLOBE with Hofstede's dimensions and found some correlations in power distance, uncertainty avoidance and individualism (there were also some similarities between masculinity and assertiveness). Nevertheless, they considered that these correlations only have small importance, not being completely equal. Hofstede (2011) disagreed, stating that despite the different approach, GLOBE data reflect the structure of his model.

Considering the similarities aforementioned, we may be tempted to say that we could choose any of them to apply in our study, however Hsu *et al.* (2013) defended the use of Hofstede's dimensions, because after comparing the major cultural dimensions they concluded that Inglehart and Schwartz cover a relatively small number of cultural dimensions when compared to Hofstede's research. Soares *et al.* (2007) also supported the use of Hofstede's dimensions after concluding that there is a great convergence between the dimensions proposed by other authors and Hofstede's dimensions. On the other hand, Ng *et al.* (2007) stated that Schwartz's model overcomes some difficulties

of Hofstede's dimensions because it is derived theoretically, it uses a more comprehensive set of value dimensions and it is done with more recent data.

Consequently, despite the pitfalls mentioned, we think that Hofstede's cultural dimensions are the most appropriate for this study because they can isolate the cultural effect, cover a wide number of countries and are still valid nowadays.

## **2.5. Prior empirical studies of cultural finance**

In our study we want to test if culture has the ability to influence investors' behavior, so we need to know if, in fact, it matters for finance. According to Stulz and Williamson (2003) culture may affect finance in three different ways: first, economic values in a country depend on its culture (e.g. charging interest in a country can be considered normal while in other is viewed as a wrong thing); second, culture affects institutions (e.g. legal systems vary from country to country according to its values); third, culture influences the way economic resources are allocated (e.g. some countries spend more money in infrastructures while other prefer to spend more in guns). The idea of culture being able to impact institutions, playing a major role in the way laws and rules are developed, is also corroborated by Anderson *et al.* (2011), however they added that it is not just through legal and regulatory environments that culture impacts investors' behavior, it also impacts their behavior directly.

Considering this we should expect culture to be relevant for financial decision-making and so, it should be taken into account when we want to study financial phenomena. However, as Guiso *et al.* (2006) noted, culture has been ignored in the past in financial literature due to its ambiguity and difficulty to measure.

In fact, including culture in financial decision-making is a very recent field of investigation, however we can find some studies concerning this issue. For instance, Chui *et al.* (2010) studied the impact of individualism on momentum profits, concluding that in individualistic countries investors tend to be more overconfident, which leads them to trade more, generating momentum profits. Also, Ferris *et al.* (2013) associated Hofstede's dimensions with CEO overconfidence, concluding that overconfidence is positively related with individualism and negatively related to uncertainty avoidance and long-term orientation. So, CEOs in individualistic countries tend to underestimate

the risks underlying a merger or overestimate the possible synergy gains, which encourage them to engage in diversifying acquisitions.

Other examples focus on the cultural impact on risk-taking decisions. For example, Li *et al.* (2013) analysed the impact of culture on the level of risk managers are willing to take in 35 countries, using individualism, uncertainty avoidance and harmony (the first two belong to Hofstede's dimensions and the last one to Schwartz's dimensions). Their results showed that individualism is positively associated with risk-taking, while uncertainty avoidance and harmony are negatively related to risk-taking. Additionally, Mihet (2012) investigated the impact of culture on firm risk-taking in 51 countries and concluded that companies tend to assume a higher level of risk in societies characterized by low uncertainty avoidance, low power distance and high individualism. Furthermore, Chang and Noorbakhsh (2009) analysed corporate managers' cash holdings in 45 countries during 1995-2004, showing that Hofstede's cultural dimensions had an impact on their decisions, since corporate managers tend to hold larger cash and liquid balances in countries characterized with higher uncertainty avoidance, masculinity and long-term orientation.

Finally, there are also studies concerning international asset allocation, as the one made by Beugelsdijk and Frijns (2010) that provided a cultural explanation for the foreign bias through Hofstede's dimensions, examining the holdings of mutual funds from 26 countries between 1999 and 2000. The results demonstrated that investors from countries with high uncertainty avoidance tend to invest in the domestic market, because they are more risk-averse, and investors from individualistic countries tend to prefer foreign investment, because they expect a higher return. Anderson *et al.* (2011) also reached the same conclusion but they added that long-term oriented cultures have less home bias and more diversification.

### **3. Hypothesis, Data and Methodology**

In this section we begin by presenting the hypothesis we intend to test regarding the impact of each cultural dimension on herd behavior, basing our formulations both conceptually, and in studies that relate cultural dimensions with psychological biases and behaviors verified in financial decision-making. Then we present the data used in our study and the methodology we followed.

#### **3.1. Hypothesis**

In the existing literature, individualism seems to be always abreast with overconfidence (the tendency of individuals to consider themselves as “above average” on positive characteristics) and self-attribution bias (individuals attribute positive outcomes to their own merit and negative outcomes to bad luck).

In fact, there are several studies that conclude that cultures with a higher degree of individualism tend to be more overconfident, which leads them to overestimate the precision of their predictions and be more tolerant to risk (e.g. Mihet, 2012; Ferris *et al.*, 2013). For example, Heine *et al.* (1999) demonstrated the relationship between individualism and overconfidence through the observation of children’s behavior, noting that in individualistic countries they are encouraged to think of themselves as superior to others, which leads them to overestimate their abilities. Also, Ferris *et al.* (2013) stated that individualism praises individual freedom and personal challenge, which leads CEOs to be more confident of their own abilities, and Li *et al.* (2013) affirmed that individualism leads to overconfidence because independent action and individual choice is encouraged. In studies concerning investment decisions, Barber and Odean (2001) claimed that overconfident individuals tend to overestimate their evaluations on stock prices related to those of others and so, they value more their own predictions, while Goodfellow *et al.* (2009) concluded that when investors’ degree of overconfidence is high, they tend to rely less on others’ behavior when making investment decisions, preferring to trust their own beliefs. Finally, Anderson *et al.* (2011) found that individualism leads to less home bias and more diversification

because investors are overconfident and think they possess more information related to other countries than the rest of the investors.

On the contrary, in collectivistic cultures investors give less importance to their private information and attribute more weight to others' opinion (Chui *et al.*, 2010). Lastly, Beckmann *et al.* (2008) and Schmeling (2009) argued that collectivism leads to herding, since managers tend to follow more the market trend.

Considering what we have just mentioned, we are able to formulate our first hypothesis as follows:

*H1: Individualistic countries tend to be associated with overconfidence and self-attribution bias, thus exhibiting less herding.*



Also, current studies show that masculinity is usually associated with overconfidence and risk-taking behavior.

According to Estes and Hosseini (1988), gender differences were the most important factor affecting investors' confidence when they had to make investment decisions, finding that women usually are less confident in their decisions. Beckmann and Menkhoff (2008) also studied gender differences in fund management through a survey in US, Germany, Italy and Thailand during 2003- 2004 and concluded that women tend to be more risk-averse, less overconfident and less competitively oriented than men. Yao and Hanna (2005) also supported this vision, affirming that even if women should invest more in risky assets because of longer life expectancy, what is observed is that they tend to be more risk-averse than men. Besides showing that women are in fact more risk-averse than man when it comes to financial decisions, Powell and Ansic (1997) also showed that they are less confident and tend to attribute their good performance to luck rather than skill. Barber and Odean (2001) stated that overconfident investors tend to trade more in the market and illustrated empirically that men trade more 45% than women in financial markets. Furthermore, Chang and

Noorbakhsh (2009) concluded that in masculine societies men tend to hold a larger amount of cash in order to exploit faster strategic opportunities and be able to get higher returns. Finally, Anderson *et al.* (2011) also tested gender differences in home bias and their results showed that masculinity leads to less home bias, because investors are overconfident and think that they possess superior information than others.

The evidence of the empirical studies made so far, lead us to formulate the following hypothesis:

*H2: Masculine countries are more prone to overconfidence and risk-taking behavior, which leads to less herding.*



Furthermore, existing studies that test the influence of uncertainty avoidance in financial decisions conclude that alongside with this dimension is risk-aversion.

Nguyen and Truong (2013) argued that investors from countries with high uncertainty avoidance tend to be more conservative, less optimistic and risk-averse. Also, Aggarwal and Goodell (2009) concluded that countries characterized by a high level of uncertainty avoidance tend to prefer a bank-based financial system instead of a market-based financial system, because bank-based systems have a superior risk-reduction capability in smoothing intertemporal risk and provide stability in investment returns, while market-based systems provide opportunities of higher returns but also carry more risk through daily fluctuations in prices. This is explained by the fact of investors from countries with uncertainty avoidance usually prefer security and predictability, thus being reluctant to accept risks.

In further empirical studies, Chang and Noorbakhsh (2009) showed that in cultures characterized by high uncertainty avoidance corporate managers are more prone to hold cash because they are afraid of unexpected losses. Mihet (2012) also explained that countries with high uncertainty avoidance are more afraid of failure, thus assuming less risk. In their study regarding CEOs' overconfidence, Ferris *et al.* (2013)



found that uncertainty avoidance is inversely related to overconfidence because in these countries investors are less willing to take risk. Finally, Beugelsdijk and Frinjs (2010) and Anderson *et al.* (2011) demonstrated that countries with high uncertainty avoidance exhibit more home bias because they are more risk-averse and prefer safer and familiar investments.

Concerning herding, Hofstede (2001) stated that uncertainty avoidance captures a propensity people have to follow the same set of rules, behaving thus in the same manner (because they view conflicts in a negative way, preferring a group-decision), which led Sinke (2012) to conclude that a higher value in this cultural dimension indicates a tendency to herd behavior.

Considering this and the empirical studies that included the uncertainty avoidance dimension, we are able to formulate the following hypothesis:

*H3: Countries with high uncertainty avoidance tend to be more risk-averse, which leads to more herding.*



The next cultural dimension to analyse is power distance. Conceptually, Hofstede (1991) argued that in countries with low power distance people are encouraged to be independent and have own initiative, while in countries with high power distance people expect to be told what to do. Also, Chui and Kwok (2008) stated that high power distance countries are said to be more collectivist.

On the other hand, Sinke (2012) argued that in cultures with low power distance values like trust, equality and cooperation are important. This idea was supported by Mihet (2012), who noted that in countries with low power distance there is more harmony and trust. Finally, House *et al.* (2004) noted that in low power distance countries information is shared.

Considering the aforementioned, we expected power distance to entail more herding but, conceptually, we cannot define a clear association.

*H4: Power distance has an ambiguous effect on herd behavior.*

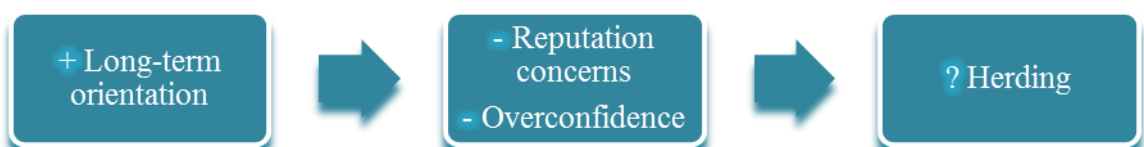


As for the last dimension of Hofstede, Anderson *et al.* (2011) found that long-term orientation leads to more diversification because investors in these countries tend to be less myopic, which would lead to less herding. Also, as noted by Serra and Barros (2011), mutual funds are usually evaluated quarterly and so they are more short-term oriented, being thus more prone to herding as a way to maintain their reputation.

On the other hand, Hofstede (2011) expanded his analysis of IBM's employees to other social environments and found that students in short-term oriented countries usually attribute success to themselves and failure to bad luck, while in long-term orientated countries performance depends on the effort. Thus, we associate students from short-term oriented countries with self-attribution bias, which means that long-term orientation would lead to more herding. Furthermore, Ferris *et al.* (2013) concluded that long-term orientation leads to less overconfidence because this kind of cultures are not capable of rapid change, which would indicate that they tend not to follow herd behavior (since it is positively related to overconfidence).

There seems to be evidence supporting contradicting points of view, not existing a consensus regarding the impact of long-term orientation on herd behavior. Although we expect long-term orientation to lead to less herding, due to institutional investors' weight in the market, evidence is mixed.

*H5: Long-term orientation has an ambiguous effect on herding.*



### 3.2. Data

In our study we use daily data for 39 countries between 2001-2013, collecting data from Datastream Global Equity Indices and the World Bank. All of our variables are measured in local currency, but according to Chui *et al.* (2010) we would reach the same conclusions if they were measured in US dollars.

Most of cross-country studies made so far use a small sample, composed by two or three countries, however, according to Fernandez *et al.* (1997), we should use a sample that would ideally include all the countries analysed by Hofstede, having in mind that it should contain different levels of economic development. To satisfy this requirement we tried to include as much countries as we could when forming the sample and reached the number referred previously. Our selection was restricted to those countries that had available information for all five Hofstede's cultural dimensions and for stock prices. Consequently, the countries under observation in this study are the following: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, Romania, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom and United States of America.

At first we also considered to include China in the sample. However, as was already mentioned, one of the downsides of using Hofstede's cultural dimensions had to do with the time at which he created them, since he did not take into account the changes that might had occurred through time. We already argued that culture does not tend to suffer a lot of changes as time goes by and there are studies that verify that the relative position of the countries did not alter considerably, notwithstanding China is a rare case that passed from a period of high isolation to an unprecedented economic development followed, at the same time, with global exposure and integration. This may have caused considerable changes especially in younger generations (Hofstede, 2011) and so, we decided to take China out of the sample.

The chosen period is related to stock data availability for each country and to the need of having, according to Christie and Huang (1995), a comparison between a tranquil period and a crisis period. This is based on the assumption, made by these

authors, that investors tend to act in accordance with traditional models during tranquil periods, but herd during phases of extreme market movements.

Combining simultaneously the wish to have a sample able to contemplate several countries and the need to fulfill the requirement concerning the comparison between both tranquil and crisis periods, our decision is to examine 13 years from 1/1/2001 to 31/12/2013.

As for data frequency, Orleán (1995) stated that to test herd behavior in a market the ideal would be to use intradaily data, because at that level, when news are disclosed, investors may not have the amount of time required to apply complex analytical models to interpret those news and predict the future direction of prices. Thus, their decisions may not be coherent with rationality and investors will have the tendency to trust the decisions of other participants in the market.

Although intradaily data would be the most suitable, the truth is that it would be extremely complicated to obtain this kind of data for such a long period of time. Nevertheless, there seems to be a consensus that herding is a short-term phenomenon and that the use of frequencies that do not consider its short-term nature would weaken the evidence of the phenomenon. For example, Lakonishok *et al.* (1992) affirmed that herd behavior would only be visible in daily or weekly data, idea that was corroborated by Radalj and McAleer (1993) who realized that the use of quarterly and annual frequencies undermine the detection of herding and so, in order to study this behavior, we should use a shorter time interval (monthly, weekly, daily or intradaily). More recently, Economou *et al.* (2011) stated that from the existing empirical studies, those that resorted to daily data were the ones that found a stronger evidence of herding. Considering this, we decide that the preferable frequency to use is daily data.

In the following subsections regarding data, we give detailed information about the stock market data, data concerning the cultural dimensions and the determinants of herding we decided to include in our regression.

### *3.2.1. Stock market data*

Stock market data is taken from Datastream Global Equity Indices. We choose this database because, according to Data and Application Support from Thomson Reuters, it has a larger universe of stocks and the methodology is consistent across

markets (allowing comparisons between them), so for those looking at several markets Datastream Global Equity Indices provide more data and history than national market indices. For example, if we look at Argentina's market, we can observe that Merval only contains information regarding 13 of its stocks, while Datastream Global Equity Index for Argentina provides information for 50 stocks.

Also, their indices cover at least 75% of the market (by market value) and in most cases this coverage is around 90% of the market, having each market a number of stocks defined on a pro rata basis according to their size and importance down to a minimum of 50 stocks (in some cases this minimum is breached due to lack of domestic stocks in the market). Finally, according to Datastream Global Equity Indices User Guide No.5, indices are updated daily and are quarterly reviewed to ensure that they continue to represent the top stocks by market capitalization.

For all these reasons, we think that the use of this particular database allows us to have a good representation of the market and, at the same time, to be able to compare several countries consistently.

As previously mentioned, the criteria we use to include a particular country in our sample is related to the availability of information concerning stock prices. In this sense, in accordance with Chui *et al.* (2010) that set up a minimum number of 30 stocks to form a portfolio to analyse the momentum phenomenon, we also establish that we should have a reasonable number of stocks in order to detect if herding occurs. Thus, we decide that in the beginning of the sample period (1/1/2001) the market has to have at least 20 stocks and not have, at any time during the rest of the period analysed, less than 10 stocks.

To compute the returns' value we apply the formula used by Chiang and Zheng (2010), that is defined as follows:

$$(3.1) \quad R_t = 100 \times (\log(P_t) - \log(P_{t-1}))$$

where  $R_t$  represents the return of a stock at time  $t$ ,  $P_t$  represents the price of a stock at time  $t$  and  $P_{t-1}$  represents the price of a stock at time  $t-1$ .

In what concerns to stock returns, we exclude the individual returns that have value equal to zero for five days in a row, because this would indicate that the price remains the same for a week, what may be illustrative of those stocks not being traded at all. This decision is made in accordance with Kallinterakis *et al.* (2010), who admitted that, in presence of thin trading, stock prices remain unchanged because stocks are not traded every day, which implies returns to be equal to zero. This obviously does not reflect the investors' action in the market and so, if we consider those returns, that reflect non trading, our estimates would be biased. Consequently, our study is based on stocks that were actually traded.

We next present, in Table 2, the descriptive statistics for the stock market data, regarding the number of stocks of each market, the individual returns and the market returns.

**Table 2** – Descriptive statistics for the stock market data of the 39 countries considered in the sample between 2001-2013

This table reports stock market statistics regarding the number of individual stocks in each country, the individual returns and the market returns for the 39 countries included in our sample and for the period analysed (2001-2013).

We set up a minimum number of stocks in order to analyse herd behavior in a financial market, not including in the sample countries without a reasonable number of individual stocks. Thus, we require each country to have at least 20 stocks in the beginning of the period analysed (1/1/2001) and not have less than 10 stocks during any other day of the sample (between 2/2/2001 to 31/12/2013).

In order to try to include only stocks that were effectively traded, we exclude from individual returns those returns that presented a value equal to zero for five days in a row, since it would be representative of no trading activity. Both individual and market returns are expressed as a percentage.

In the column “Total” we show the minimum and maximum number of stocks, individual and market returns and the mean of the number of stocks, individual and market returns across countries, as well as the mean of their standard deviations.

Country	Number of stocks			Individual returns (%)		Market returns (%)	
	Min	Max	Mean	Mean	Std Dev	Mean	Std Dev
Argentina	11	48	36	0,0326	1,4134	0,0247	0,6742
Australia	90	160	132	0,0117	1,1040	0,0066	0,4399
Austria	23	47	37	0,0068	1,1142	0,0089	0,5340
Belgium	51	88	74	0,0045	1,0489	0,0038	0,5264
Brazil	32	98	66	0,0254	1,2259	0,0174	0,6068
Canada	46	75	65	0,0169	1,3340	0,0062	0,4708
Chile	20	46	37	0,0226	0,8955	0,0135	0,3542
Denmark	31	50	45	0,0116	1,1378	0,0097	0,5267
Finland	35	49	45	0,0086	0,9702	-0,0085	0,7846
France	173	242	214	0,0051	1,0519	-0,0009	0,5882
Germany	160	246	207	0,0085	1,1845	0,0020	0,5622
Greece	39	50	47	-0,0114	1,2757	-0,0162	0,7190
Hong Kong	64	129	98	0,0202	1,2547	0,0079	0,5997
Hungary	14	46	26	-0,0224	2,0505	0,0041	0,6624
India	125	200	167	0,0330	1,1913	0,0208	0,6613
Indonesia	12	50	36	0,0386	1,5010	0,0258	0,6638
Ireland	10	34	24	-0,0012	2,2645	-0,0015	0,6136
Israel	31	49	44	0,0152	1,0655	0,0040	0,4903
Italy	92	159	131	-0,0036	0,9875	-0,0074	0,5947
Japan	643	999	906	0,0072	1,0737	-0,0015	0,6136
Korea	65	101	87	0,0270	1,2237	0,0177	0,6823
Malaysia	34	75	60	0,0221	0,8306	0,0132	0,3448
Mexico	26	85	47	0,0364	1,1563	0,0249	0,4716
Netherlands	76	110	97	-0,0064	1,5129	-0,0042	0,5937
New Zealand	19	50	34	0,0123	0,9560	0,0062	0,2763
Norway	18	50	39	0,0112	1,2830	0,0095	0,6582
Pakistan	11	50	41	0,0357	1,1457	0,0243	0,6403
Peru	10	34	22	0,0436	1,5198	0,0176	0,4141
Philippines	13	49	34	0,0334	1,5159	0,0167	0,5116
Portugal	27	42	34	-0,0148	1,7813	-0,0042	0,4750
Romania	11	50	33	0,0222	1,8017	0,0215	0,7925
Singapore	40	91	67	0,0163	1,1400	0,0076	0,4662
Spain	62	107	85	-0,0042	1,0993	0,0023	0,5946
Sweedan	52	70	65	0,0151	0,9829	0,0050	0,6647
Switzerland	94	150	130	0,0052	0,9068	0,0011	0,4856
Thailand	25	50	41	0,0262	1,0809	0,0195	0,6491
Turkey	24	49	41	0,0290	1,3216	0,0235	0,9097
UK	261	548	445	0,0101	0,9974	0,0024	0,5255
USA	712	997	845	0,0159	1,1445	0,0052	0,5544
Total	10	999	122	0,0140	1,2403	0,0080	0,5716

From Table 2, we can conclude that there are nine countries that have at certain time less than the 20 stocks requested in the beginning of the period to be included, being Ireland and Peru the ones with the lowest minimum number of stocks. This has to do with the exclusion of the stocks that were not traded in some days (so, even if these countries have started with 20 stocks, in determined days some of the stocks were excluded due to non trading activity).

The countries with the highest number of stocks are the Japan and the United States, with almost 1000 stocks each. If we look at the total number of stocks, we would say that, on average, we have 120 stocks per country.

If we pay attention to the comparison between the mean values of the individual and market returns, we can observe that in some countries like Hungary, the United States and Philippines, the distance of the mean individual returns to the mean market returns is higher, and in some countries like Romania, Norway and Denmark, this difference is lower. At first sight, this may denote the presence of herding in certain markets and the absence of such behavior in others.

### 3.2.2. *Cultural dimensions*

Data regarding cultural dimensions is obtained from Hofstede's book (1991) "Cultures and organizations: software of the mind" and from Geert Hofstede's website ([www.geerthofstede.nl](http://www.geerthofstede.nl)). Although there are, as we have seen previously, some criticisms around Hofstede's dimensions, the fact is that they are currently used in recent studies that reveal the maintenance of relative position of the countries, holding the validity of his dimensions, and they are widely accepted because of their clarity and applicability (Kirkman *et al.*, 2006).

To measure culture we made the assumption, as in Sivakumar and Nakata (2001), that country is a proxy for culture, because even if there are several different cultural groups within a country (and this is more evident in countries with higher immigration rates or that suffered political redefinitions), it is still possible to observe a model set of values that is predominant. Inkeles and Levinson (1969) enhanced this idea arguing that, although other values may co-exist, there is one set that is more common and broadly descriptive of the whole society.



In our study we use, as already mentioned, Hofstede's (2001) five cultural dimensions: individualism vs. collectivism (*IND*), masculinity vs. femininity (*MAS*), uncertainty avoidance (*UA*), power distance (*PD*) and long-term orientation (*LTO*). Each dimension is measured on a scale between 0 and 100 (constructed through a factorial analysis based on the answers to the author's survey), being the most important not the value itself but the country's position related to other countries (if it has a higher or lower value when compared to others).

It is important to mention that the survey made by Hofstede generates a single value for each country (for each dimension), not evolving through time. So, we consider this value to be constant during the period analysed (for example, Argentina has a value for individualism of 46 and that is the value to be considered in every year from 2001 to 2013).

In Hofstede's view this makes sense, since he considers culture to be difficult to change over time, being the position of a country when compared to another relatively stable over time.

The values for each dimension of the countries that compose our sample are expressed in the table below (Table 3):

**Table 3** – Values for each country's cultural dimensions

This table shows the values each country has for each of the five Hofstede's cultural dimensions.

Each dimension assumes a value between 0 and 100. When the value for a dimension is close to 0, the country scores low on that dimension and when the value for a dimension is close to 100, the country scores high on that dimension. For example, the higher the value of a country on individualism, the more individualistic the country is.

*IND* stands for individualism, *MAS* for masculinity, *UA* for uncertainty avoidance, *PD* for power distance and *LTO* for long-term orientation.

The value a country obtains for each dimension is the one to be applicable during the entire sample period, since the cultural dimensions are time-invariant.

<b>Country</b>	<b>IND</b>	<b>MAS</b>	<b>UA</b>	<b>PD</b>	<b>LTO</b>
Argentina	46	56	86	49	20
Australia	90	61	51	36	21
Austria	55	79	70	11	60
Belgium	75	54	94	65	82
Brazil	38	49	76	69	44
Canada	80	52	48	39	36
Chile	23	28	86	63	31
Denmark	74	16	23	18	35
Finland	63	26	59	33	38
France	71	43	86	68	63
Germany	67	66	65	35	83
Greece	35	57	100	60	45
Hong Kong	25	57	29	68	61
Hungary	80	88	82	46	58
India	48	56	40	77	51
Indonesia	14	46	48	78	62
Ireland	70	68	35	28	24
Israel	54	47	81	13	38
Italy	76	70	75	50	61
Japan	46	95	92	54	88
Korea	18	39	85	60	100
Malaysia	26	50	36	100	41
Mexico	30	69	82	81	24
Netherlands	80	14	53	38	67
New Zealand	79	58	49	22	33
Norway	69	8	50	31	35
Pakistan	14	50	70	55	50
Peru	16	42	87	64	25
Philippines	32	64	44	94	27
Portugal	27	31	99	63	28
Romania	30	42	90	90	52
Singapore	20	48	8	74	72
Spain	51	42	86	57	48
Sweeden	71	5	29	31	53
Switzerland	68	70	58	34	74
Thailand	20	34	64	64	32
Turkey	37	45	85	66	46
UK	89	66	35	35	51
USA	91	62	46	40	26

Source: [www.geerthofstede.nl](http://www.geerthofstede.nl)

### 3.2.3. Determinants of herding

Our study is undertaken to test the additional power of culture in explaining herding, so we also have to consider the main variables that are usually referred in the literature to influence this behavior and then observe if, in fact, cultural dimensions are able to impact herding.

Thus, in this subsection we present the determinants that are usually considered in the literature to explain herd behavior. These are the book to market ratio, volatility, size, turnover, market movements (extreme movements and bull/bear markets), market capitalization to GDP ratio and gross domestic product per capita (GDPpc). For each determinant we suggest in which way it can influence herd behavior.

#### a) Book-to-market ratio

One of the financial variables considered by Blasco *et al.* (2009) and Chui *et al.*(2010) that may have influence on herd behavior was the book-to-market ratio (*BTM*). As argued by Fama and French (1995), this ratio can be responsible for cross-section return variability since it can be seen as a proxy for risk, observing that a higher ratio value corresponded to a higher return explained by the risk premium that investors required. Also, Lakonishok *et al.* (1994) noticed that a higher book-to-market ratio was connected to investors' underreaction, since they tend to lower their expectations by extrapolating past prices to the future. Finally, Blasco *et al.* (2009) made an empirical study to analyse herd behavior in the Spanish market and reached the conclusion that a lower book-to-market ratio leads to a higher level of herding.

Considering the aforementioned, we collect data from Datastream Global Equity Indices for the book-to-market ratio (*BTM*), defined as the balance sheet value of the ordinary (common) equity in the company divided by the market value of the ordinary (common) equity and expressed in local currency:

$$(3.2) \quad BTM = \frac{\text{Balance sheet value}}{\text{Market value}}$$

*b) Volatility*

Another factor we should consider as being influent on herd behavior is volatility since, on one hand, Chiang *et al.* (2011) found an association between volatility and the characteristics of herding formation that occurs during periods of market stress and, on the other hand, Chui *et al.* (2010) stated that volatility could be used as a proxy of information uncertainty. In this sense, volatility would make information more ambiguous and less reliable, leading to the formation of cascades, since investors would seek information in other agents' signals (even if they do not reflect relevant information).

The first hypothesis has empirical support (Butler and Joaquin, 2002; Forbes and Rigobon, 2002; Corsetti *et al.*, 2005), showing that in periods characterized by high volatility cross-market correlations tend to rise.

Although most theories predict a positive relationship between volatility and herding, we should also note the empirical study made by Lobão and Serra (2006) in the Portuguese market, where they found that the level of herding is lower when the market is more volatile. According to the authors, higher volatility can also be considered a proxy for new and unexpected information, reflecting instead more information, thus resulting in a lower level of herding. The argument for this lies in the informational cascades, that may predict a negative relationship between these two dimensions (volatility and herding) when occurs the arrival of an investor that has a deviant information or when unexpected public information arises, since investors are not identical ex-ante.

Having this into account, we decide to include volatility as a determinant of herding and, adopting the same approach of Chui *et al.* (2010) we define stock market volatility ( $V_t$ ) for each country as follows:

$$(3.3) \quad V_t = \frac{\sum_{i=1}^n R_{it}^2}{n}$$

where  $R_{it}$  is the return on stock  $i$  in day  $t$  and  $n$  is number of stocks in the market.

c) *Size*

Another important variable to include when we are analysing herd behavior is the size of firms, since is associated with the information flows that companies produce.

According to Sias (2004) large companies are more susceptible to investors' imitation, however this may happen because they are just following the same information. Nevertheless, this imitative behavior can also be caused by uninformed investors that tend to invest in large companies instead of small companies (Palomino, 1996), probably because they are widely known and are more salient.

On the other hand, Wermers (1999) claimed that herd behavior is more likely to occur in smaller companies since they provide scarce information that is difficult to evaluate, which forces people to decide in an ambiguous environment without being fully aware of the risk involved. In this situation information seems to contain a large amount of noise and is not easy to interpret, so investors tend to infer information through other signals like the decisions made by other investors in the market.

Empirically there seems to be conflicting results, since Blasco *et al.* (2009) found that there is a positive relationship between market capitalization and herd behavior, whereas Lakonishok *et al.* (1994) showed that herding is more intense when market capitalization is lower.

To figure out the impact this variable may have on herding, we collect from Datastream Global Equity Indices the market value (also known as market capitalization), which is defined as the share price multiplied by the number of ordinary shares in issue and is displayed in local currency. In order to make a comparison based on companies' dimension, we divide the value by the number of existing firms in the market, reaching thus the median size of companies in a particular market (as suggested by Chui *et al.*, 2010).

Thus, the size of firms (*SIZE*) is represented in the following way:

$$(3.4) \quad \text{Size} = \frac{\text{Share price} \times \text{Number of ordinary shares}}{\text{Number of firms}}$$

d) *Turnover*

An additional factor we should take into account when referring to herding is the turnover, since according to Campbell *et al.* (1993), it can be considered as a proxy of

trading volume, being its use is preferable due to its relative character (because it is normalized by the number of shares outstanding, we can be sure that this measure is not only capturing larger firms).

Also, Chui *et al.* (2001) stated that turnover can be seen as a proxy for information vagueness and Christoffersen and Tang (2010) supported this view affirming that it can measure information precision and asymmetry. Besides that, Bikhchandani *et al.* (1992) and Avery and Zemsky (1998) defended that herding increases when the information quality is poor, which can be measure by turnover.

Furthermore, Suominen (2001), and Blume *et al.* (1994) suggested that a higher level of trading volume is synonym of better quality information. On the other hand, Harris and Raviv (1993) and Wang (1998) performed studies proving that turnover is a good proxy for investors' consensus in the market.

Empirically, Economou *et al.* (2011) did not find any specific relationship between trading volume and herding when they analysed this behavior for four Mediterranean countries. Indeed, their evidence was mixed, indicating that in Portugal tends to be a higher level of herding when the trading volume is higher, in Italy, on the other hand, this behavior is more evident when trading volume is low, in Greece herding exists in both situations and in Spain never exists. Also, Christoffersen and Tang (2009) tested herding in the United States market and concluded that, overall, herding is higher when turnover is lower.

These reasons make us conclude that there is a potential relationship between turnover and herding and so, we decide to include this variable, collecting data for turnover ratio from World Bank. Turnover ratio is defined as the total value of shares traded during the period divided by the average market capitalization and is expressed in US dollars. Since the variable is measured in relative terms, there is no need to convert it to local currency.

To measure turnover in a daily frequency, we have to divide the collected value for the number of daily observations in the year. This happens because the data from the World Bank, regarding turnover, is only available in annual terms.

Turnover ratio is thus calculated in the following way:

$$(3.5) \text{ Turnover ratio} = \frac{\text{Total value of shares traded}}{\text{Average market capitalization}}$$

*e) Bull and bear markets*

One more feature we have to consider has to do with different market movements, since investors can react differently when facing a rising or a falling market. That was already studied by Tan *et al.* (2008) and Chiang and Zheng (2010), who showed evidence of asymmetric herd behavior under different market movements.

According to Chiang *et al.* (2011), one explanation for this asymmetry is related to the flow of information. For instance, if analysts tend to recommend more actively on the buy-side than on the sell-side and investors base their decisions on analysts' recommendations, there will probably exist more herding in rising markets. On the other hand, investors may think that the government always intervenes when markets decline significantly and so, in falling markets, there is less herding.

Empirically, Chang *et al.* (2000) analysed five different markets (US, Hong Kong, Japan, South Korea and Taiwan) and suggested that investors react differently under different market conditions, being the dispersions of returns higher in up markets relatively to down markets, thus existing more herding in down markets. On the other hand, Ohlson (2010) when analysing the Swedish market, found that herding was more intense during the bullish phase.

For our analysis, we define bull and bear market as in Chauvert and Potter (2000). Thus, bull and bear markets correspond to periods of generally increasing and decreasing market prices, respectively. This definition implies that, in order to switch from a bull to a bear state, prices have to decline for a considerable period since their previous local peak, however, it does not exclude sequences of price rises (falls) during a bear (bull) market, existing restrictions on the extent to which these sequences of price reversals can occur.

There are in the literature methods to classify stock returns into bull and bear markets, called dating algorithms, that try to use a sequence of rules in order to isolate patterns. An algorithm widely known is the one proposed by Bry and Boschan (1971) to identify business cycles' turning points, that was further adopted by Pagan and Sossounov (2003) to characterize bull and bear phases in financial markets, using monthly stock returns.

The criteria used in this algorithm are the location of potential peaks and troughs (points higher or lower than a window of surrounding points) and the length of each phase and cycle. The Bry and Boschan (1971) algorithm can be summarized as follows:

1. Identify the peaks and troughs by using a window of 6 months;
2. Enforce alternation of phases by the higher of adjacent troughs and the lower of adjacent peaks (removing irrelevant local extreme points);
3. Eliminate phases with duration less than 4 months;
4. Eliminate cycles with duration less than 15 months.

Therefore, we use RATS software to compute the Bry and Boschan (1971) algorithm to identify relevant turning points and classify the resulting phases into bull and bear market through a dummy variable. This dummy assumes the value 1 when we face a bull market and a value 0 when we face a bear market.

*f) Extreme market movements*

We mentioned above that investors can make different decisions when they are facing a rising or a falling market, but this asymmetric behavior may be intensified in the presence of extreme market conditions.

According to Christie and Huang (1995) and Chang *et al.* (2000), investors tend to act rational in periods of tranquil stock market phases, since they trade mostly basing their decisions on their private information, but herd in periods of extreme market movements. Also, Christie and Huang (1995) concluded that herding responds asymmetrically to extreme market movements being the phenomenon more relevant on the downside, idea also supported by Chiang *et al.* (2011) since mutual fund managers have the need to sell securities in order to raise cash when they face significant redemption requests, which are more likely to happen during market declines, being thus more prone to herding in these situations.

To observe if herding is more pronounced during extreme market movements (and also test the asymmetry between the upside and downside of these extreme conditions), we use the 5% lower tail and 5% upper tail of the returns' distribution to create dummy variables reflecting both situations. The dummy reflecting extreme up movements takes the value 1 if the return is located on the 5% upper tail of the returns' distribution and 0 otherwise. The dummy reflecting extreme down movements has the



value 1 if the returns is in the 5% lower tail of the returns' distribution and the value 0 otherwise.

*g) Market capitalization to GDP ratio*

In previous literature the market capitalization to GDP ratio is viewed as a proxy for economic and institutional development, being thus positively associated with stock market development (De Jong *et al.*, 2008; Beugelsdijk and Frijns, 2010; Nguyen and Truong, 2013).

De Jong *et al.* (2008) defended that institutional development has influence on the decision of a particular country to rely more on a market-based or a bank-based system, while Beugelsdijk and Frijns (2010) stated that the ratio can be seen as a proxy for a country's liquidity, which would attract more investors to the market. In fact, in their study, they concluded that a higher market capitalization to GDP ratio reflects a higher stock market development, which in turn leads to an increase in foreign investment and diversification.

For all the exposed reasons, we include market capitalization to GDP ratio in our analysis. The data for the market capitalization is taken from Datastream Global Equity Indices and the GDP is taken from the World Bank, as specified as follows:

$$(3.6) \quad MC = \frac{\text{Market capitalization}}{GDP}$$

*h) Gross domestic product per capita (GDPpc)*

In the literature, just like market capitalization to GDP ratio, GDPpc tends to be associated with economic and institutional development. Kwok and Tadesse (2006) and La Porta *et al.* (1997) argued that GDPpc is closely related to institutional quality and financial development and so, a country with a higher GDPpc will tend to exhibit a lower level of herding.

Empirically, Anderson *et al.* (2011) found that a higher GDPpc was associated with a higher diversification, which lead us to think that it tends to exist less herding in countries characterized by high GDPpc. Another interesting result was discovered by Li *et al.* (2013), who found GDPpc to be related to individualism, which tends to entail a lower level of herding.

In order to have a clear picture of what causes herding, we decide that it would be relevant to control for this macroeconomic factor and so, we collect data for GDPpc from the World Bank. The gross domestic product (GDP) is defined as the gross value added by resident producers in the economy plus product taxes minus subsidies that are not included in the products' value. The data collected regarding this variable is given in annual terms, therefore we divide the value by the number of observations that exist in one year to have the daily value of GDPpc.

$$(3.7) \quad GDPpc = \frac{GDP}{Population}$$

In table 4 we summarize the expected impact each determinant has on herd behavior, explaining the reasons behind that influence.

**Table 4** – Expected impact of the determinants of herding

This table shows the expected influence that the determinants usually considered in literature have on herd behavior.

Based on what we have exposed previously, we give the reasons that may be able to explain this influence.

Regarding the expected impact on herding, “Positive” means that the higher the value for the determinant, the higher would be the level of herding; “Negative” means that the higher the value the determinant has, the lower would be the level of herding; and “Ambiguous” stands for the situation where we cannot define what is the correct direction of that influence.

<b>Determinants of herding</b>	<b>Reason</b>	<b>Expected impact on herding</b>
<b>Book-to-market ratio</b>	Risk premium required / investors' underreaction	Negative
<b>Volatility</b>	Information uncertainty	Positive
<b>Size</b>	Saliency / information flow	Ambiguous
<b>Turnover</b>	Information quality / differences of opinion	Negative
<b>Bull market</b>	Analysts' recommendations	Positive
<b>Bear market</b>	Government interventions	Negative
<b>Extreme market movements</b>	Information uncertainty	Positive
<b>Market capitalization to GDP ratio and GDPpc</b>	Stock market development	Negative

### 3.3. Methodology

Here we present the approach we follow in our study to detect herding and the main measures of herding used in empirical studies, discussing the advantages and disadvantages of utilizing each of the measures. We end this section with our model specification.

#### 3.3.1. Herding approach

There are two different ways to study herd behavior, depending on the focus of the analysis intended to follow.

The first one is concerned with herding at a micro-level and focus on the behavior of specific groups of investors or of individual investors, analysing for example the capital allocation of mutual funds, the trading behavior of an investor or the recommendations of stock analysts (Ohlsen, 2010).

The second one is the market wide approach, where the market aggregated data is used and the focus is on the cross-sectional correlations of the entire stock market (Ohlson, 2010). According to Henker *et al.* (2006), this approach concentrates on tendencies that are observable in the market as a whole and the way to detect herding has to do with the distance between the individual returns and the market returns. This is based on the argument that, in case this phenomenon occurs, the returns of individual stocks tend to cluster around the market return, thus indicating that investors suppress their own opinions in favour of the market consensus.

The difference between the two methods is related to the purpose of the study, since the market wide approach focus on measuring the quantity of herding, while the micro-level herding approach allows us to identify the investors that are leading and following the herd.

The majority of existing studies focus on the micro-level herding (Kallinterakis and Ferreira, 2006) and, based on them, we can state that institutional investors are more prone to rational herding (Kim and Wei, 2002), while individual investors are more prone to irrational herding (Wermers, 1999). Nevertheless, in our study we intend to verify the existence of herding in the market as a whole without concerns to the type of investor that causes it, so our approach is to study market wide herding.

### 3.3.2. Measure of herding

As for the herding measure to apply, the most used ones in empirical studies are those proposed by Lakonishok *et al.* (1992), Christie and Huang (1995) and Chang *et al.* (2000), but the first one is mostly used for studies concerning institutional investors while the other two are used independently of investors' type (individual or institutional).

The measure proposed by Lakonishok *et al.* (1992) is widely used, which may facilitate the comparison with previous studies, however, our purpose is to study the market as a whole and not analyse only the institutional investors, so this measure would not interest us. Besides that, it has a limitation regarding the fact that it only considers the number of funds in the buy and sell side without concerning the funds' trading volume, that is, the quantity they buy and sell (Bikhchandani and Sharma, 2001; Xu, 2006).

On the other hand, the measure of Christie and Huang (1995) considers the whole market without differentiating individual and institutional investors and is expressed through a cross-sectional analysis of asset returns. In their model, a smaller dispersion is viewed as a movement towards the market consensus, since it seems to indicate a parallel movement between individual returns and market return.

This measure is calculated as follows:

$$(3.8) \quad CSSD_t = \sqrt{\frac{\sum_{i=1}^N (R_{i,t} - R_{m,t})^2}{N-1}},$$

where  $R_{i,t}$  is the stock return of firm  $i$  at time  $t$  and  $R_{m,t}$  is the cross-sectional average of the  $N$  returns in the market portfolio at time  $t$ .

Therefore, we can observe herd behavior when the dispersions are relatively low, since rational asset pricing models predict an increase in dispersion due to the difference in individual assets' sensitivity to market movements, which leads the individual returns to be repelled away from the market return (Christie and Huang, 1995). However, even if when we have herding we have low dispersions, we cannot conclude that low dispersions by themselves are synonym of herding, since there are other factors capable of causing low dispersions. For example, the lack of new information during a certain trading period would generate low dispersion without the presence of herd behavior.

Additionally, these authors argued that herding is more likely to occur during periods of great instability, since there seems to be a conflict between rational asset pricing models and herding as for the behavior of dispersions during periods of market stress (Christie and Huang, 1995). To test the presence of herding in opposition to the behavior in dispersions to be observed if asset pricing models is considered, during periods of extreme price movements, they used a dummy method considering the extreme tails of market returns' distribution:

$$(3.9) \quad CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t,$$

where  $D_t^L = 1$  if the market return on day  $t$  is in the extreme lower tail of the return distribution ( $D_t^L = 0$ , otherwise) and  $D_t^U = 1$  if the market return on day  $t$  lies in the upper tail of the return distribution ( $D_t^U = 0$ , otherwise).

Although the measure proposed by Christie and Huang (1995) seems very intuitive to capture herding, the truth is that it can also be affected by outliers (Economou *et al.*, 2011). Also, according to Ohlson (2010), this measure tests the existence of herding during periods of market stress, but for Hwang and Salmon (2004) herding may be present during quiet periods (because during these times the role of the market portfolio is replaced by different factors that may serve as herding objectives).

Having in mind all the criticisms around Christie and Huang's (1995) measure, in our study we decide to adopt the measure proposed by Chang *et al.* (2000). Their measure is a variant of the one proposed by Christie and Huang (1995), that follows the same logic of it, but with the advantages of mitigating the problem of outliers' existence and of being able to detect herding during normal conditions (Lindhe, 2012). The measure of Chang *et al.* (2000) uses the cross-sectional absolute deviation as a better measure of dispersion, since Granger and Ding (1995) stated that standard deviations are inherently more sensitive to outliers than mean absolute deviations.

Chang *et al.* (2000) argued that herding can be captured through cross-sectional dispersion of asset returns, concluding that when we observe a low dispersion, there seems to be a movement towards the market consensus (which would indicate the presence of herding). Thus, the measure we apply in our work is the cross-sectional absolute deviation (CSAD) and is specified below:

$$(3.10) \quad CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}|,$$

where  $N$  represents the number of firms,  $R_{i,t}$  represents the observed return of firm  $i$  at time  $t$  and  $R_{m,t}$  is the cross-sectional average stock of  $N$  returns in the portfolio at time  $t$ .

So, if there is evidence of herding, individual asset returns will not diverge substantially from the overall market return, being CSAD close to zero when returns move in unison with the market and increases as individual returns begin to deviate from the market return (Chang *et al.*, 2000).

To conduct a test for detecting herd behavior, Chang *et al.* (2000) established a relationship between the dispersion of returns and market return as follows:

$$(3.11) \quad CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t,$$

where  $CSAD_t$  is the cross-sectional stock return dispersion on day  $t$  and  $R_{m,t}$  is the market return on day  $t$ .

Under normal conditions, a linear positive relationship between the dispersion of returns and market return is predicted, however, in periods of large price swings, investors may have the tendency to decide upon the market consensus, which reflects into a nonlinear and negative relationship between  $CSAD$  and  $R_m$  (Chiang *et al.*, 2011). In fact, according to Belgacem and Lahiane (2013), the CSAD methodology assumes that investors' behavior suffers alterations depending on the market conditions, stating that during calm periods investors tend to trade on the basis of their private information (leading to an increase of dispersion around the cross-sectional market return), whereas in periods characterized by large market movements they tend to suppress their own beliefs in favour of market consensus, imitating other agents in the market. Thus, if we are in the presence of herding, we should expect an increase at a decreasing rate or even a decrease (in case of severe evidence of herding) in dispersion with an increase in the market return, so a negative sign in  $\beta_2$  would indicate evidence of herd behavior (Chang *et al.*, 2000).

Albeit better than the measure proposed by Christie and Huang (1995), since it surpasses the outliers' problem, the measure proposed by Chang *et al.* (2000) is also

subject to some criticisms, namely the non-consideration of other factors that might be important to explain asset returns.

In our study, we try to detect the intensity of herding through CSAD (as proposed by Chang *et al.* (2000)), interpreting a higher dispersion between individual returns and market return as being indicative of less herding, not considering the nonlinear relationship that measure has with the market return.

### 3.3.3. Model specification

In our model, our dependent variable is the cross-sectional absolute deviation (CSAD), defined by Chang *et al.* (2000) as being a measure of returns' dispersion. In order to analyse the impact that some determinants may have on the dispersion of individual returns around the market return, we develop a model using the abovementioned controls (determinants of herding, control variables and cultural dimensions). Although we have to control herding for some determinants that influence the dispersion of returns, our main goal is to test the impact of culture on the propensity for this behavior, so our focus will be the analysis of the cultural dimensions included in the regression.

Therefore, our regression is specified as follows:

$$(3.12) \quad CSAD_{i,t} = \beta_1 + \beta_2 BTM_{i,t} + \beta_3 VOL_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 TURN_{i,t} + \beta_6 EXTREME\_UP_{i,t} + \beta_7 EXTREME\_DOWN_{i,t} + \beta_8 BULL\_BEAR_{i,t} + \beta_9 MC/GDP_{i,t} + \beta_{10} GDPpc_{i,t} + \beta_{11} IND_i + \beta_{12} MAS_i + \beta_{13} UA_i + \beta_{14} PD_i + \beta_{15} LTO_i + \varepsilon_{i,t}$$

where  $CSAD_{i,t}$  is de cross-sectional absolute deviation (that informs us about the dispersion of individual returns to market returns) in country  $i$  at moment  $t$ ;

$BTM_{i,t}$  is the book-to-market ratio in country  $i$  at moment  $t$ ;

$VOL_{i,t}$  represents the daily volatility in country  $i$  at moment  $t$ ;

$SIZE_{i,t}$  represents the average size of firms in a certain market, expressed by the market capitalization, in country  $i$  at moment  $t$ ;

$TURN_{i,t}$  is the turnover rate that reflects the trading activity of the market in country  $i$  at moment  $t$ ;

$EXTREME\_UP_{i,t}$  is a dummy variable that represents extreme rising movements and assumes the value 1 when the returns fall into the 5% upper tail of the returns' distribution, in country  $i$  at moment  $t$ , and 0 otherwise.

$EXTREME\_DOWN_{i,t}$  is a dummy variable that shows extreme decline movements and assumes the value 1 when the returns lie on the 5% lower tail of returns' distribution, in country  $i$  at moment  $t$ , and 0 otherwise.

$BULL\_BEAR_{i,t}$  is a dummy variable that reflects market movements, assuming the value 1 when we face a bull market and 0 when we face a bear market, in country  $i$  at moment  $t$ ;

$MC/GPD_{i,t}$  represents the market capitalization relative to gross domestic product, in country  $i$  at moment  $t$ ;

$GDPpc_{i,t}$  shows the value of gross domestic product per capita, in country  $i$  at moment  $t$ ;

$IND_i$ ,  $MAS_i$ ,  $UA_i$ ,  $PD_i$  and  $LTO_i$  are the cultural dimensions, which are constant over time, that represent respectively the level of individualism, masculinity, uncertainty avoidance, power distance and long-term orientation of a country  $i$ .

In order to decide the best approach to estimate a model, we have to consider the objective of the study and the context of the data. So, to estimate our model we use panel data, applying the EGLS method with cross-section random effects.

Although the performance of the Hausman (1978) test led to the use of fixed effects (see appendix 1.1), we cannot follow that approach, since we have individual time-invariant variables that are the same for a given cross-sectional unit through time, but vary across cross-sectional units. According to Hsiao (2006), Greene (2012) and Kaur *et al.* (2013) one of the major shortcomings of the fixed effects model is that it does not allow the estimation of time-invariant coefficients, being the random effects model able to include those time-invariant variables among the regressors. This situation happens because, in fixed effects models, constant terms are perfectly collinear with country, being unable to cause any change in the dependent variable (Kaur *et al.*, 2013) and thus, are absorbed from the regression (Greene, 2012).

These authors defended that one of the main advantages of random effects models is the fact that it can accommodate time-invariant variables. So, when we have constant terms in a regression, the random effects approach should be used. We do not



incur in a risk of having an unbiased estimation because our time series data is large when compared to cross-sectional data and, according to Gujarati (2003), when we face this situation, there is little difference in the value of parameters estimated by fixed and random effects.

Furthermore, a major problem that we can find in panel data analysis that we have to take into account is heteroskedasticity. Therefore, to make our estimators consistent we use the Period Weight (PCSE) correction to control for heteroskedasticity.

As this method seems to be less stringent regarding standard deviations than the White period correction, we also perform the analysis using White period to control for heteroskedasticity.

In order to get more information regarding panel data analysis, fixed and random effects and the Hausman test, consult the appendix (1.1).

To estimate our model, we use Eviews 8. The results obtained from that estimation are described in the next section.

## 4. Results and Implications

In this section we present the results obtained from the regression model exposed in the previous section. We divide the interpretation in two parts: the first one concerns the results for the determinants of herding (4.1.1), while the second one emphasizes the results we got for the cultural dimensions (4.1.2), since these are the main focus of our study. Then, we analyse the pre-crisis and crisis period, to see if the influence of the variables suffered any alterations in those situations (4.1.3).

We further perform a time series analysis with the original Chang *et al.* (2000) measure for each country and analyse the relationship herding has with each cultural dimension individually (4.2). In this case, we test too if there are differences between the pre-crisis and crisis period (see appendix, 1.3.1). Here, we can observe that most of the countries that exhibit herding are more likely to have this behavior in tranquil periods, which represents a flight to fundamentals during periods of market stress (as suggested by Hwang and Salmon, 2004). In fact, contrary to common belief, Hwang and Salmon (2004) found evidence that herding would manifest strongly during quiet periods rather than crisis periods. The authors reached that conclusion when they studied the US and South Korean markets from 1993 to 2002 and observed that the Asian crisis in 1997 and the Russian crisis in 1998 decreased the level of herding.

However, in this time series analysis, we can also observe that some countries that did not exhibit herding before the crisis, started to have evidences of this behavior during crisis, or even if it exhibited herding before, during the crisis the behavior became more intense. For these countries, we also test if herd behavior increased even more after the Euro crisis (2/5/2010). After the financial global crisis that was initiated with the Lehman Brothers' bankruptcy, we are now facing a sovereign debt crisis in the Eurozone. Thus, we consider this date to be representative of the beginning of the Euro crisis, since it is the time when the first bailout to Greece occurred, leading to the realization of the destabilization of the Eurozone. In fact, we can consider the Greek case as being the "Lehmann Brothers" of sovereign debt that led to the contagion to other countries in the Eurozone. The results that are shown in the appendix (1.3.1), suggest that for the countries that present herding (or a higher level of herding) during the crisis period, the behavior is amplified with the Euro debt crisis.

Finally, we discuss the implications these results may have in financial markets and other fields, such as entrepreneurship and management decisions (4.3).

#### 4.1. Results

As we mentioned previously, we use two different methods to correct for heteroskedasticity, being one less stringent than the other when it comes to standard deviations. The main purpose of this is to analyse what are the variables that can effectively be considered to have an impact on herd behavior.

In Panel A we present the results obtained using the Period Weights (PCSE) to correct for heteroskedasticity, while in Panel B we show the results we get through the use of White Period correction for heteroskedasticity.

The results for both methods are presented in Table 5, below.

**Table 5** – Results for the determinants of herding and cultural dimensions

Daily cross-sectional absolute dispersion of returns are regressed on Hofstede's cultural dimensions, (Individualism – IND, masculinity – MAS, uncertainty avoidance – UA, power distance – PD and long-term orientation – LTO) and a set of explanatory variables that are usually mentioned in the literature as being determinants of herd behavior (book-to-market ratio – BTM, volatility – VOL, size of the firms – SIZE, turnover rate – TURN, market capitalization related to GDP – MC/GDP, gross domestic product per capita – GDPpc and dummies expressing extreme up and down movements – EXTREME\_UP and EXTREME\_DOWN – as well as market phases – BULL\_BEAR).

Panel A is estimated using Panel EGLS with cross-section random effects and Period Weights (PCSE) consistent estimates of standard errors and covariance are used to compute  $t$ -statistics.

Panel B is estimated using Panel EGLS with cross-country random effects and White Period (PCSE) consistent estimates of standard errors and covariance are used to compute  $t$ -statistics.

$F_1$  ( $F$ -statistic test) is used to test the hypothesis that all the estimated slope coefficients except the coefficients of cultural dimensions are jointly equal to zero, while  $F_2$  ( $F$ -statistic test) is used to test the hypothesis that all the estimated slope coefficients are jointly equal to zero. These two tests are made to show the global significance of the regression with and without the cultural dimensions. The  $p$ -values are in parenthesis.

A positive sign in the coefficient means that the variable has a positive impact in the dispersion of returns, which means that it has a negative impact on herding.

\* means that a variable is significant at a 10% level, \*\* means the variable is significant at a 5% level and \*\*\* means that a variable is significant at a 1% level.

**Panel A – Period Weights (PCSE) standard errors and covariance**

Dependent variable: CSAD

Method: Panel EGLS (cross-section random effects)

Periods included: 3392

Total panel (unbalanced) observations: 130661

Variable	Coefficient	Std. Error	t-statistic	Prob.
C	0.284887	0.076134	3.741913	0.0002
BTM	0.103345***	0.001483	69.68870	0.0000
VOL	0.017374***	0.000325	53.45721	0.0000
SIZE	0.0000000000000001***	0.000000	-9.472347	0.0000
TURN	0.128775***	0.005318	24.21327	0.0000
MC/GDP	-0.000219***	1.04E-05	-21.05496	0.0000
GDPpc	0.00000375***	0.00000039	9.618555	0.0000
EXTREME_UP	0.485705***	0.005216	93.10987	0.0000
EXTREME_DOWN	0.411216***	0.004494	91.50774	0.0000
BULL_BEAR	-0.004424***	0.001618	-2.734685	0.0062
IND	0.001157*	0.000640	1.808110	0.0706
MAS	0.001863***	0.000601	3.099440	0.0019
UA	-0.001017**	0.000505	-2.012697	0.0441
PD	0.001815***	0.000695	2.610085	0.0091
LTO	0.000307	0.000588	0.522248	0.6015

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Adjusted R<sup>2</sup> = 0.382610

F<sub>1</sub>= 3403.054 (0.00)    F<sub>2</sub>= 2291.368 (0.00)

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**Panel B – White Period standard errors and covariance**

Dependent variable: CSAD

Method: Panel EGLS (cross-section random effects)

Periods included: 3392

Total panel (unbalanced) observations: 130661

Variable	Coefficient	Std. Error	t-statistic	Prob.
C	0.284887	0.100592	2.832114	0.0046
BTM	0.103345***	0.012202	8.469408	0.0000
VOL	0.017374***	0.002532	6.860737	0.0000
SIZE	0.000000000000001***	0.000000	-2.594405	0.0095
TURN	0.128775**	0.056666	2.272532	0.0231
MC/GDP	-0.000219*	0.000132	-1.658055	0.0973
GDPpc	0.00000375**	0.00000174	2.154335	0.0312
EXTREME_UP	0.485705***	0.024428	19.88308	0.0000
EXTREME_DOWN	0.411216***	0.023331	17.62514	0.0000
BULL_BEAR	-0.004424	0.009148	-0.483607	0.6287
IND	0.001157	0.000788	1.467801	0.1422
MAS	0.001863**	0.001015	1.835765	0.0664
UA	-0.001017	0.000672	-1.514897	0.1298
PD	0.001815*	0.001060	1.711875	0.0869
LTO	0.000307	0.000910	0.337723	0.7356

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Adjusted R<sup>2</sup> = 0.382676

F<sub>1</sub>= 177.1424 (0.00)    F<sub>2</sub>= 207.8794 (0.00)

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#### 4.1.1. Determinants of herding

In panel A, our results show that every variable considered as a determinant of herding is statistically significant, which means that they can in fact explain the phenomenon. In panel B, only the variable representing market movements (*Bull\_Bear*) is not statistically significant, at a 10% level.

We present in Table 6 the confrontation between the expected and obtained results regarding the impact each determinant has on herd behavior.

**Table 6** – Expected vs. obtained results for determinants of herding

The expected results are the ones based on the hypothesis formulated previously and the obtained results are the outcome of the regression model.

If the sign is “+”, the determinant has a positive impact on herding (and therefore, a negative impact on the dependent variable, CSAD); if the sign is “-”, the determinant has a negative impact on herding (which means it has a positive impact on CSAD); if the sign is “?”, it means the result is ambiguous; if the result is “NS”, it means that the variable is not statistically significant at a level of 10%.

Variable	Expected Result	Obtained Result	
		Panel A	Panel B
BTM	-	-	-
VOL	+	-	-
SIZE	?	+	+
TURN	-	-	-
MC/GDP	-	+	+
GDPpc	-	-	-
EXTREME_UP	+	-	-
EXTREME_DOWN	+	-	-
BULL_BEAR	+	+	NS

We can observe that book-to-market ratio, volatility, turnover, GDPpc and both dummies that reflect extreme market movements reveal a positive relation with the

dependent variable (CSAD), meaning that an increase in those variables (or in case of the dummies, the evidence of the situation to which they respect) will cause a decrease in the observed level of herding. On the contrary, size and market capitalization to GDP seem to have a negative relation with the dependent variable, thus evidencing that an increase in this variable leads to an increase in the level of herd behavior.

*a) Book-to-market ratio*

In what concerns the book-to-market ratio, the negative relationship with herding is consistent with Lakonishok *et al.* (1994) and Blasco *et al.* (2009), supporting the vision that investors are uninformed and so, they tend to underreact.

The explanation for this fact may be related to the degree of investors' information, because companies that present a lower book-to-market ratio tend to have higher expected returns, but offer lower current returns and show worse financial indicators (for example, a low number of sales and high PER). So, uninformed investors look at companies that currently show better financial indicators (and thus, that are more salient) and invest on them, disregarding the fact that usually they have lower returns in the future.

*b) Volatility*

Regarding volatility, we found a negative relationship with herding, which goes against our expectation, since we anticipated that a higher volatility would be associated to a higher degree of uncertainty, making the information more ambiguous and less reliable, leading to a formation of cascades. Our results point in the same direction as those found by, for example, Lobão and Serra (2006), showing that volatility is probably associated with the arrival of unexpected public information.

*c) Size*

With respect to the size of the firms, they are in sync with the ones of Blasco *et al.* (2009) and contradictory to Lakonishok *et al.* (1994), since we found a positive relationship between size and herding, which means that firms with a higher dimension tend to generate imitative behavior. The discrepancy with Lakonishok's *et al.* (1994) results may be related to the fact that their study focused only institutional investors

whereas we analyse the market as a whole, so in their sample investors tend to be more informed and not invest in companies just because they are more salient (what may happen with individual investors that are usually less informed).

Hence, our outcome tend to show a little more support to Sias (2004) and Palomino (1996) that defended size to be positively related to investors' acting in the same way. This may happen because they are effectively herding, investing in larger companies because they are widely known and easily recognized, but it may also have to do with the fact they are just following the same information, since larger companies tend to release more information, turning the decision environment less ambiguous.

However, we can observe that the value of this particular coefficient is very small, which lead us to think that, although size is statistically significant, it does not have a considerable impact on determining herding. Then, even if the coefficient sign points to larger firms be more prone to herding, the fact is that smaller firms may also be susceptible to this kind of behavior due to their lack of information that causes uncertainty.

#### *d) Turnover*

Regarding turnover, our findings show that a higher turnover leads to less herding, which is in accordance with Christoffersen and Tang (2010). This may happen because low turnover is associated with poorer information and a higher turnover reflects higher differences of opinion among investors with respect to a stock's intrinsic value, as suggested by Harris and Raviv (1993) and Lee and Swaminathan (2000).

#### *e) Extreme movements*

In the results for both dummies (up and down) that reflect extreme market movements we found, against our expectations, that they exhibit an inverse relationship with herding, meaning that herding is less likely to happen during these extreme situations.

As a matter of fact, we tend to associate market stress with noise trading or ambiguous information and, since during these times uncertainty seems to be higher, it is more likely that people suppress their beliefs preferring to stick with the market consensus. This is well illustrated in some models used to measure herding, for example



the one of Christie and Huang (1995), that incorporates dummies referring to the up and down extreme market movements, expecting that if herding exists, it has to be evident during those periods of market stress.

Nevertheless, there are also some authors (for example, Hwang and Salmon) that consider herding to be a behavior more intense in quiet periods than in extreme situations, because in crisis periods investors tend to turn to fundamentals instead of market movements.

*f) Market capitalization to GDP*

As opposed to our expectation, our results show that a higher ratio would lead to more herding. The explanation for this may lie on the fact that a more developed stock market is more liquid and attracts more investors to trade. Then, if there is more opportunity to trade stocks in the market, investors are more able to pursue herding strategies in that market.

On the other hand, the result we obtained may be capturing informational herding instead of “pure” herd behavior that we want to analyse. In fact, in more developed stock markets, information quality is better and investors may trade in the same direction just because they all had access to the same information.

*g) GDPpc*

The results for GDPpc were in consonance with Anderson *et al.* (2011), leading us to think that it tends to exist less herding in countries characterized by a higher GDPpc.

This can be explained through the fact that countries with a higher GDPpc tend to have more supervision, regulation and informational institutions, such as credit rating agencies and analysts (De Jong *et al.*, 2008), which would provide more information and institutional quality, thus leading to less herding.

*h) Bull and bear markets*

In panel A, our results regarding market phases corroborate our expectation that herding tends to be more intense in bull markets. That may be related to investors' sentiment in rising markets, which is enlarged by good news from their friends and the media. In phases that the market is in an upward trend, buy recommendations tend to be issued and incentive investors to follow other investors that were succeeded. However, in panel B, our results were not significant, which lead us to the conclusion that maybe herd behavior is not influenced by the market phases, since it can exists in both rising and falling markets.

*4.1.2. Cultural dimensions*

The intention of our study was to test if culture has some kind of impact in the decision of investors to follow one another, then the results that matter the most are those of the cultural dimensions we opted to include.

We perform a similar comparison that we made for the determinants of herding, confronting the expected and obtained results for cultural dimensions in Table 7.

**Table 7** – Expected vs. obtained results for cultural dimensions

The expected results are the ones based on the hypothesis formulated previously and the obtained results are the outcome of the regression model.

If the sign is “+”, the dimension has a positive impact on herding (negative impact on CSAD); if the sign is “-”, the dimension has a negative impact on herding (positive impact on CSAD); if the sign is “?”, the result is ambiguous; if the sign is “NS”, the variable is not statistically significant at a level of 10%.

Variable	Expected Result	Obtained Result	
		Panel A	Panel B
IND	-	-	<b>NS</b>
MAS	-	-	-
UA	+	+	<b>NS</b>
PD	?	-	-
LTO	?	<b>NS</b>	<b>NS</b>

The results obtained allowed us to conclude that culture may in fact play a major role in financial decision-making and, in particular, on herd behavior, since we found in panel A individualism, masculinity, uncertainty avoidance and power distance to be statistically significant and so, with explanation power for this phenomenon. In panel B, only masculinity and power distance have explanation power for herd behavior.

We begin our analysis with the results we got from panel A and then we analyse the results from panel B.

*a) Individualism*

Regarding individualism, we can observe that it has a negative impact on herd behavior, noticing that an increase of one level of the scale in individualism would cause an increase in dispersion by 0,001157. This denotes that herding is more likely to occur in collectivistic countries, which is in consonance with what is predicted both theoretically and empirically. People from countries with individualist values, tend to think of themselves as above average and more capable of achieving success with their own abilities. Thus, they tend to be overconfident and ignore some risks, acting more autonomously, not depending on a group to make their decisions.

Empirically, our findings are in tune with the majority of studies concerning the individualism dimension and its impact on financial decision-making. They all point to a link between individualism and overconfidence, resulting in investors from individualistic countries to make their investment decisions focusing more on the “I” than on the “We”, being thus less susceptible to engage in herd behavior.

*b) Masculinity*

The results for the masculinity dimension are also in tune with the predictions from previous literature and the hypothesis we formulated, presenting a negative relation with herding, having an impact of 0,001863 on returns’ dispersion per every unity increase in this dimension.

Our findings are theoretically consistent, showing that men tend to be self-confident and ambitious, being driven by competition and success (Hofstede, 1991), which leads them to trust their own abilities and have risk-taking behaviors. Empirically, our evidence is consistent with Barber and Odean (2001) that establish a

positive relationship between gender and trading, showing that men are usually overconfident investors (thus trading too much) and with Yao and Hanna (2005) and Beckmann and Menkhoff (2008) who concluded that women are less confident and more risk-averse.

*c) Uncertainty Avoidance*

Considering uncertainty avoidance, there is a positive relationship between this dimension and herd behavior, leading an increase on this dimension to a decrease in the returns of about 0,001017. This is in accordance with the theory behind the definition of this variable, which states that countries with high uncertainty avoidance want to avoid unknown situation preferring predictability and countries with low uncertainty avoidance are more prone to accept differences of opinion. Previous empirical studies also support this outcome, in the sense that uncertainty avoidance is directly related to risk-aversion (e.g. Aggarwall and Goodell, 2009; Beugelsdijk and Frijns, 2010; Anderson *et al.*, 2011; Nguyen and Truong, 2013) and inversely related to overconfidence (e.g. Ferris *et al.*, 2013).

*d) Power Distance*

Regarding power distance, our results seem to support the idea suggested by Sinke (2012) and Mihet (2012) that low power distance is closely related to values such as trust, equality and cooperation, thus being observable more harmony. We can observe that an increase of one unit in power distance causes an increase in dispersions by 0,001815.

The explanation for our result may lie on the link, suggested by Sinke (2012), between power distance and institutions quality. The author argued that higher power distant countries usually have institutions protecting the welfare, thus existing more shareholder protection. Therefore, those countries tend to have higher institutional quality that reflects better developed flow of information (Chui *et al.*, 2010), which entails less herding.

*e) Long-Term Orientation*

In what comes to long-term orientation, the result is not statistically significant, albeit the sign presents a negative relationship with herding.

The relationship considering the sign seems to go in the same direction on what was found in prior empirical studies, instead of the association that, conceptually, this dimension has with self-attribution bias (that would cause less evidence of herding). However, it is not possible to conclude anything on this result, since it is statistically insignificant to a 60% (Panel A) or 70% (Panel B) level, which means that the sign of this relationship may not be accurate at all.

In panel B, masculinity and power distance are the only significant variables, at a 10% level, both leading to a lower level of herding. These variables emphasize the fact that, people from countries characterized by this cultural background are less risk-averse and value less harmony and cooperation. Therefore, they tend to trade more and overestimate their investment abilities. However, if we consider a 15% level, the previous four dimensions that were significant in Panel A, would also be significant in Panel B, being the interpretation of these results equal to the one presented before.

In sum, our finding suggest that cultural dimensions have an impact in investors' decision-making and should be considered when we want to analyse the behavior of investors in financial markets. Specifically, we reached the conclusion that masculinity and power distance influence negatively the existence of herding in the market and that individualism and uncertainty avoidance may also play a role in the sense that the first one decreases the likelihood of the occurrence of herd behavior, whereas the second one would imply more herding. Long-term orientation is not statistically significant.

*4.1.3. Pre-crisis and crisis period*

So far, we analysed the period between 2001 and 2013 as a whole. However, we have to consider that this sample is not homogeneous in what concerns to financial markets. In fact, 2008 is a year marked by great instability, where financial market started to be extremely volatile and international contagion began. It is not easy to define precisely when did the crisis begin, but we can say that a major event that contributed for that instability in the markets was the bankruptcy of Lehman Brothers

on the 15<sup>th</sup> of September 2008. Therefore, we divide our sample into two different periods that we call “pre-crisis” (01/01/2001 – 14/09/2008) and “crisis” (17/09/2008 – 31/12/2013) and investigate if the influence of cultural dimensions changed in both periods. In Table 8 are illustrated the results for both periods.

**Table 8** – Results of cultural dimensions in “pre-crisis” and “crisis” period

In this table we present the results of the impact that cultural dimensions have on herd behavior during a “pre-crisis” (01/01/2001 – 14/09/2008) and a “crisis” (17/09/2008 – 31/12/2013) period. The t-statistics are in parenthesis. \* means that a variable is statistically significant at a 10% level, \*\* means that it is statistically significant at a 5% level and \*\*\* means it is statistically significant at a 1% level.

Variable	Pre-crisis period	Crisis period
IND	0.000976 (0.987410)	-0.002280 (-1.126902)
MAS	0.000864 (0.790464)	0.003062 (1.993387)**
UA	-0.000527 (-0.632354)	-0.004521 (-3.238399)***
PD	0.001806 (1.439803)	0.002340 (1.191568)
LTO	0.000908 (0.865475)	0.002398 (1.595617)

Considering the results above, we can observe that before the crisis none of the cultural variables were significant, but after the crisis masculinity and uncertainty avoidance became significant. This may be explained by the fact that information is now more ambiguous which leads by, on one hand, to the increase of risk-aversion from investors who are from cultures characterized by fear of uncertain outcomes and, on the other hand, to the raise of more masculine attitudes, because information is not clear, so investors that are confident may bet on their own abilities to perform better than others.

This leads us to think that maybe, in countries more characterized by uncertainty aversion there is a tendency to the occurrence of herd behavior during a crisis period, but on countries where masculinity is predominant this phenomenon tends to disappear during a crisis period. That is why it is important to consider cultural factors to understand how investors in a specific market will react to certain situations.

## 4.2. Time series analysis

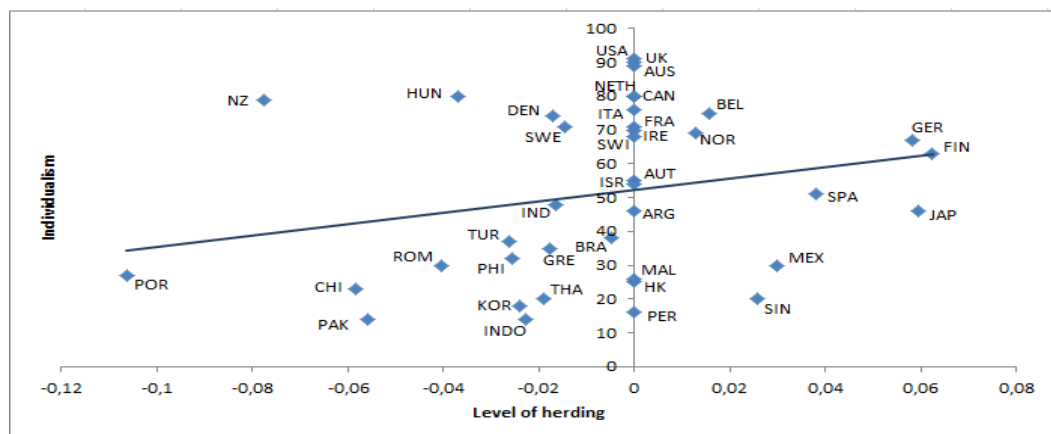
In our study we use panel data to test the impact of culture on herd behavior, however, this does not allow us to use the measure of herding proposed by Chang *et al.* (2000) entirely. In fact, we only use the cross-sectional absolute deviations as our dependent variable, but then we do not consider the relationship between CSAD and the market return to detect the presence of herding. In other words, we assume that lower levels of dispersions indicates more herding than higher levels of dispersion, but we do not have a coefficient (like in Chang *et al.*, 2000) that detects clearly the presence and intensity of this phenomenon.

So, at this point, we decide to perform a time-series analysis for each country, using the measure of Chang *et al.* (2000) in whole (equation 3.11), suggesting then a relationship between each cultural dimension and herding. Basically we regress their measure for each country individually and then obtain the value for the coefficient  $\beta_2$ , confronting it with the value the country has for a certain cultural dimension (if the coefficient is negative, it means that herding exists). Then, we compare all the countries against each other and observe the relationship between these cultural dimensions and herding. The regressions for each country can be found in appendix (1.3).

The relationship between individualism and herd behavior is shown in Figure 1.

**Figure 1** – Relationship between individualism and herding

In this figure we present the comparison between countries' individualism and herding. In the X-axis is represented the level of herding. In this case, a negative value indicates the presence of herding in that market and, the lower the value, the higher the intensity of the phenomenon. In the Y-axis is represented the value for the individualism dimension of each country. In this case, a higher value indicates a higher degree of individualism.



Observing figure 1, we can conclude that there is a negative relationship between individualism and herding, since countries with a higher level of herding (for example, Portugal) tend to be the ones that are more collectivist. This corroborates the hypothesis we formulated in section 3, when we associated individualism to overconfidence, leading that to a lower imitative behavior.

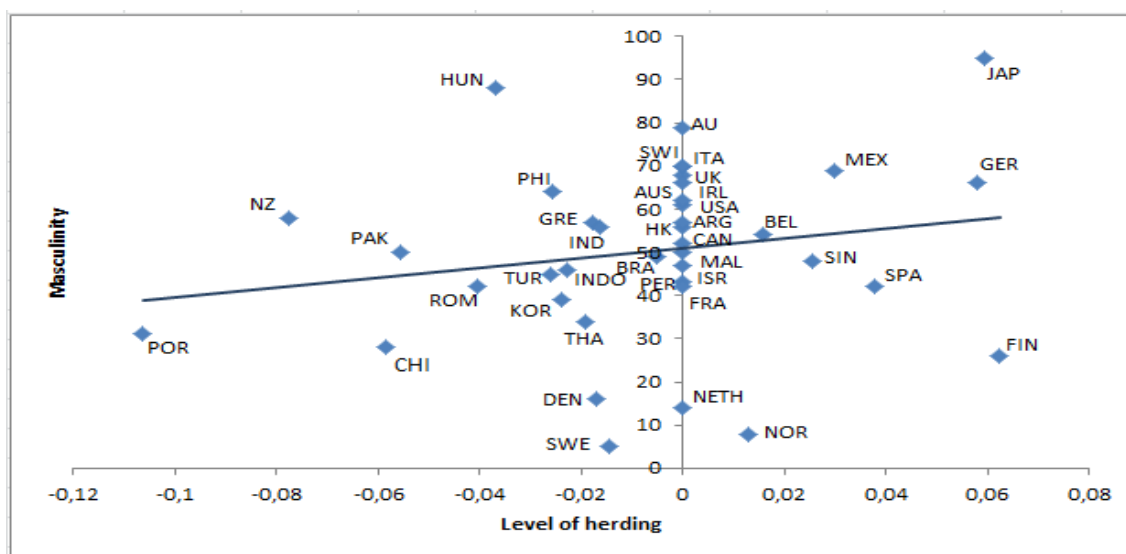
The relationship between masculinity and herding is next presented, in Figure 2.

**Figure 2 – Relationship between masculinity and herding**

In this figure we present the comparison of all the countries in terms of masculinity and level of herding, observing the existing relationship between those two variables.

In the X-axis is represented the level of herding. In this case, a negative value indicates the presence of herding in that market and, the lower the value, the higher the intensity of the phenomenon.

In the Y-axis is represented the value for the masculinity dimension of each country. In this case, a higher value indicates that the country is more masculine.



From Figure 2, we can also observe that there is a negative relationship between masculinity and herding, since countries more masculine tend to exhibit a lower level of herding. This is also in tune with our hypothesis that investors from countries characterized by high masculinity, tend to be less risk-averse, thus showing a lower propensity to herd.

The following analysis related uncertainty avoidance with herd behavior and the results of it are shown in Figure 3.

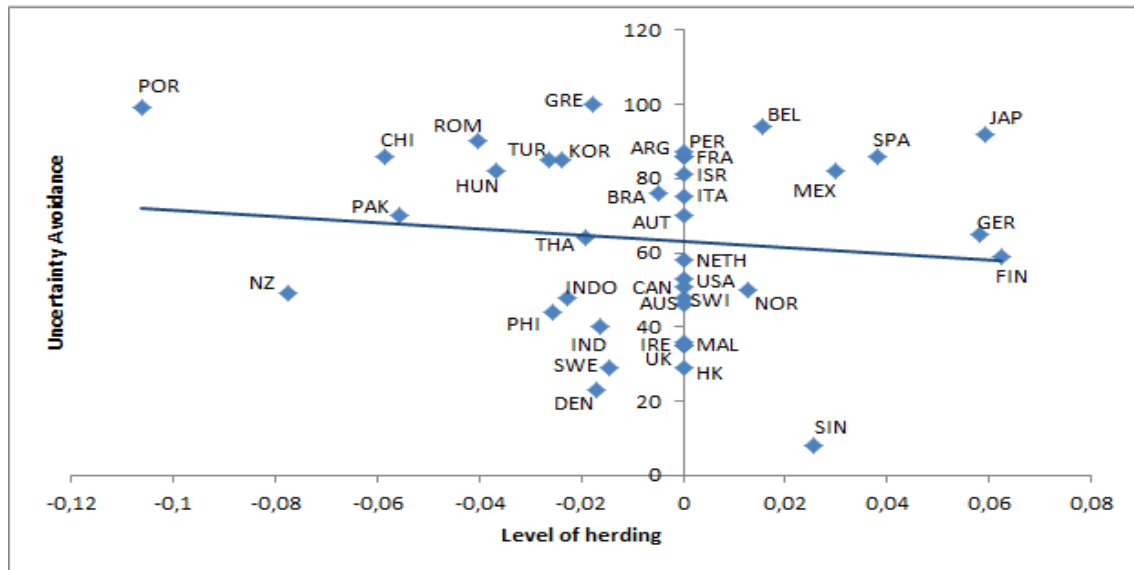


**Figure 3 – Relationship between uncertainty avoidance and herding**

In this figure we present the comparison of all the countries in terms of uncertainty avoidance and level of herding, observing the existing relationship between those two variables.

In the X-axis is represented the level of herding. In this case, a negative value indicates the presence of herding in that market and, the lower the value, the higher the intensity of the phenomenon.

In the Y-axis is represented the value for the uncertainty avoidance dimension of each country. In this case, a higher value indicates that the country has a higher degree of uncertainty avoidance.



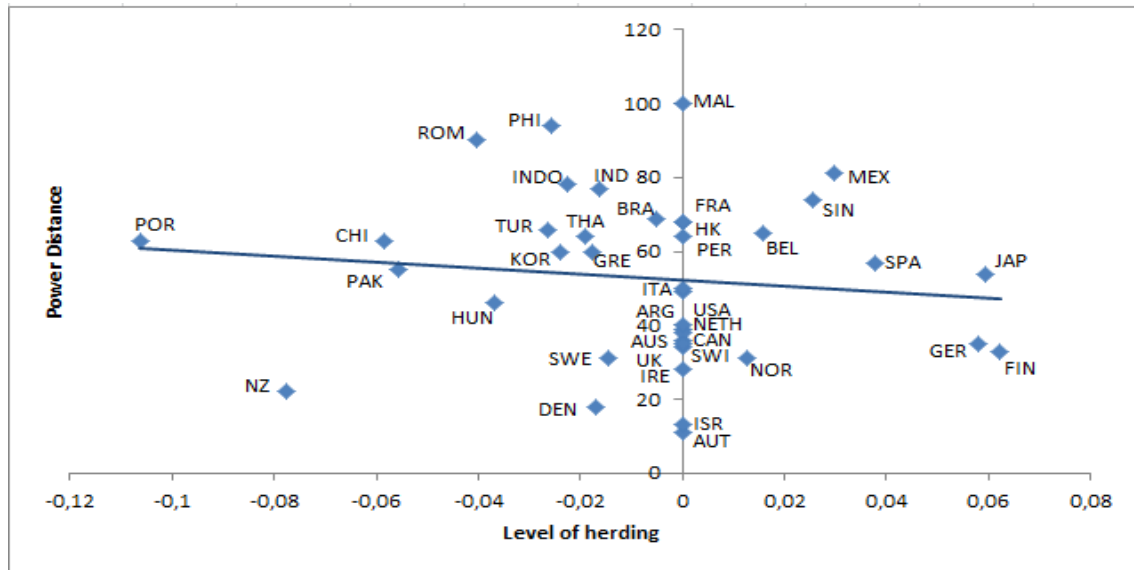
Regarding Figure 3, we can conclude that there is a positive relationship between uncertainty avoidance and herd behavior, being countries highly characterized by uncertainty avoidance (for example, Portugal) the ones that show higher level of herding, while countries with lower uncertainty avoidance (for example, Singapore) show no evidence of herding.

This result is also in consonance with our expectations when formulating our hypothesis, since investors from countries with higher uncertainty avoidance tend to be more risk-averse.

Next, we show the relationship between power distance and herding, in Figure 4

**Figure 4 – Relationship between power distance and herding**

In this figure we present the comparison of all the countries in terms of power distance and level of herding, observing the existing relationship between those two variables. In the X-axis is represented the level of herding. In this case, a negative value indicates the presence of herding in that market and, the lower the value, the higher the intensity of the phenomenon. In the Y-axis is represented the value for the power distance dimension of each country. In this case, a higher value indicates that the country is more power distant.



From the observation of Figure 4, we can conclude that there is a positive relationship between power distance and herding, which is in sync with Hofstede (1991). This makes sense, because investors from countries characterized by lower power distance tend to be more autonomous.

This result goes against the result we obtained when estimating our regression before, however, this implies a different model to include cultural dimensions than the one applied in section 3.

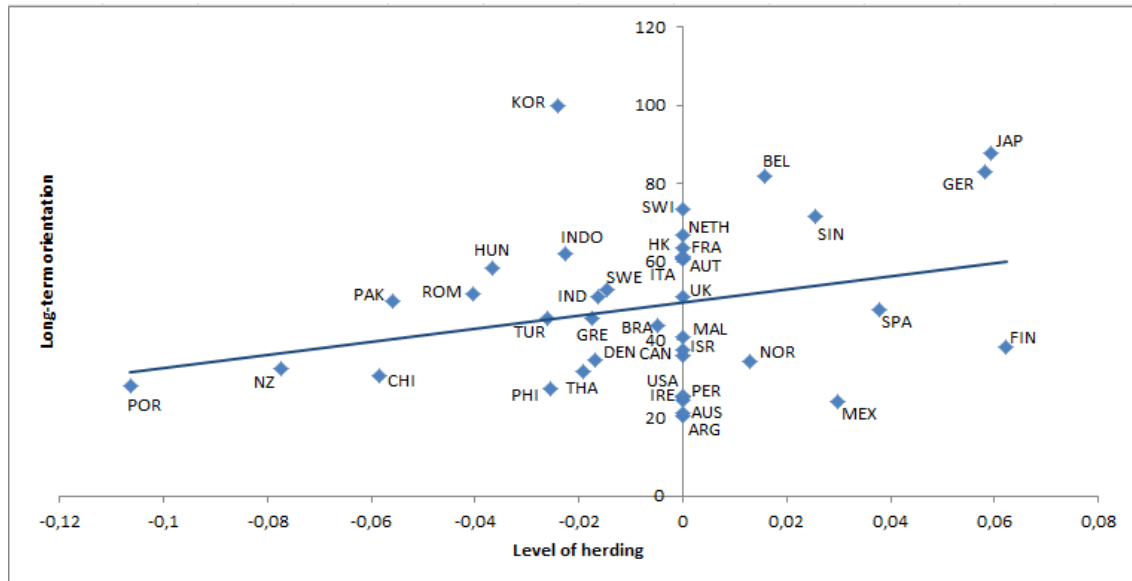
Finally, we show in Figure 5 the relationship between long-term orientation and herd behavior.

**Figure 5 – Relationship between long-term orientation and herding**

In this figure we present the comparison of all the countries in terms of long-term orientation and level of herding, observing the existing relationship between those two variables.

In the X-axis is represented the level of herding. In this case, a negative value indicates the presence of herding in that market and, the lower the value, the higher the intensity of the phenomenon.

In the Y-axis is represented the value for the long-term orientation dimension of each country. In this case, a higher value indicates that the country is more power distant.



The results from Figure 5 tell us that there is a negative relationship between long-term orientation and herd behavior. This gives weight to the argument that institutional investors represent a major part of the financial markets and they tend to be short-term oriented, since they have to present results quarterly.

### 4.3. Implications

We have seen during our study that culture can have a role in explaining a crowd behavior in financial markets, where investors follow one another even when their private information seem to tell them not to. It is important to understand what is behind this behavior because it can be a destabilizing force in the market, provoking price bubbles and mispricing. In fact, Hott (2012) related the occurrence of herding with the housing price bubble, arguing that more people decided to enter in the housing market expecting to win a fortune, just like other investors won.

Also, Welch (1992) argued that herding can partly determine a success of an IPO, since investors that are approached after some time tend to infer information from previous investors. In our view, it is relevant to include cultural dimensions here, since investors would put different weights on prior investors' action depending on the values that are predominant in their culture.

Furthermore, understanding the reasons that lead to herd behavior can help investors to define better their portfolio decisions and policymakers to adequate their policy setting to each market.

However, it is not only in investors and financial markets that culture can have influence. In fact, we have seen before that psychological and cultural factors can have impact in all of our decision-making processes. We next present some example of fields where culture can have a role to play.

Let's begin with entrepreneurship. We can see all around us people that want to be entrepreneurs and, in fact, there are currently TV shows (for example, Shark Tank) that promote their ideas and incentive people to follow that path. But we also know that starting a new business is not an easy thing to do: the risk and initial investment involved are huge. Sometimes is it needed to create a demand for the product or a brand and that will necessarily consume a lot of financial resources. According to Hamilton (2000) a person employed will win more 35% than a person that is self-employed over a period of 10 years. So, there seems to be psychological and social factors that attract people to pursue the path of starting a business on their own. Cultural factors may be related to the decision of individuals to become entrepreneurs, since they have to have characteristics such as overconfidence and risk-seeking profile to embark in a project of their own, being entrepreneurship related to dimensions such as individualism and masculinity.

Next, we explore the influence that culture can have in management decisions. Lobão (2013) suggested in his book that managers' decisions are influenced by psychological factors. Indeed, we can observe that companies belonging to the same activity sector, and facing similar situations, follow different paths and strategies, regarding investments, the way to get financing, dividends policy and mergers and acquisitions.

Managers are the ones responsible for making those decisions that impact the course of the company and their decisions are dependent on psychological factors and social interactions that are partly inherent to their cultural background. For example, when a manager needs financial resources, he can choose to get them internally or externally. His decision may be related to the masculinity dimension, since a manager belonging to a country where masculinity is deeply embedded, is more reluctant to use external funds. Also, when a manager has to decide whether to invest or not in a project, his risk profile may be dependent on cultural characteristics, such as individualism, masculinity and uncertainty avoidance. In this sense, a manager from a culture with a high degree of individualism and masculinity, and a low degree of uncertainty avoidance, will tend to underestimate the risk and be more confident on the future results of the investment.

Furthermore, M&A processes can be also related to cultural characteristics of the managers. Ferris *et al.* (2013) reached the conclusion that overconfident managers tend to be more prone to mergers and acquisitions because they underestimate the risk involved, and are also more prone to acquire diversified businesses that are not related to his core business, because they think they possess superior decision-making abilities than their peers. So, M&A processes may be associated with dimensions such as individualism and masculinity, which are directly related to overconfidence.

Finally, the dividend policy can be also influenced by culture, since the decision to distribute dividends implies that the money to distribute will not be available to invest in the company. Therefore, cultural dimensions such as long-term orientation may help to understand this decision, because in long-term oriented countries maybe people would prefer to save the money in order to invest and earn a higher return in the future and short-term oriented countries may prefer to distribute dividends.

## 5. Conclusion

Given the low correspondence between the predictions of theoretical models in finance and what we observe empirically in financial markets, there has been over the last years an increase in the relevance of studying investors' behavior, since it may create patterns capable of impacting stock prices. This helps us to understand how investors act in reality and why they make certain decisions.

In fact, interveners in financial markets are human beings and then, when they have to face some decision-making situations, they are susceptible to psychological biases that would move them away from what should be the "rational" decision. Besides, agents in financial markets are not isolated from other participants, they interact with each other, and that social interaction can also lead them to adopt a different decision from the one they would choose if they were not facing social interaction.

Considering this, there has been some studies concerning the outcomes that may result from those psychological and social forces underlying investors' behavior, especially the imitative behavior that may emerge. Our study also focused the herd behavior, but our approach distinguished from all previous studies in the sense that we were the first, as far as we know, to include a cultural view to this phenomenon. The rationale for this analysis was that in our daily life, when interacting with people from different cultural background, we can observe that we have different ways to see reality and thus, think and act differently. If the decisions we face every day are influenced by our culture, is expected that what occurs in financial markets are also influenced, since it is based on the decisions its participants make (e.g. when to invest, which stock to sell or buy, how much money to invest).

Therefore, our main goal with the present study was to test the influence cultural factors could have in the existence and intensity of mimetic behavior. For that purpose we used Hofstede's (2001) five cultural dimensions and the measure of herding proposed by Chang *et al.* (2000), as well as some determinants of herding and variables related to institutional quality and economic development that are often explored in literature to explain herd behavior (book-to-market ratio, volatility, turnover, size, market capitalization to GDP ratio and GDPpc).

Our analysis was made for 39 countries during the period from 01/01/2001 to 31/12/2013. We then divided the sample into two different periods, called “pre-crisis” and “crisis”, because the financial crisis that began with the bankruptcy of Lehman Brothers caused a great instability in the markets and that may lead to some changes in investors’ behavior.

Our results suggested that culture has indeed the ability to influence the dispersion of returns, impacting evidence of herding. Countries characterized by a higher level of masculinity and power distance are less prone to herd behavior. The results for individualism and uncertainty avoidance were only statistically significant when we considered a less stringent approach on standard deviations. However, they suggest that individualistic countries less prone to herd behavior and countries with high uncertainty avoidance more likely to exhibit herding. Long-term orientation was not statistically significant.

Nevertheless, we have to admit that our study presents some limitations. In first place, there were issues regarding data availability that prevented us from analysing a larger sample of countries and forced us to use daily values that may not correspond exactly to its true daily value (some variables were only available annually and in order to have its daily value we divided the annual value for the number of observations of the year, assuming that they present the same value every day).

Secondly, the measure of herding we employed has two problems: on one hand, it does not capture herding if this is only evident in a specific asset or group of assets, for example, from a particular economic sector; on the other hand, it considers “spurious” herding, since it does not have any mechanism able to distinguish changes in returns’ dispersion driven by sentiment from those driven by adjusting to new information.

One of the ways to attenuate this limitation is the use of Hwang and Salmon’s (2004) measure, that assumes herding to be stronger during quiet periods, since in a crisis periods there tends to be a flight to fundamentals.

Their measure presents some similarities with Christie and Huang’s (1995), in the sense that they also exploit cross-sectional movement of the market. However, their focus is more on the cross-sectional variability of factor sensitivities rather than returns, which gives them the advantage of capturing convergence on market beliefs on a

specific asset or asset classes. This is important because, according to Hwang and Salmon (2004), market stress does not imply that the market as a whole has to show large negative or positive returns, since even without the existence of a large movement in the market as a whole we may be able to find a considerable reallocation towards particular sectors. For instance, if we observe some euphoria in certain sectors (e.g. technology), investors will start to sell the unattractive stocks and buy the hot stocks, while new investors enter the market to invest in those appealing stocks. The outcome of this is that dispersions to the market return increase because investors are only investing in a specific group of stocks, but this is not captured by the measure we employed.

On the other hand, the dummy method that we used to reflect extreme market movements does not include any sort of device that enables us to control for movements in fundamentals, which makes impossible to distinguish if it is herding or adjustment to fundamentals. In other words, the measure of herding we used in our study is incapable of separating “spurious” herding from herd behavior induced by investors’ sentiment. The model proposed by Hwang and Salmon (2004) can overcome this problem at some extent because it is based on observed deviations from equilibrium beliefs expressed in CAPM.

Finally, we used daily data but literature suggests that the ideal time frequency is intradaily, since in such a short period of time investors are more likely to “act by feeling”, not having enough time to apply complex models to their decision.

Considering the aforementioned limitations, we suggest for further investigation the use of a different herding measure (e.g. the measure proposed by Hwang and Salmon (2004) that eliminates the evidence of “spurious” herding), a sectorial analysis that is able to detect herding in a specific economic sector that is not showed in the market as whole and the use of intradaily data to explore the short-term feature of herd behavior. Also, the potential influence of culture in several financial should be explored, since there are not currently many studies considering cultural aspects in finance and, as it is suggested in our study, they have the ability to influence investors’ behavior in financial markets.



Furthermore, we showed that Hostede's dimensions are prone to several criticisms, so it would be important to have studies that include other cultural dimensions, for example, the ones of Schwartz (1994) or Project GLOBE (2004).

Our study was undertaken to pose the question if different views, resulting in different decisions, may be increased because investors have different cultural background. Thus, we hope that our study helps to motivate future research on the influence of cultural differences in stock returns, as well as in other financial, economics and management fields, in order to have a clearer picture about certain phenomena that occur and cannot be explained by the models currently used.

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## Appendix:

### 1.1. Fixed and Random Effects

Panel data or longitudinal data is a data set that combines time series and cross-sections, allowing an analysis that captures the heterogeneity across individuals, firms or countries, and the dynamic effects invisible in cross-sections.

According to Hsiao (2006), a panel data analysis offers a set of advantages over time series or cross-section data, namely the accuracy regarding inference of model parameters. The author suggested that a panel data provides a larger number of observations (increasing the degrees of freedom) and contains less multicollinearity, which improves the efficiency of econometric estimates. Also, he argued that this data set has a higher capacity for capturing the complexity of human behavior, because it is possible to construct and test more complicated behavioral hypothesis and the impact of omitted variables is controlled.

The general model of panel data is presented as follows:

$$y_{it} = x_{it}\beta + c_i + u_{it}, \quad t = 1, 2, \dots, T; i = 1, 2, \dots, n$$

where  $t$  is the time period and  $i$  represents different individuals.

$y_{it}$  is the independent variable,  $x_{it}$  is a  $1 \times K$  vector containing the explanatory variables,  $\beta$  is a  $1 \times K$  vector of parameters to be estimated,  $c_i$  is the unobserved heterogeneity and  $u_i$  are the random errors.

A panel data is called balanced, when for each individual we have the same number of time periods, and is called unbalanced, when we do not have the same time period for all the individuals. Although there is a distinction between them, the estimation methods are the same regardless of the model is with balanced or unbalanced data (Greene, 2012).

#### Fixed and Random effects models:

In panel data models, the question we have to have in mind is whether  $c_i$  is correlated or not with  $x_{it}$ , because that is the answer we need to know if we should use fixed effects or random effects when estimating our model. If  $Cov(x_{it}, c_i) = 0$  for  $t = 1, 2, \dots, T$ , then  $c_i$  is assumed to be uncorrelated with the explanatory variables and is referred as an individual random effect. Otherwise, if  $Cov(x_{it}, c_i) \neq 0$  for  $t = 1, 2, \dots, T$ ,

then  $c_i$  is assumed to be correlated with the explanatory variables and is referred as a fixed effect.

To detect the appropriate model to use, Hausman (1978) provided a test where the null and alternative hypothesis are the following, respectively:

$$H_0: Cov(x_{ib}, c_i) = 0 \text{ (random effects)}$$

$$H_1: Cov(x_{ib}, c_i) \neq 0 \text{ (fixed effects)}$$

Therefore, he suggested the use of the following statistic to test fixed effects vs. random effects specification:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})' [V_{FE} - V_{RE}]^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE}) \sim \chi^2,$$

where  $\hat{\beta}_{FE}$  and  $\hat{\beta}_{RE}$  are the estimators' vector of the model with fixed effects and random effects, respectively; and  $V_{FE}$  and  $V_{RE}$  are the asymptotic covariance matrix of the model with fixed effects and random effects, respectively.

The Hausman Test is presented in Table 9, below.

**Table 9 – Hasuman Test**

Correlated Random Effects - Hausman Test				
Equation: Untitled				
Test cross-section random effects				
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Cross-section random	97.970143	9	0.0000	
Cross-section random effects test comparisons:				
Variable	Fixed	Random	Var(Diff.)	Prob.
BTM	0.103569	0.103177	0.000000	0.0049
VOL	0.017368	0.017376	0.000000	0.0000
SIZE	-0.000000	-0.000000	0.000000	0.0000
TURN	0.129987	0.128438	0.000000	0.0034
MC_GDP	-0.000224	-0.000217	0.000000	0.0001
GDPPC	0.000004	0.000004	0.000000	0.0000
EXTREME_UP	0.485593	0.485754	0.000000	0.0000
EXTREME_DOWN	0.411057	0.411270	0.000000	0.0000
BULL_BEAR	-0.004666	-0.004293	0.000000	0.0000

## 1.2. Results

**Table 10 – Period Weight (PCSE)**

Dependent Variable: CSAD				
Method: Panel EGLS (Cross-section random effects)				
Date: 09/13/14 Time: 18:06				
Sample: 1/01/2001 12/31/2013				
Periods included: 3392				
Cross-sections included: 39				
Total panel (unbalanced) observations: 130661				
Swamy and Arora estimator of component variances				
Period weights (PCSE) standard errors & covariance (d.f. corrected)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.284887	0.076134	3.741913	0.0002
BTM	0.103345	0.001483	69.68870	0.0000
VOL	0.017374	0.000325	53.45721	0.0000
SIZE	-1.35E-16	1.43E-17	-9.472347	0.0000
TURN	0.128775	0.005318	24.21327	0.0000
MC_GDP	-0.000219	1.04E-05	-21.05496	0.0000
GDPPC	3.75E-06	3.90E-07	9.618555	0.0000
EXTREME_UP	0.485705	0.005216	93.10987	0.0000
EXTREME_DOWN	0.411216	0.004494	91.50774	0.0000
BULL_BEAR	-0.004424	0.001618	-2.734685	0.0062
IND	0.001157	0.000640	1.808110	0.0706
MAS	0.001863	0.000601	3.099440	0.0019
UA	-0.001017	0.000505	-2.012697	0.0441
PD	0.001815	0.000695	2.610085	0.0091
LTO	0.000307	0.000588	0.522248	0.6015
Effects Specification				
			S.D.	Rho
Cross-section random			0.070240	0.0673
Idiosyncratic random			0.261440	0.9327
Weighted Statistics				
R-squared	0.382676	Mean dependent var	0.044001	
Adjusted R-squared	0.382610	S.D. dependent var	0.332827	
S.E. of regression	0.261504	Sum squared resid	8934.144	
F-statistic	5784.773	Durbin-Watson stat	1.264432	
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.374022	Mean dependent var	0.684594	
Sum squared resid	10513.86	Durbin-Watson stat	1.074465	

**Table 11 – White Period**

Dependent Variable: CSAD					
Method: Panel EGLS (Cross-section random effects)					
Date: 09/13/14 Time: 18:48					
Sample: 1/01/2001 12/31/2013					
Periods included: 3392					
Cross-sections included: 39					
Total panel (unbalanced) observations: 130661					
Swamy and Arora estimator of component variances					
White period standard errors & covariance (d.f. corrected)					
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
C	0.284887	0.100592	2.832114	0.0046	
BTM	0.103345	0.012202	8.469408	0.0000	
VOL	0.017374	0.002532	6.860737	0.0000	
SIZE	-1.35E-16	5.22E-17	-2.594405	0.0095	
TURN	0.128775	0.056666	2.272532	0.0231	
MC_GDP	-0.000219	0.000132	-1.658055	0.0973	
GDPPC	3.75E-06	1.74E-06	2.154335	0.0312	
EXTREME_UP	0.485705	0.024428	19.88308	0.0000	
EXTREME_DOWN	0.411216	0.023331	17.62514	0.0000	
BULL_BEAR	-0.004424	0.009148	-0.483607	0.6287	
IND	0.001157	0.000788	1.467801	0.1422	
MAS	0.001863	0.001015	1.835765	0.0664	
UA	-0.001017	0.000672	-1.514897	0.1298	
PD	0.001815	0.001060	1.711875	0.0869	
LTO	0.000307	0.000910	0.337723	0.7356	
Effects Specification					
				S.D.	Rho
Cross-section random				0.070240	0.0673
Idiosyncratic random				0.261440	0.9327
Weighted Statistics					
R-squared	0.382676	Mean dependent var	0.044001		
Adjusted R-squared	0.382610	S.D. dependent var	0.332827		
S.E. of regression	0.261504	Sum squared resid	8934.144		
F-statistic	5784.773	Durbin-Watson stat	1.264432		
Prob(F-statistic)	0.000000				
Unweighted Statistics					
R-squared	0.374022	Mean dependent var	0.684594		
Sum squared resid	10513.86	Durbin-Watson stat	1.074465		



**Table 12 – Pre-crisis period**

Dependent Variable: CSAD				
Method: Panel EGLS (Cross-section random effects)				
Date: 09/13/14 Time: 19:38				
Sample (adjusted): 1/01/2001 9/14/2007				
Periods included: 1750				
Cross-sections included: 39				
Total panel (unbalanced) observations: 66992				
Swamy and Arora estimator of component variances				
White period standard errors & covariance (d.f. corrected)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.455958	0.180681	2.523552	0.0116
BTM	0.081166	0.019229	4.220925	0.0000
VOL	0.018188	0.004081	4.457082	0.0000
SIZE	-2.16E-16	1.21E-16	-1.779771	0.0751
TURN	-0.087234	0.096160	-0.907176	0.3643
MC_GDP	-0.000246	0.000184	-1.336687	0.1813
GDPPC	-8.17E-07	3.23E-06	-0.253219	0.8001
IND	0.000155	0.001451	0.106760	0.9150
MAS	0.000393	0.001230	0.319667	0.7492
UA	-0.001197	0.001018	-1.175041	0.2400
PD	0.001332	0.001641	0.811709	0.4170
LTO	0.002951	0.001522	1.939788	0.0524
Effects Specification				
			S.D.	Rho
Cross-section random			0.067968	0.0592
Idiosyncratic random			0.270892	0.9408
Weighted Statistics				
R-squared	0.239830	Mean dependent var	0.064400	
Adjusted R-squared	0.239705	S.D. dependent var	0.310954	
S.E. of regression	0.271067	Sum squared resid	4921.510	
F-statistic	1921.079	Durbin-Watson stat	1.224874	
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.248201	Mean dependent var	0.672109	
Sum squared resid	5829.850	Durbin-Watson stat	1.034028	

**Table 13 – Crisis period**

Dependent Variable: CSAD				
Method: Panel EGLS (Cross-section random effects)				
Date: 09/13/14 Time: 19:39				
Sample: 9/17/2007 12/31/2013				
Periods included: 1642				
Cross-sections included: 39				
Total panel (unbalanced) observations: 63669				
Swamy and Arora estimator of component variances				
White period standard errors & covariance (d.f. corrected)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.463703	0.173169	2.677754	0.0074
BTM	0.188177	0.028446	6.615272	0.0000
VOL	0.019127	0.003981	4.804093	0.0000
SIZE	-1.05E-18	5.11E-17	-0.020485	0.9837
TURN	0.530371	0.103149	5.141779	0.0000
MC_GDP	-0.000846	0.000291	-2.906373	0.0037
GDPPC	-1.11E-06	2.35E-06	-0.474290	0.6353
IND	-0.002224	0.001713	-1.298811	0.1940
MAS	0.002916	0.001308	2.228139	0.0259
UA	-0.003793	0.001144	-3.316740	0.0009
PD	0.001809	0.001668	1.084556	0.2781
LTO	0.002389	0.001331	1.794324	0.0728
Effects Specification				
			S.D.	Rho
Cross-section random			0.083221	0.0775
Idiosyncratic random			0.287217	0.9225
Weighted Statistics				
R-squared	0.289770	Mean dependent var	0.059444	
Adjusted R-squared	0.289648	S.D. dependent var	0.341351	
S.E. of regression	0.287687	Sum squared resid	5268.514	
F-statistic	2361.069	Durbin-Watson stat	1.121159	
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.135713	Mean dependent var	0.697731	
Sum squared resid	7795.795	Durbin-Watson stat	0.757696	

**Table 14 – Correlation Matrix**

Correlation														
	BTM	VOL	TURN	SIZE	EXTREME_UP	EXTREME_...	BULL_BEAR	MC_GDP	GDPPC	IND	MAS	UA	PD	LTO
BTM	1.000000	0.117913	-0.300290	-0.092573	0.029351	0.024952	0.153836	-0.310303	-0.017649	-0.171762	-0.071500	0.120582	-0.044042	-0.243060
VOL	0.117913	1.000000	-0.022798	-0.009090	0.067562	0.079039	0.021978	-0.043060	-0.000470	-0.003754	0.023371	0.019363	0.009512	-0.024531
TURN	-0.300290	-0.022798	1.000000	0.010373	0.029377	0.034691	-0.134767	0.108834	0.117945	0.183528	-0.063476	-0.052808	-0.182622	0.330467
SIZE	-0.092573	-0.009090	0.010373	1.000000	-0.008071	-0.005129	0.007765	-0.043156	0.858583	-0.258864	0.010314	0.009877	0.160857	0.264460
EXTREME_UP	0.029351	0.067562	0.029377	-0.008071	1.000000	-0.044163	0.024535	-0.012489	-0.002588	-0.001367	-0.001816	0.002706	0.000595	0.000665
EXTREME_...	0.024952	0.079039	0.034691	-0.005129	-0.044163	1.000000	-0.012761	-0.012050	-0.000442	0.002165	-0.001817	0.006805	-0.009281	0.005958
BULL_BEAR	0.153836	0.021978	-0.134767	0.007765	0.024535	-0.012761	1.000000	-0.063155	0.021486	-0.047485	0.039112	0.012744	0.061158	-0.030377
MC_GDP	-0.310303	-0.043060	0.108834	-0.043156	-0.012489	-0.012050	-0.063155	1.000000	-0.055140	-0.038171	0.021805	-0.393075	0.043909	0.196404
GDPPC	-0.017649	-0.000470	0.117945	0.858583	-0.002588	-0.000442	0.021486	-0.055140	1.000000	-0.332004	-0.057912	0.090020	0.164374	0.386346
IND	-0.171762	-0.003754	0.183528	-0.258864	-0.001367	0.002165	-0.047485	-0.038171	-0.332004	1.000000	0.102955	-0.221114	-0.662714	-0.018798
MAS	-0.071500	0.023371	-0.063476	0.010314	-0.001816	-0.001817	0.039112	0.021805	-0.057912	0.102955	1.000000	0.160565	0.051404	0.188247
UA	0.120582	0.019363	-0.052808	0.009877	0.002706	0.006805	0.012744	-0.393075	0.090020	-0.221114	0.160565	1.000000	0.147872	0.089796
PD	-0.044042	0.009512	-0.182622	0.160857	0.000595	-0.009281	0.061158	0.043909	0.164374	-0.662714	0.051404	0.147872	1.000000	0.045291
LTO	-0.243060	-0.024531	0.330467	0.264460	0.000665	0.005958	-0.030377	0.196404	0.386346	-0.018798	0.188247	0.089796	0.045291	1.000000

**Table 14 – Ridge Regression**

Dependent Variable: CSAD				
Ridge Regression				
Date: 09/16/14 Time: 01:31				
Sample: 1/01/2001 12/31/2013				
Included observations: 132288				
Lambda: 0				
Variable	Raw Ridge	Std. Ridge	V.I.F	
BTM	0.102190	0.264844	1.427200	
VOL	0.018550	0.379880	1.027552	
SIZE	7.21E-17	0.056768	4.391159	
TURN	0.114657	0.079823	1.344994	
MC_GDP	-6.56E-05	-0.037673	1.461858	
GDPPC	-7.39E-07	-0.038576	5.133351	
EXTREME_UP	0.482355	0.258268	1.010175	
EXTREME_DOWN	0.410985	0.241960	1.011421	
BULL_BEAR	0.013236	0.018286	1.042573	
IND	0.000696	0.047506	2.392843	
MAS	0.001376	0.076315	1.174070	
UA	-0.000290	-0.019094	1.401648	
PD	0.001333	0.081024	1.983772	
LTO	0.000943	0.052407	1.554657	
R-squared:	0.394619			

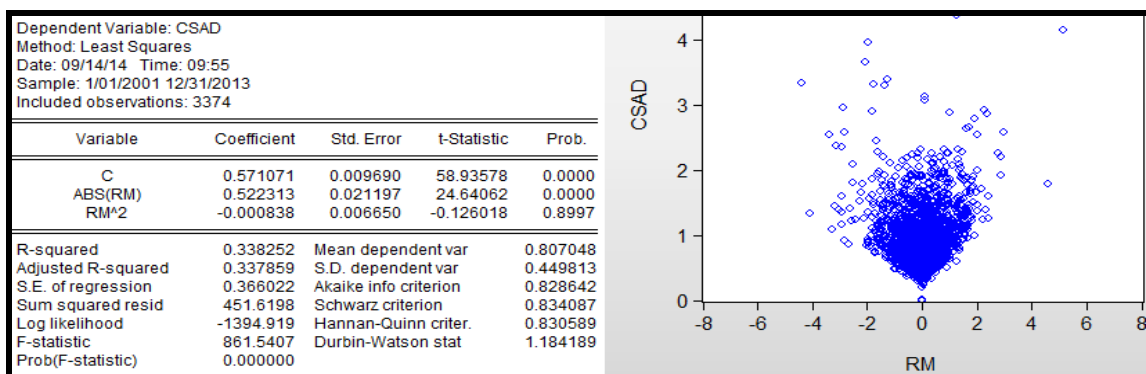
We perform the ridge regression to see if the variables are strongly correlated to each other, since in panel data a major problem that may emerge is multicollinearity. So, to examine the issue of multicollinearity in the independent variables we compute

the variance inflation factor (VIF). According to Kaur *et al.* (2013), VIF are considered bad if they exceed 5 and, on the other hand, O'Brien (2007) considered this limit to be 10. Since the higher number we have for VIF is 5,133 (GDPpc), we do not consider to have a problem of multicollinearity.

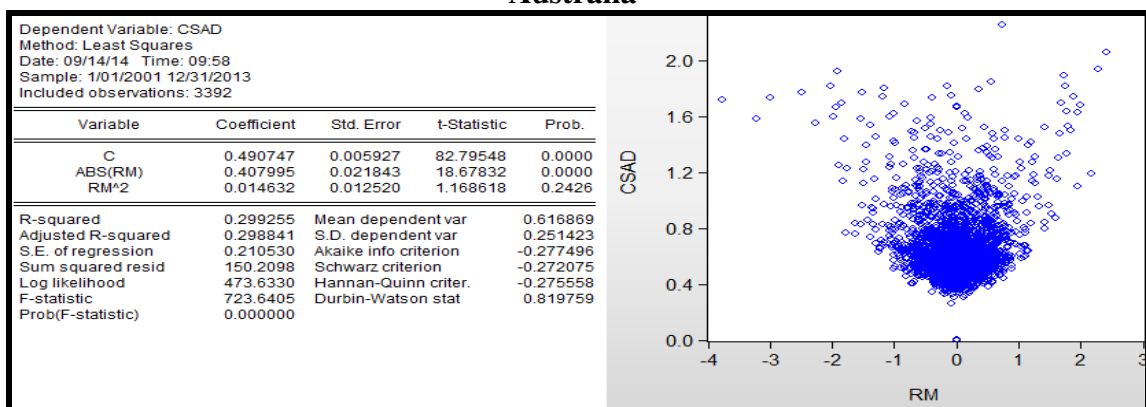
### 1.3. Time series analysis

Here we perform a time series analysis for each country, applying the measure of Chang *et al.* (2000) to detect herding. We also performed the same test using the measure from Christie and Huang (1995) but found out that there was no evidence of herding for any of the countries. This may be related to the limitation that we presented before, that this measure only captures herding in extreme market situations, but the behavior can exist during quiet periods as well.

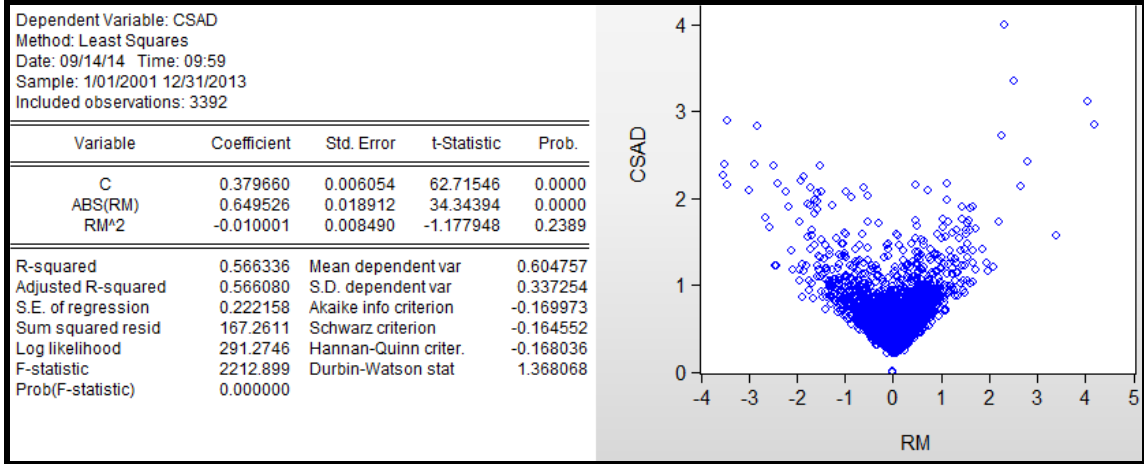
#### Argentina



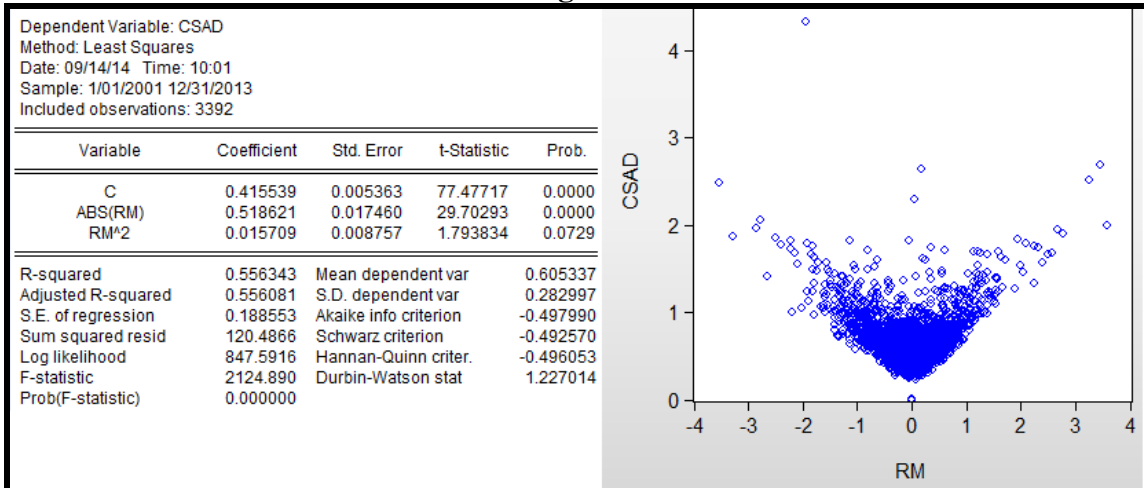
#### Australia



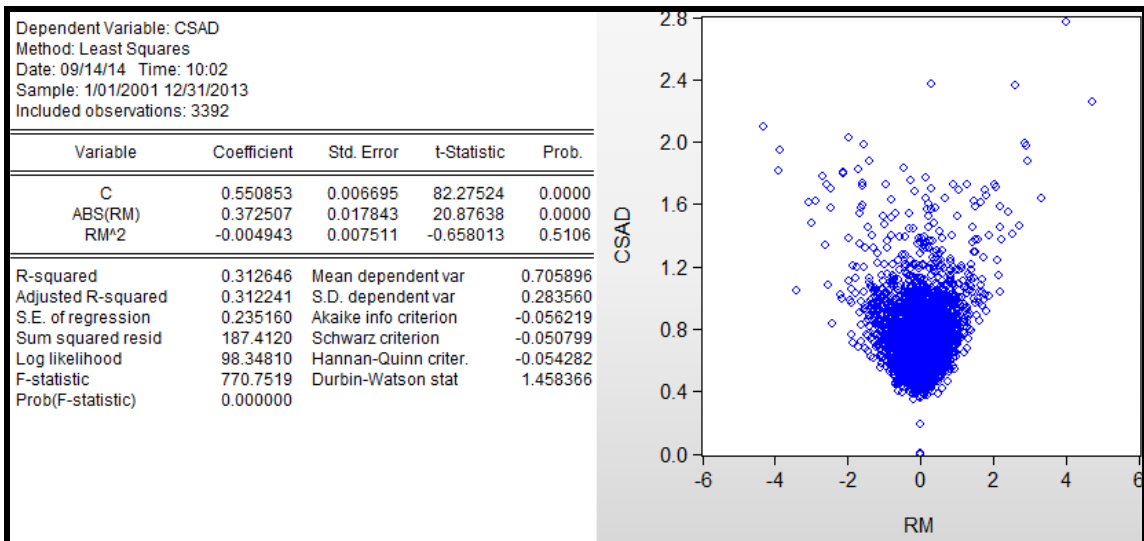
## Austria



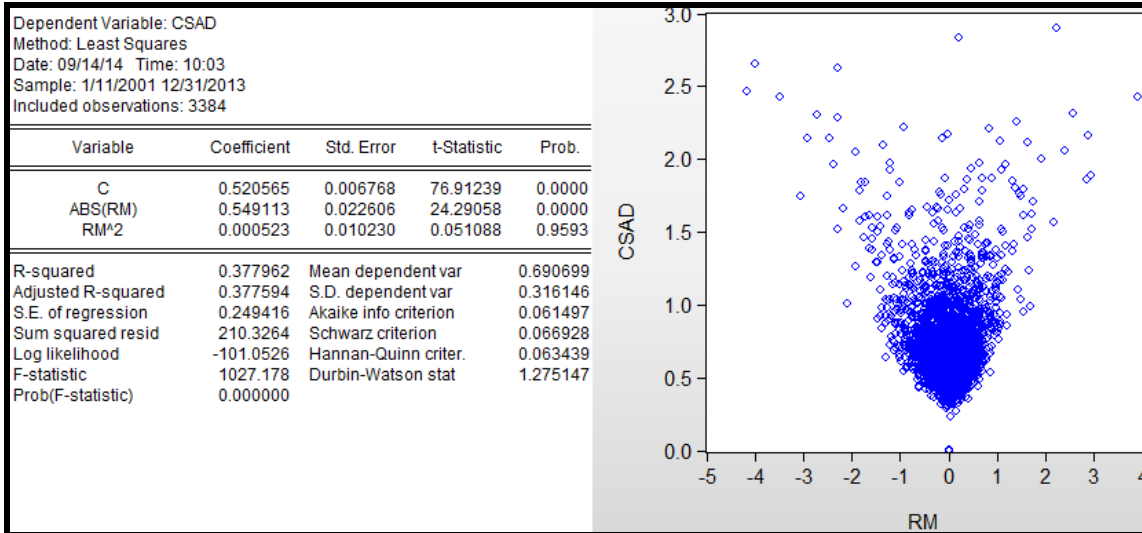
## Belgium



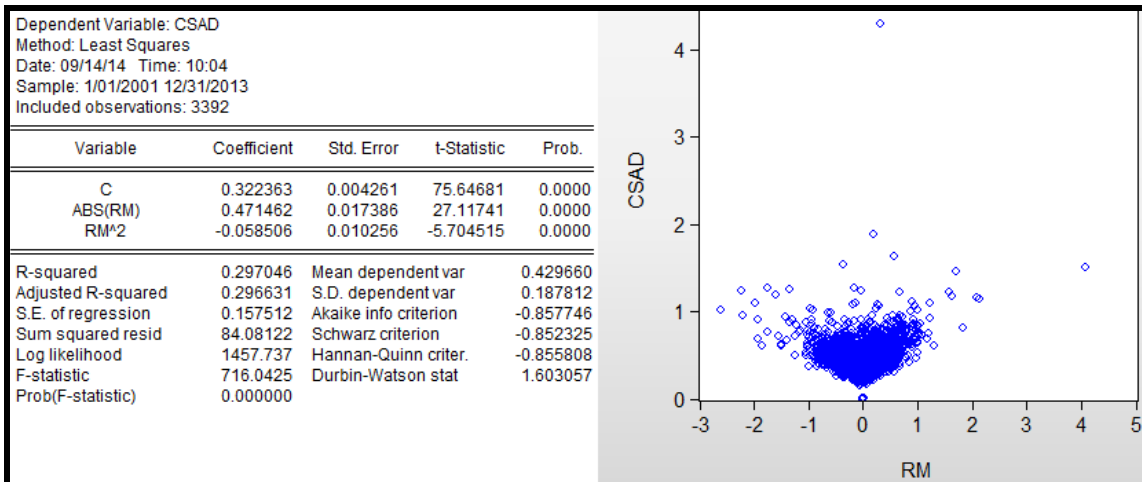
## Brazil



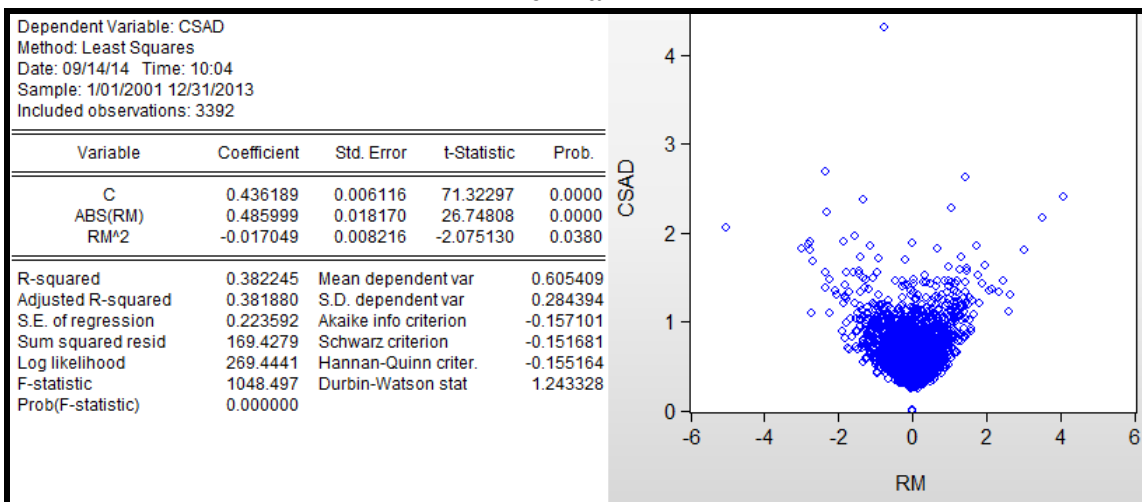
## Canada



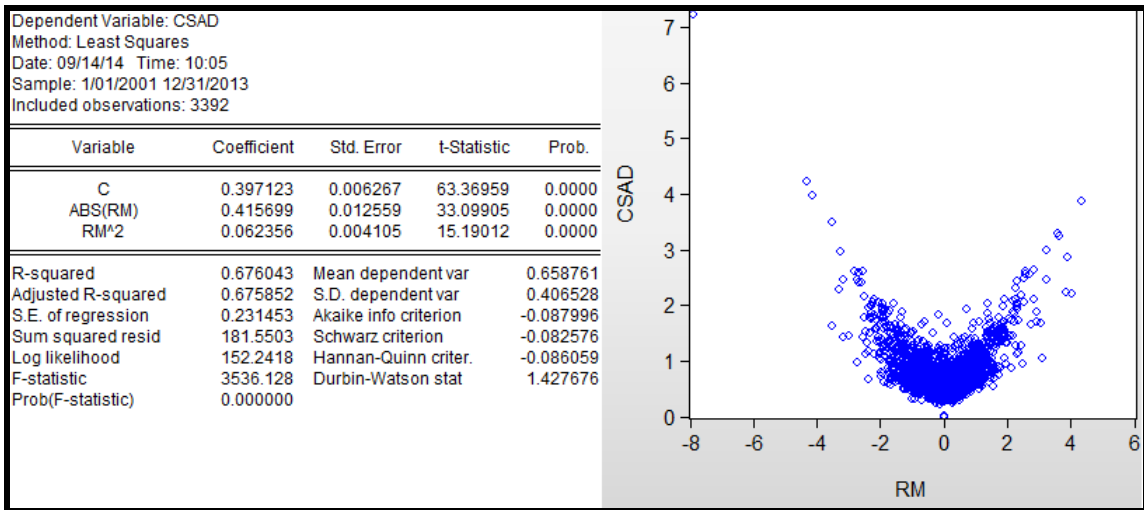
## Chile



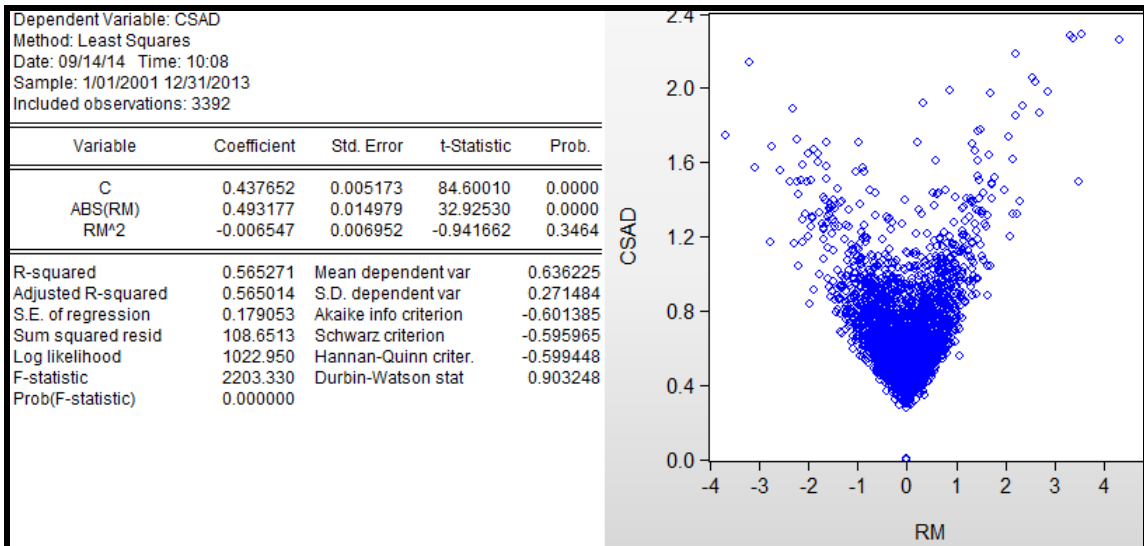
## Denmark



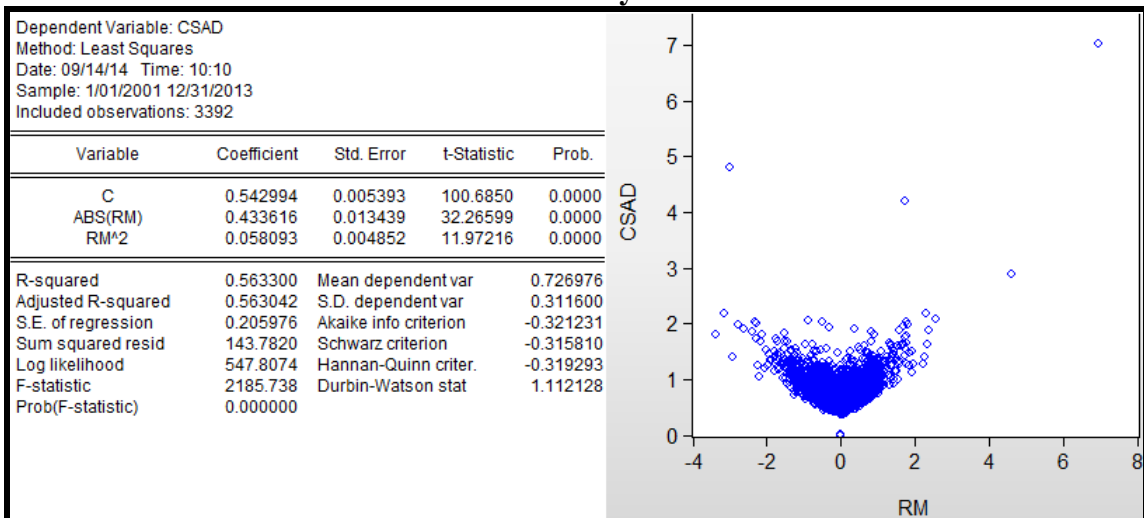
## Finland



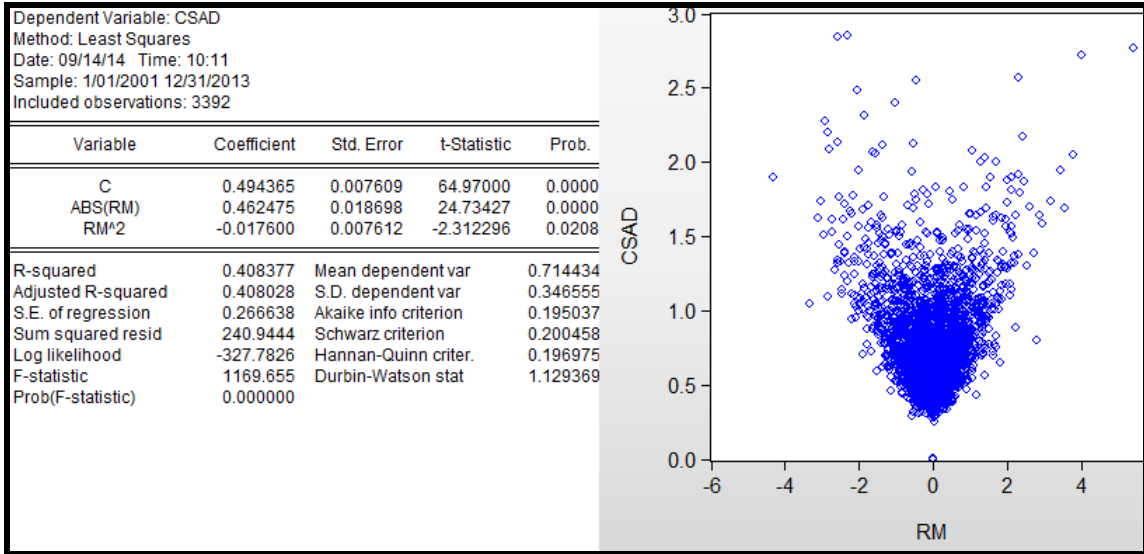
## France



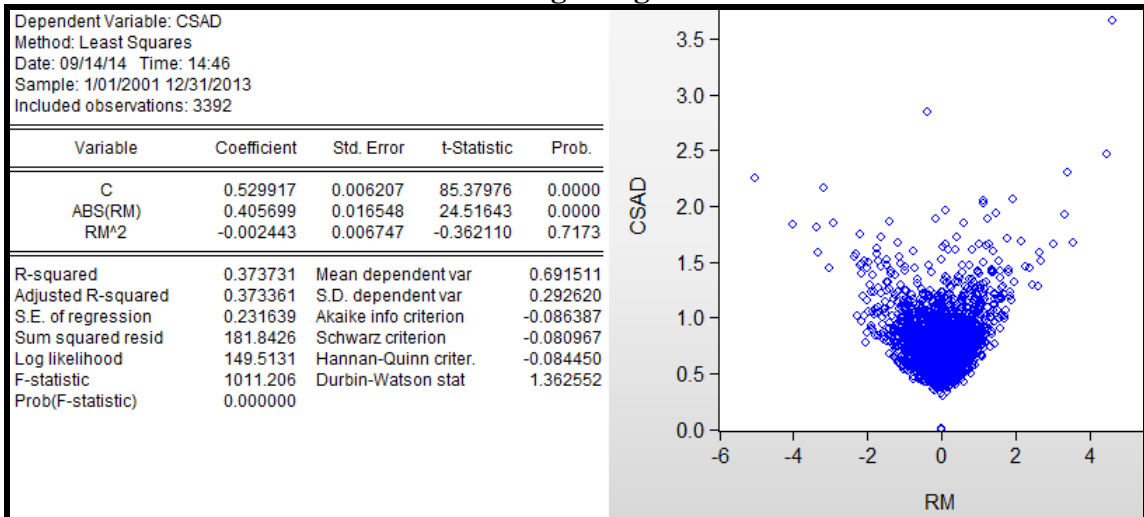
## Germany



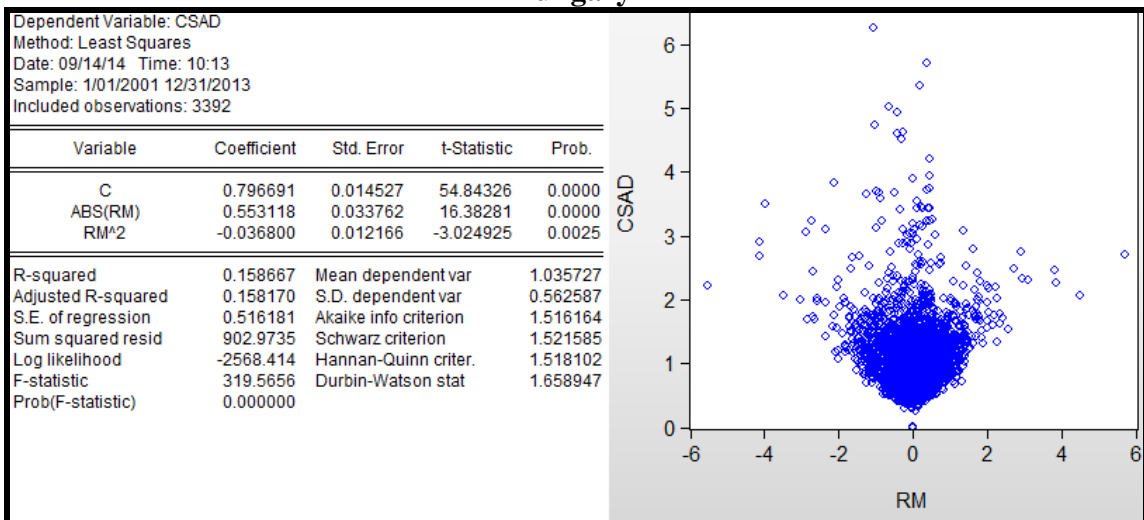
## Greece



## Hong Kong

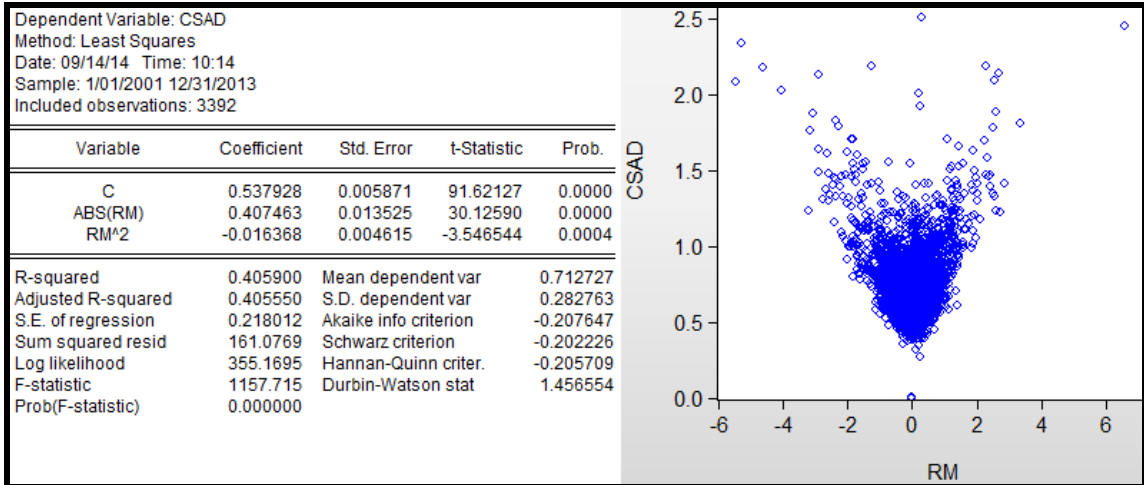


## Hungary

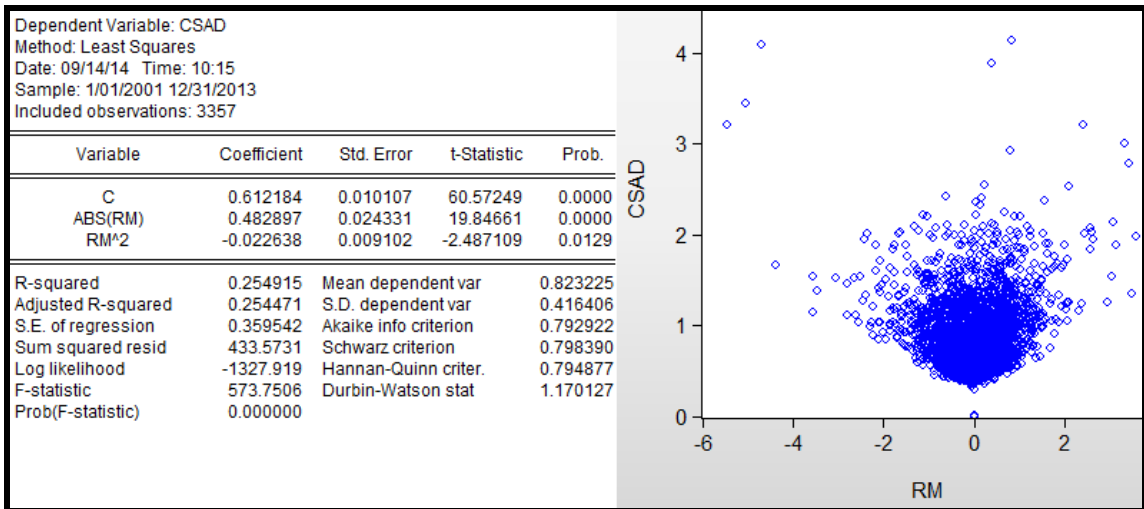




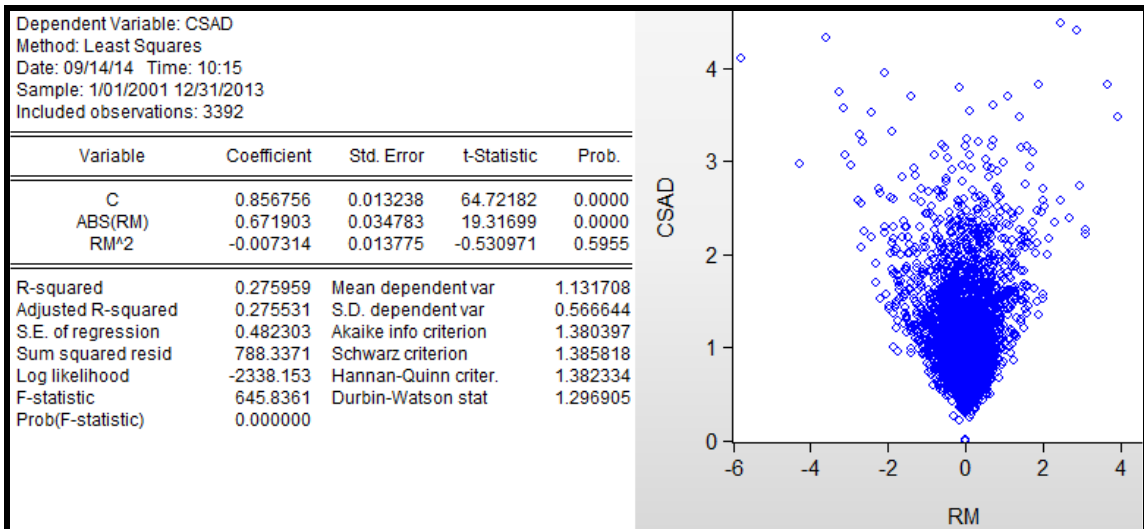
### India



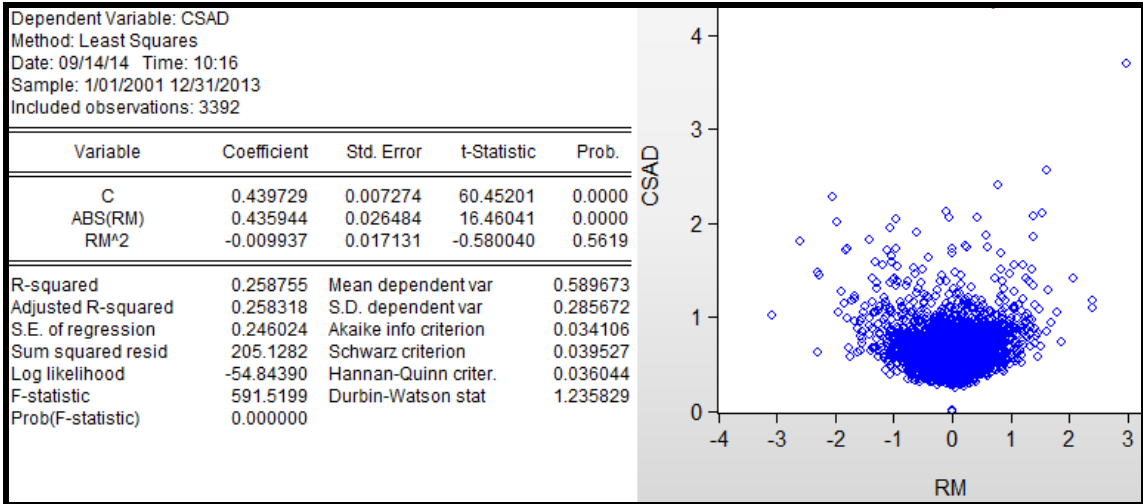
### Indonesia



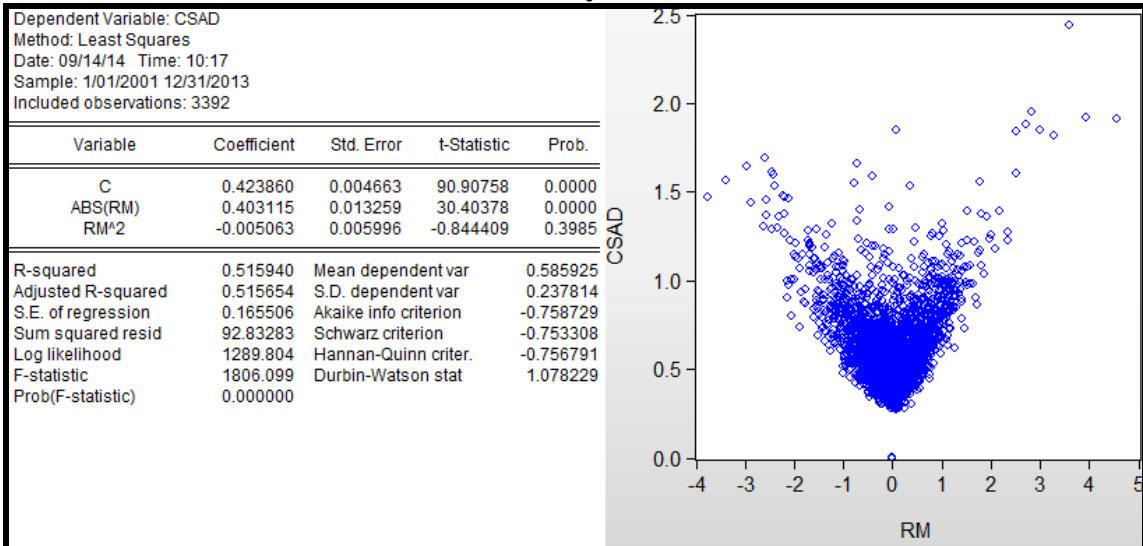
### Ireland



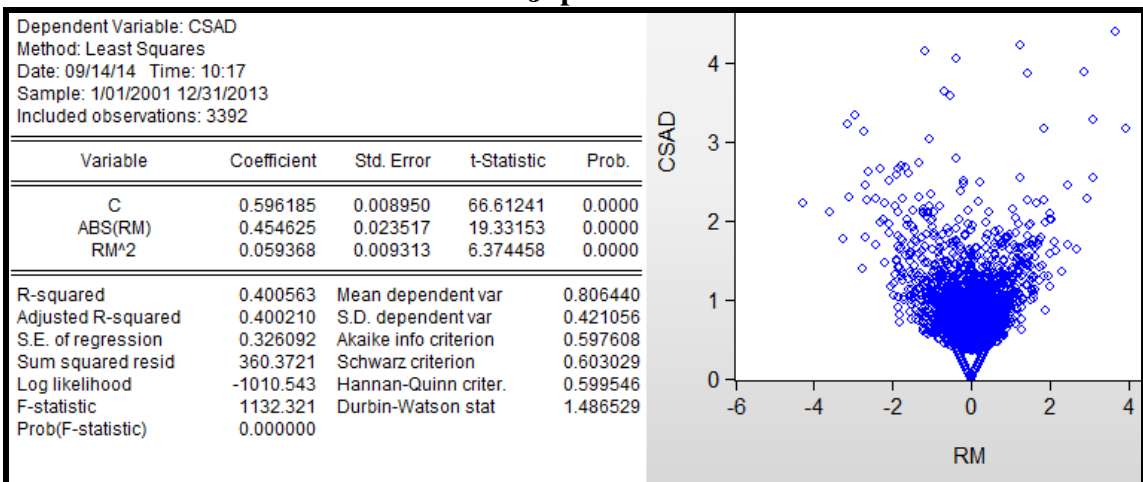
### Israel



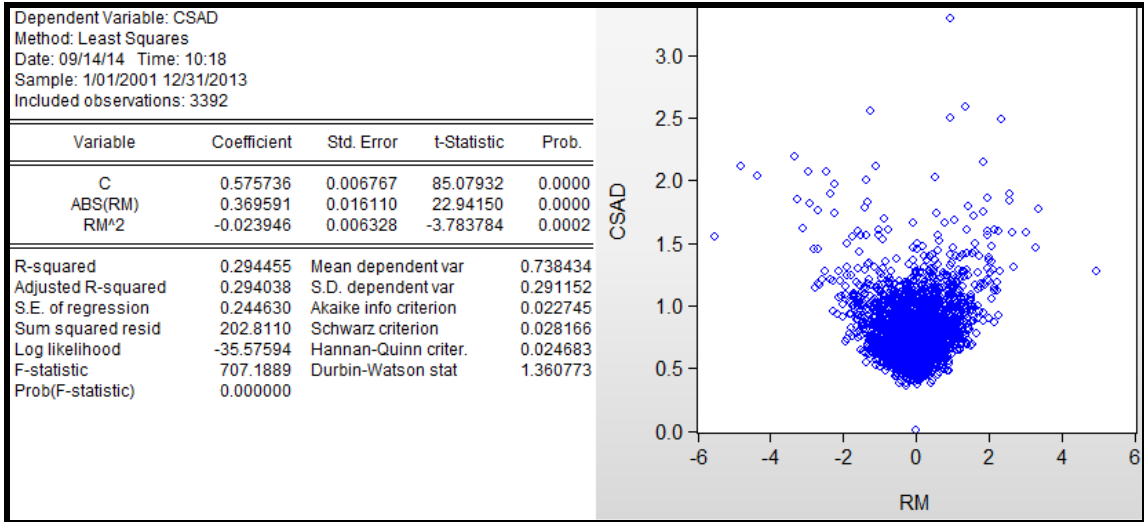
### Italy



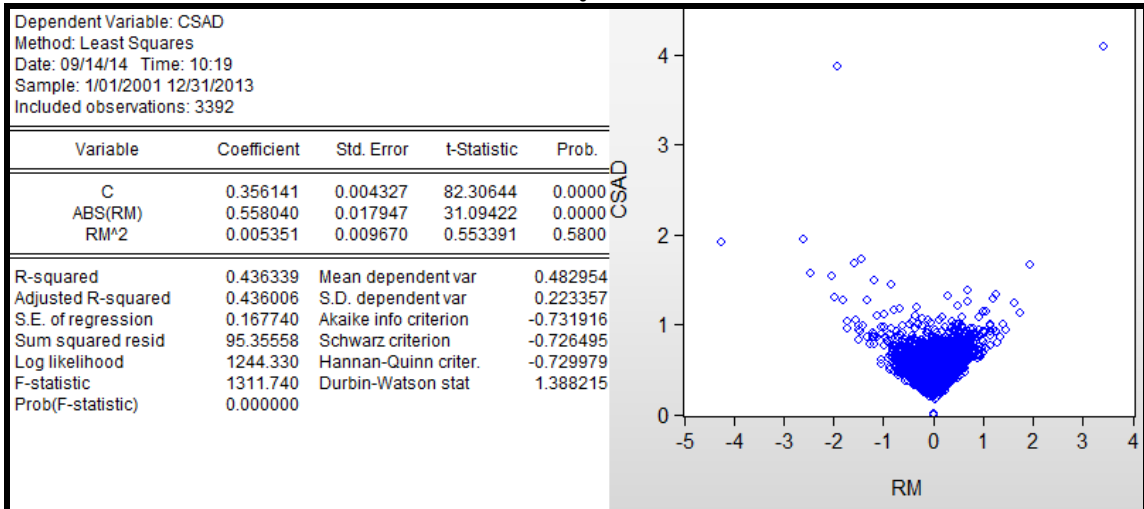
### Japan



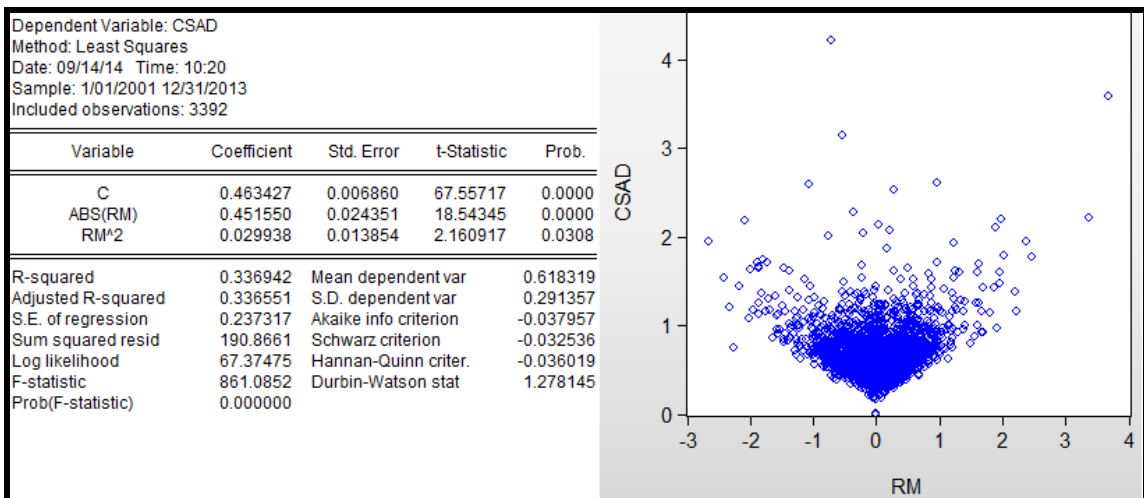
## Korea



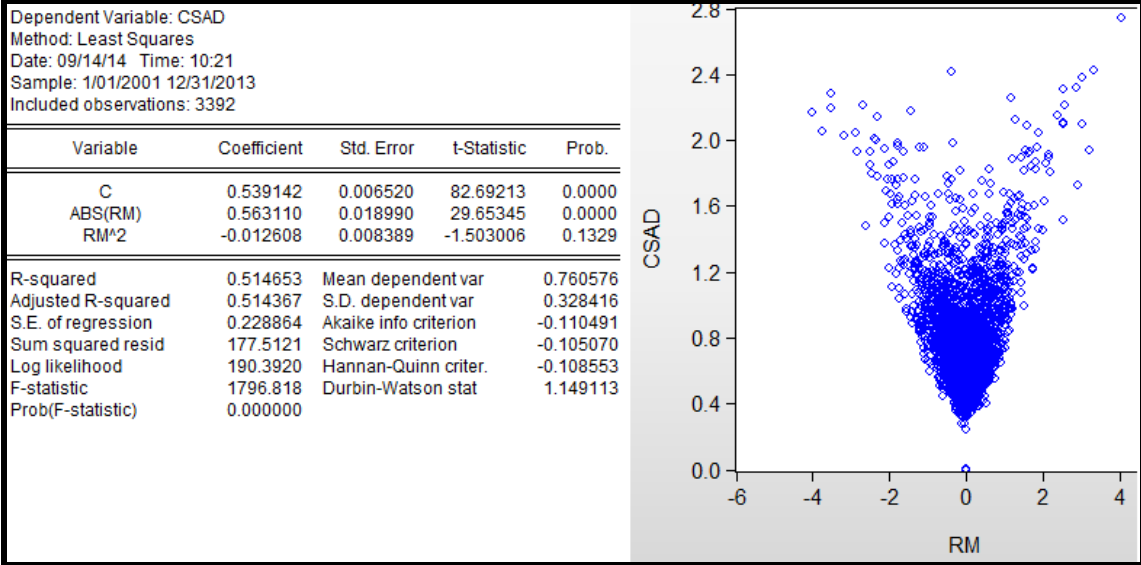
## Malaysia



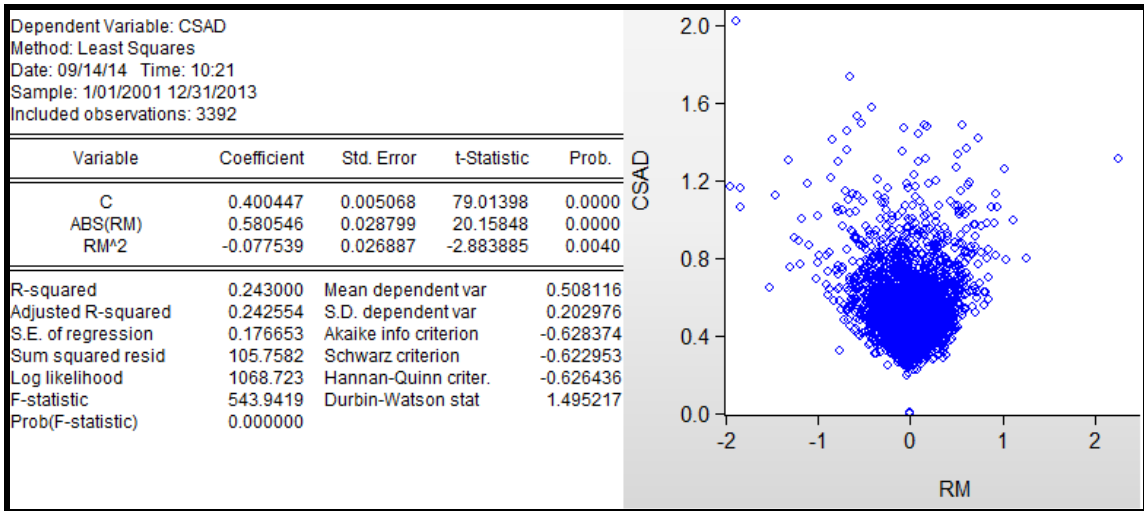
## Mexico



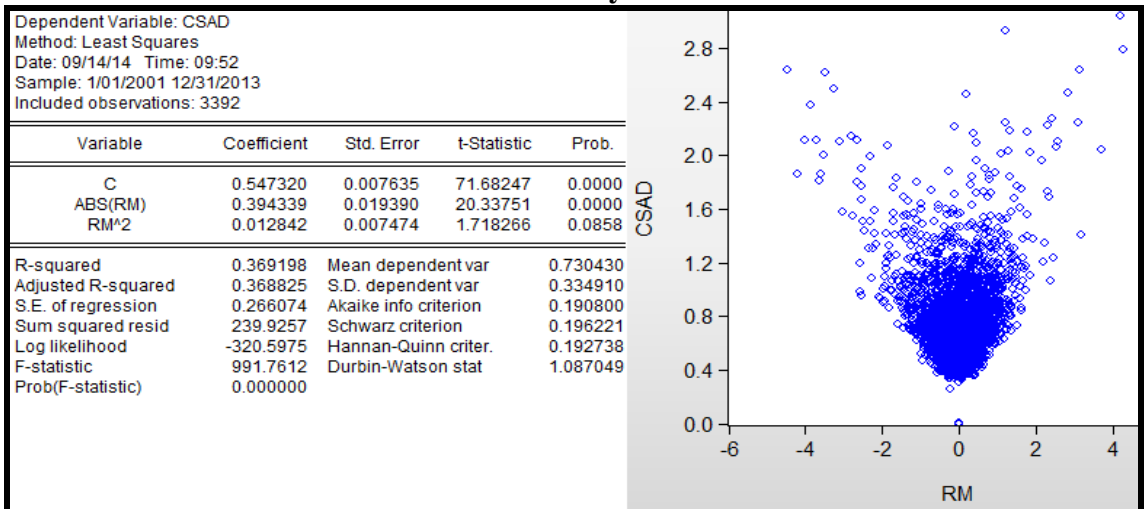
## Netherlands



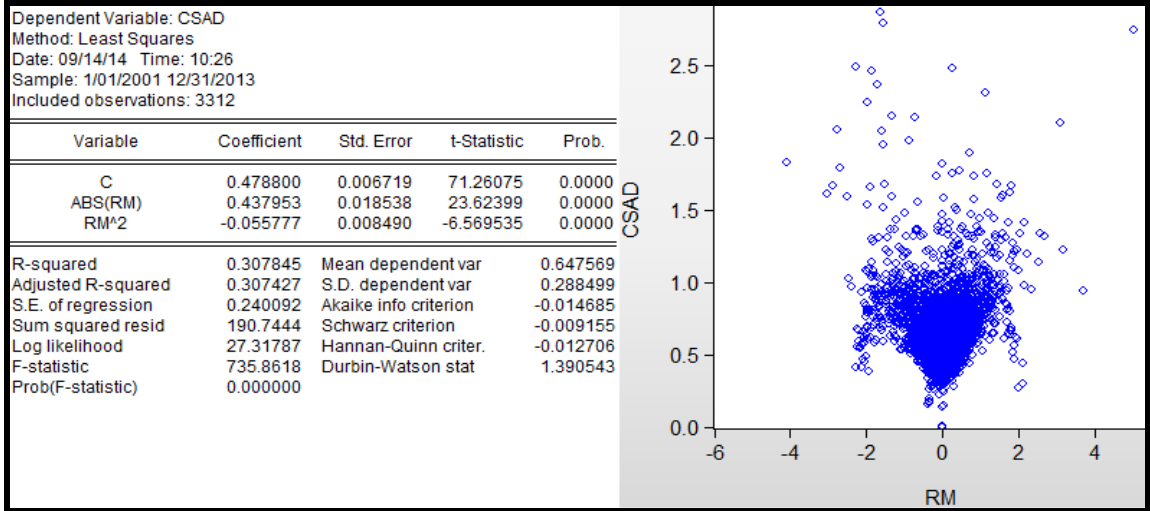
## New Zealand



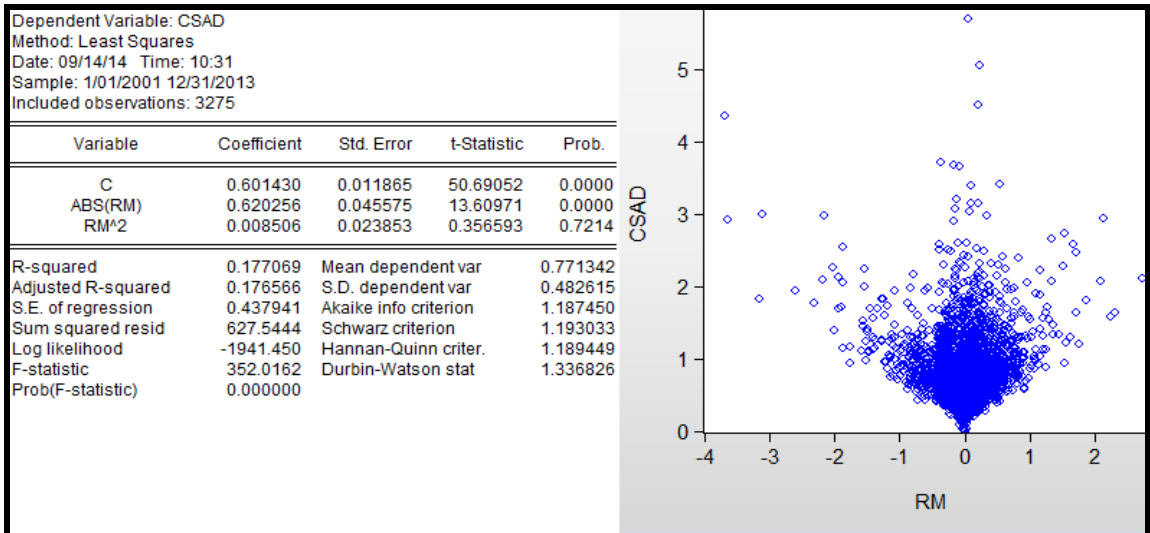
## Norway



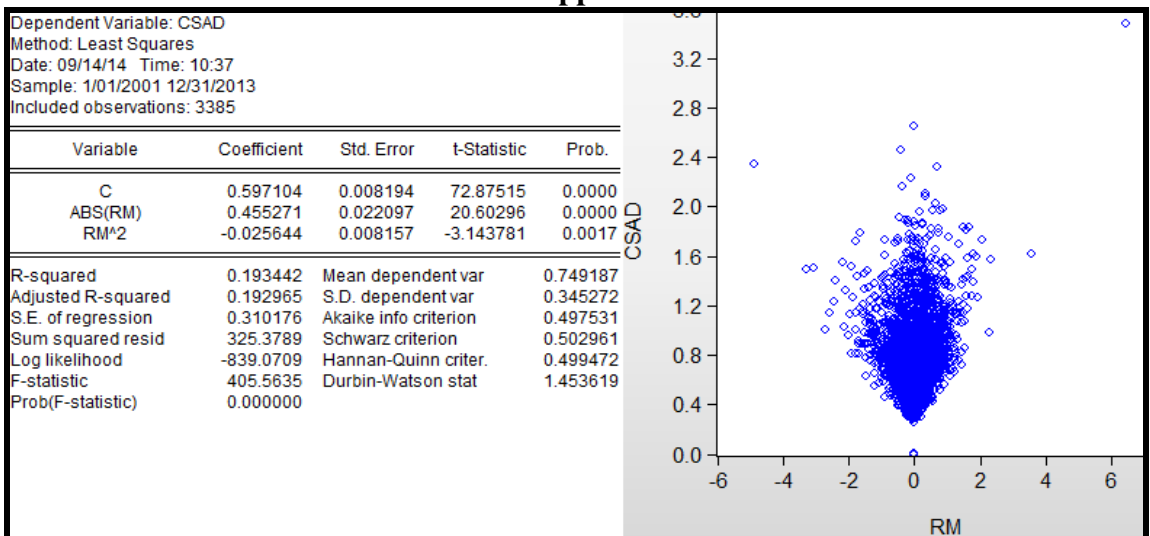
## Pakistan



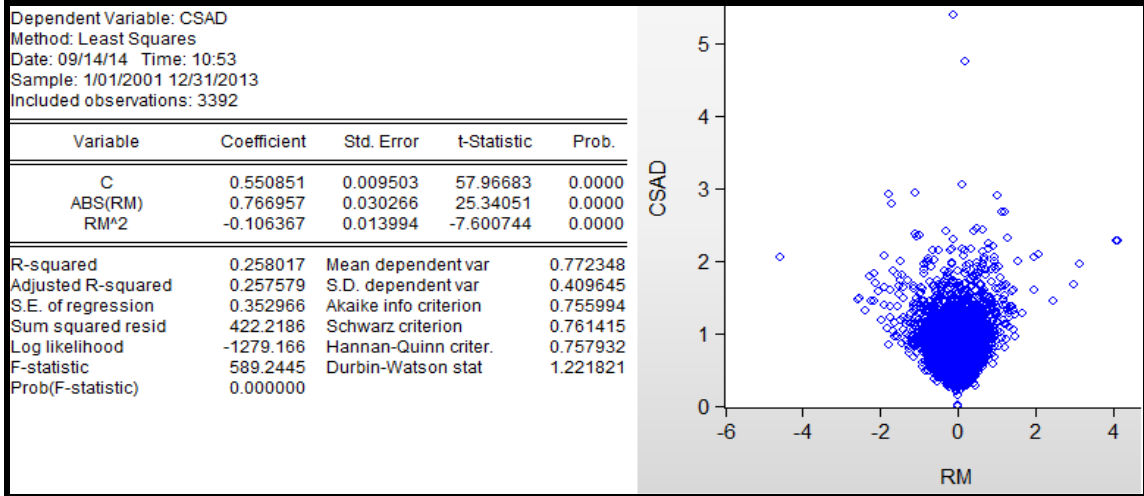
## Peru



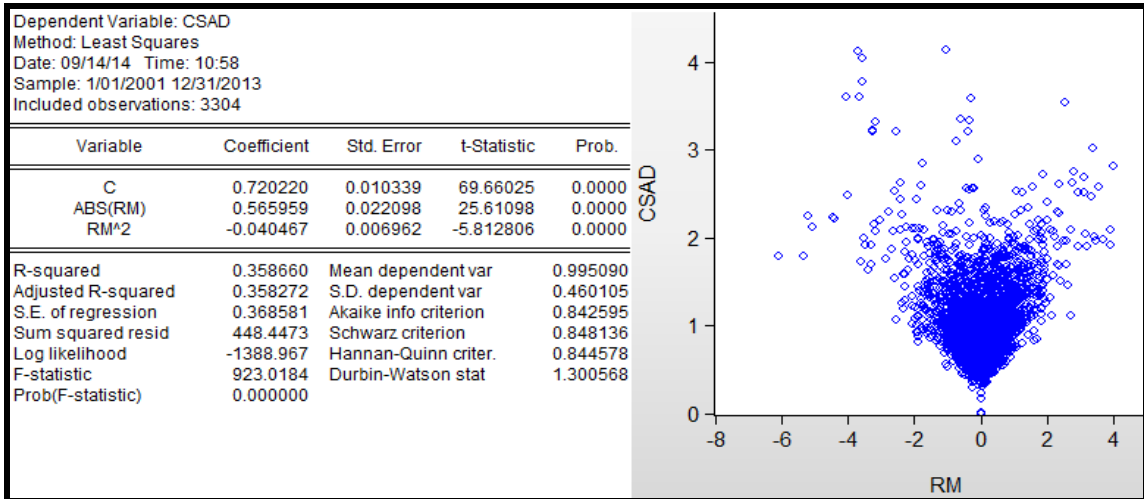
## Philippines



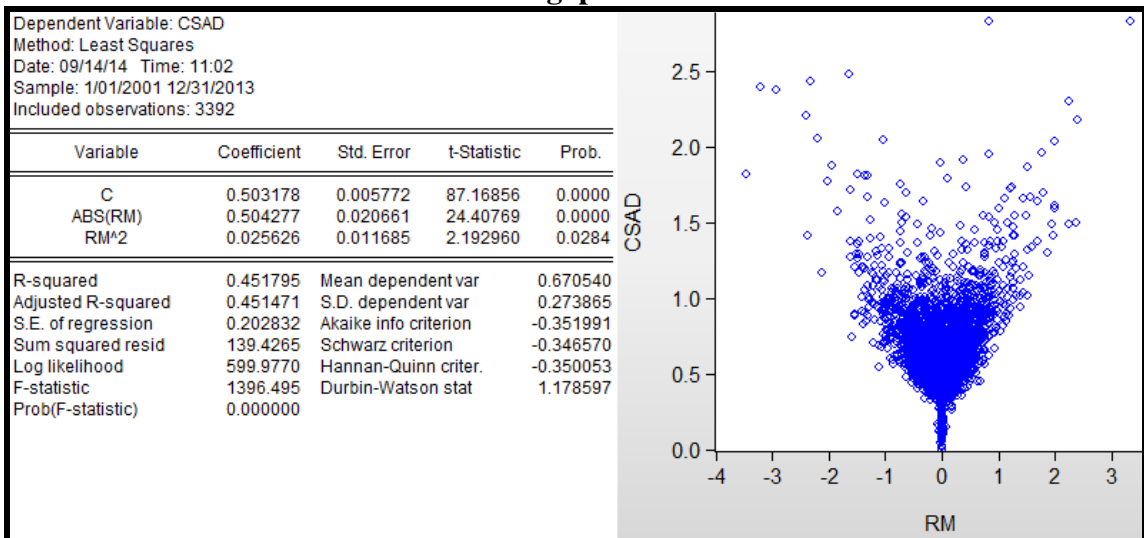
## Portugal



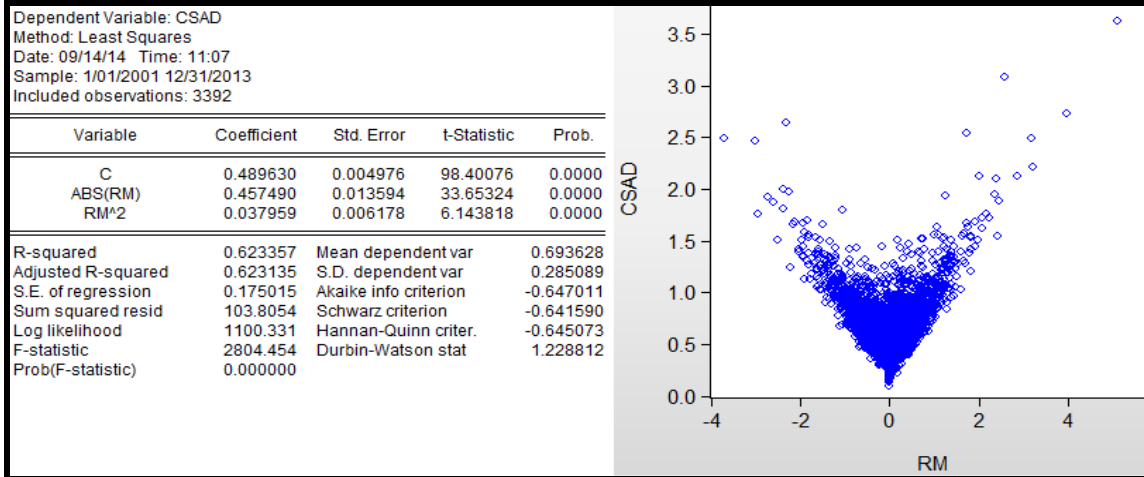
## Romania



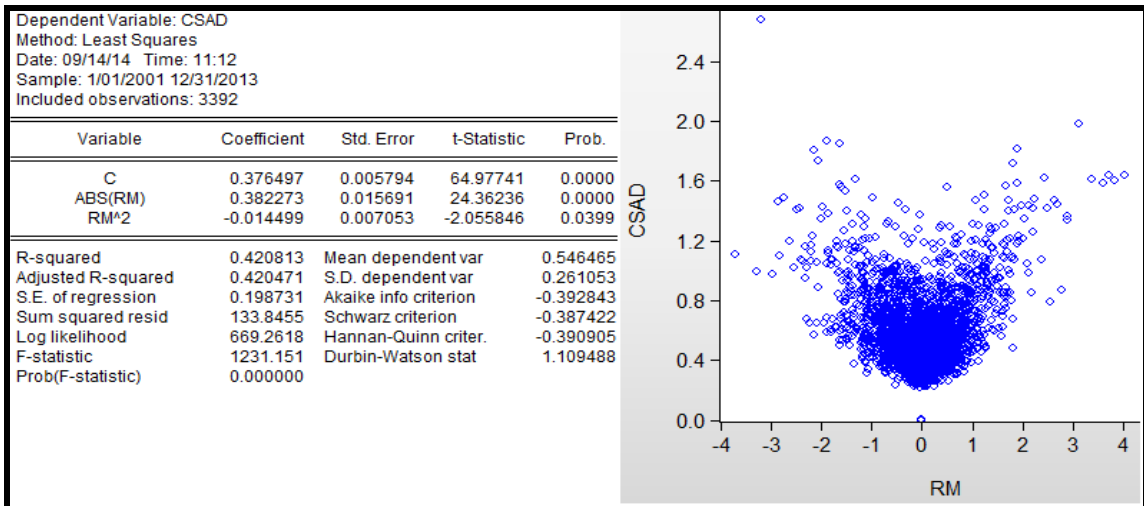
## Singapore



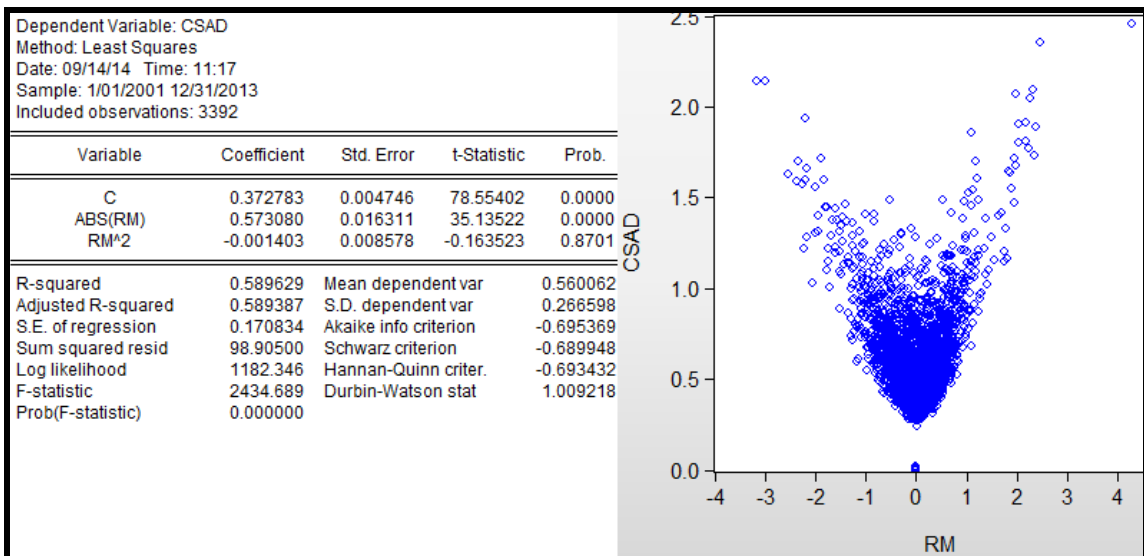
## Spain



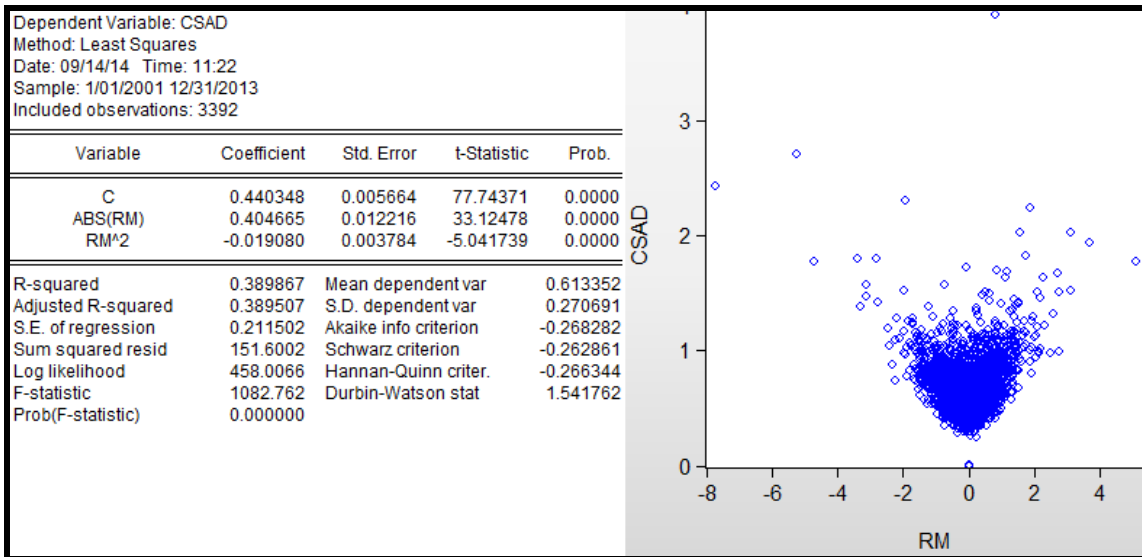
## Sweden



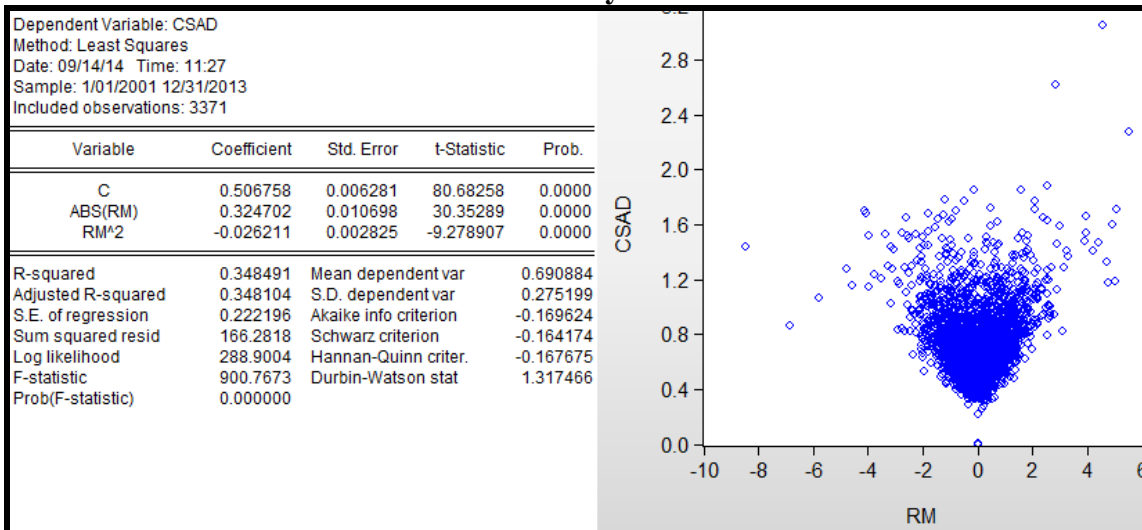
## Switzerland



## Thailand

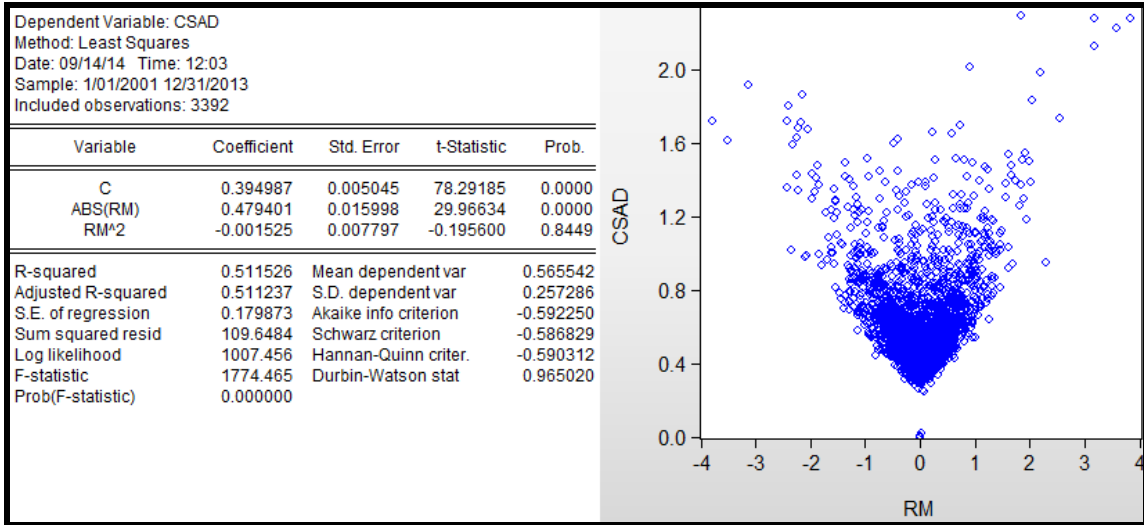


## Turkey

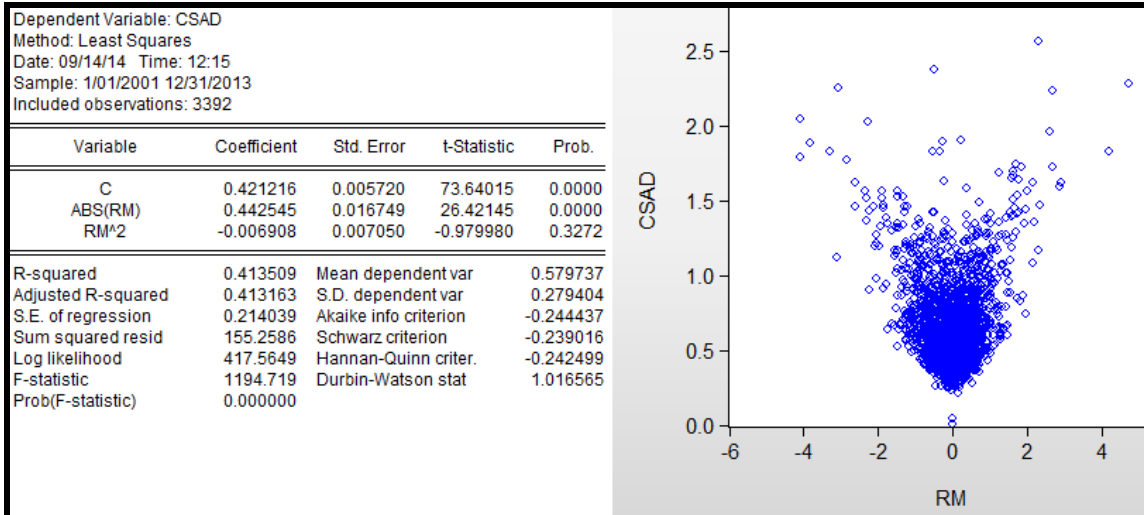




## UK



## USA



### 1.3.1. Pre-crisis, crisis and Euro crisis

Here, we perform a test to see if there are differences between the pre-crisis (1/1/2001) and crisis (15/9/2008) period in the time series analysis performed before. Also, we test if a country that observes a higher level of herding, has the intensity of this behavior amplified with the beginning of the Euro debt crisis (2/5/2010).

On the left is shown the pre-crisis period, while on the right is the crisis period. If a country has more herding during the crisis, at the bottom there is the analysis of euro crisis (on the left is before euro crisis and on the right during euro crisis).

## ARGENTINA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:24 Sample: 1/01/2001 9/15/2008 Included observations: 1993					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:24 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.595943	0.013860	42.99845	0.0000	C	0.530317	0.012451	42.59106	0.0000
ABS(RM)	0.531742	0.030515	17.42557	0.0000	ABS(RM)	0.521500	0.027501	18.96291	0.0000
RM^2	-0.002465	0.008990	-0.274199	0.7840	RM^2	-0.000130	0.009431	-0.013784	0.9890
R-squared	0.283878	Mean dependent var	0.824948		R-squared	0.463385	Mean dependent var	0.781214	
Adjusted R-squared	0.283159	S.D. dependent var	0.479834		Adjusted R-squared	0.462606	S.D. dependent var	0.401325	
S.E. of regression	0.406258	Akaike info criterion	1.037848		S.E. of regression	0.294200	Akaike info criterion	0.393059	
Sum squared resid	328.4410	Schwarz criterion	1.046274		Sum squared resid	119.2712	Schwarz criterion	0.404421	
Log likelihood	-1031.216	Hannan-Quinn criter.	1.040943		Log likelihood	-268.4070	Hannan-Quinn criter.	0.397309	
F-statistic	394.4287	Durbin-Watson stat	1.097195		F-statistic	594.9735	Durbin-Watson stat	1.471848	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## AUSTRALIA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:37 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:37 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.498486	0.006079	81.99931	0.0000	C	0.468963	0.011806	39.72201	0.0000
ABS(RM)	0.444461	0.025661	17.32053	0.0000	ABS(RM)	0.418352	0.037979	11.01547	0.0000
RM^2	-0.036010	0.017288	-2.082955	0.0374	RM^2	0.026798	0.019705	1.359935	0.1741
R-squared	0.295577	Mean dependent var	0.609372		R-squared	0.308021	Mean dependent var	0.628038	
Adjusted R-squared	0.294875	S.D. dependent var	0.196520		Adjusted R-squared	0.307017	S.D. dependent var	0.314477	
S.E. of regression	0.165022	Akaike info criterion	-0.763990		S.E. of regression	0.261788	Akaike info criterion	0.159608	
Sum squared resid	54.68211	Schwarz criterion	-0.755627		Sum squared resid	94.50722	Schwarz criterion	0.170964	
Log likelihood	771.1921	Hannan-Quinn criter.	-0.760920		Log likelihood	-107.2890	Hannan-Quinn criter.	0.163856	
F-statistic	421.2799	Durbin-Watson stat	1.119000		F-statistic	306.9169	Durbin-Watson stat	0.696274	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## AUSTRIA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 14:58 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 14:58 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.345434	0.006383	54.11920	0.0000	C	0.434662	0.012292	35.36257	0.0000
ABS(RM)	0.723813	0.028661	25.25386	0.0000	ABS(RM)	0.619734	0.031166	19.88512	0.0000
RM^2	-0.127037	0.021071	-6.029047	0.0000	RM^2	-0.000908	0.012312	-0.073745	0.9412
R-squared	0.470813	Mean dependent var	0.520818		R-squared	0.571355	Mean dependent var	0.727096	
Adjusted R-squared	0.470286	S.D. dependent var	0.228640		Adjusted R-squared	0.570733	S.D. dependent var	0.421916	
S.E. of regression	0.166408	Akaike info criterion	-0.747260		S.E. of regression	0.276433	Akaike info criterion	0.268471	
Sum squared resid	55.60464	Schwarz criterion	-0.738896		Sum squared resid	105.3765	Schwarz criterion	0.279827	
Log likelihood	754.3700	Hannan-Quinn criter.	-0.744190		Log likelihood	-182.5138	Hannan-Quinn criter.	0.272719	
F-statistic	893.2507	Durbin-Watson stat	1.646643		F-statistic	919.0559	Durbin-Watson stat	1.217737	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## BELGIUM

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:03 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:03 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.415641	0.006543	63.52697	0.0000	C	0.418014	0.009444	44.26151	0.0000
ABS(RM)	0.498633	0.024576	20.28902	0.0000	ABS(RM)	0.533152	0.027208	19.59556	0.0000
RM^2	0.023733	0.014455	1.641888	0.1008	RM^2	0.010001	0.012125	0.824885	0.4096
R-squared	0.526592	Mean dependent var	0.580887		R-squared	0.576641	Mean dependent var	0.641265	
Adjusted R-squared	0.526121	S.D. dependent var	0.255862		Adjusted R-squared	0.576027	S.D. dependent var	0.315239	
S.E. of regression	0.176132	Akaike info criterion	-0.633671		S.E. of regression	0.205262	Akaike info criterion	-0.326891	
Sum squared resid	62.29339	Schwarz criterion	-0.625308		Sum squared resid	58.10066	Schwarz criterion	-0.315535	
Log likelihood	640.1566	Hannan-Quinn criter.	-0.630601		Log likelihood	228.8819	Hannan-Quinn criter.	-0.322644	
F-statistic	1116.793	Durbin-Watson stat	1.223682		F-statistic	939.1426	Durbin-Watson stat	1.225084	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## BRAZIL

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:05 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:05 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.583942	0.009828	59.41523	0.0000	C	0.476840	0.008886	53.66189	0.0000
ABS(RM)	0.472258	0.032643	14.46747	0.0000	ABS(RM)	0.385812	0.022719	16.98175	0.0000
RM^2	-0.102563	0.020012	-5.125103	0.0000	RM^2	0.006476	0.007993	0.810274	0.4179
R-squared	0.213566	Mean dependent var	0.746139		R-squared	0.496490	Mean dependent var	0.647295	
Adjusted R-squared	0.212782	S.D. dependent var	0.272428		Adjusted R-squared	0.495759	S.D. dependent var	0.289280	
S.E. of regression	0.241712	Akaike info criterion	-0.000648		S.E. of regression	0.205417	Akaike info criterion	-0.325375	
Sum squared resid	117.3169	Schwarz criterion	0.007716		Sum squared resid	58.14654	Schwarz criterion	-0.314012	
Log likelihood	3.651412	Hannan-Quinn criter.	0.002422		Log likelihood	227.6714	Hannan-Quinn criter.	-0.321125	
F-statistic	272.6482	Durbin-Watson stat	1.586542		F-statistic	679.3930	Durbin-Watson stat	1.486597	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## CANADA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:38 Sample: 1/11/2001 9/15/2008 Included observations: 2003					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:38 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.579286	0.009861	58.74268	0.0000	C	0.429009	0.009853	43.53917	0.0000
ABS(RM)	0.489286	0.045940	10.65065	0.0000	ABS(RM)	0.648564	0.029251	22.17256	0.0000
RM^2	0.004900	0.038387	0.127645	0.8984	RM^2	-0.020352	0.011505	-1.769014	0.0771
R-squared	0.207928	Mean dependent var	0.713133		R-squared	0.569802	Mean dependent var	0.658159	
Adjusted R-squared	0.207135	S.D. dependent var	0.276650		Adjusted R-squared	0.569178	S.D. dependent var	0.363588	
S.E. of regression	0.246337	Akaike info criterion	0.037267		S.E. of regression	0.238648	Akaike info criterion	-0.025483	
Sum squared resid	121.3642	Schwarz criterion	0.045658		Sum squared resid	78.48113	Schwarz criterion	-0.014121	
Log likelihood	-34.32337	Hannan-Quinn criter.	0.040348		Log likelihood	20.59618	Hannan-Quinn criter.	-0.021233	
F-statistic	262.5108	Durbin-Watson stat	1.453299		F-statistic	912.5891	Durbin-Watson stat	1.246191	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:40 Sample: 9/15/2008 4/30/2010 Included observations: 425					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:40 Sample: 5/03/2010 12/31/2013 Included observations: 957				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.543013	0.026287	20.65728	0.0000	C	0.430769	0.007884	54.64122	0.0000
ABS(RM)	0.737027	0.056810	12.97358	0.0000	ABS(RM)	0.424788	0.040236	10.55742	0.0000
RM^2	-0.061806	0.019358	-3.192883	0.0015	RM^2	-0.044519	0.036207	-1.229550	0.2192
R-squared	0.586173	Mean dependent var	0.937423		R-squared	0.328455	Mean dependent var	0.534982	
Adjusted R-squared	0.584211	S.D. dependent var	0.504718		Adjusted R-squared	0.327047	S.D. dependent var	0.169314	
S.E. of regression	0.325450	Akaike info criterion	0.599820		S.E. of regression	0.138895	Akaike info criterion	-1.107074	
Sum squared resid	44.69736	Schwarz criterion	0.628423		Sum squared resid	18.40427	Schwarz criterion	-1.091827	
Log likelihood	-124.4618	Hannan-Quinn criter.	0.611120		Log likelihood	532.7350	Hannan-Quinn criter.	-1.101267	
F-statistic	298.8746	Durbin-Watson stat	1.198827		F-statistic	233.3022	Durbin-Watson stat	1.684758	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## CHILE

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:43 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:44 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.328886	0.005776	56.93874	0.0000	C	0.301458	0.006811	44.26107	0.0000
ABS(RM)	0.537107	0.029873	17.97950	0.0000	ABS(RM)	0.470269	0.025304	18.58504	0.0000
RM^2	-0.138061	0.026854	-5.141162	0.0000	RM^2	-0.048300	0.012373	-3.903544	0.0001
R-squared	0.270821	Mean dependent var	0.438115		R-squared	0.341961	Mean dependent var	0.417349	
Adjusted R-squared	0.270094	S.D. dependent var	0.176414		Adjusted R-squared	0.341006	S.D. dependent var	0.202705	
S.E. of regression	0.150718	Akaike info criterion	-0.945317		S.E. of regression	0.164553	Akaike info criterion	-0.768999	
Sum squared resid	45.61376	Schwarz criterion	-0.936954		Sum squared resid	37.31302	Schwarz criterion	-0.757637	
Log likelihood	953.5165	Hannan-Quinn criter.	-0.942247		Log likelihood	533.9939	Hannan-Quinn criter.	-0.764749	
F-statistic	372.8901	Durbin-Watson stat	1.537507		F-statistic	358.0498	Durbin-Watson stat	1.728730	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## DENMARK

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:45 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:46 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.423317	0.007855	53.89211	0.0000	C	0.444309	0.010774	41.23735	0.0000
ABS(RM)	0.534113	0.032014	16.68371	0.0000	ABS(RM)	0.501202	0.028455	17.61404	0.0000
RM^2	-0.076874	0.022903	-3.356575	0.0008	RM^2	-0.018199	0.010863	-1.675269	0.0941
R-squared	0.328140	Mean dependent var	0.580296		R-squared	0.417551	Mean dependent var	0.641978	
Adjusted R-squared	0.327471	S.D. dependent var	0.242669		Adjusted R-squared	0.416706	S.D. dependent var	0.332735	
S.E. of regression	0.199008	Akaike info criterion	-0.389454		S.E. of regression	0.254122	Akaike info criterion	0.100166	
Sum squared resid	79.52507	Schwarz criterion	-0.381091		Sum squared resid	88.98850	Schwarz criterion	0.111528	
Log likelihood	394.5964	Hannan-Quinn criter.	-0.386384		Log likelihood	-66.16443	Hannan-Quinn criter.	0.104416	
F-statistic	490.3596	Durbin-Watson stat	1.160536		F-statistic	493.9361	Durbin-Watson stat	1.326350	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## FINLAND

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:47 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:48 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.374204	0.007255	51.58100	0.0000	C	0.413678	0.010773	38.39844	0.0000
ABS(RM)	0.525908	0.013567	38.76313	0.0000	ABS(RM)	0.338591	0.028189	12.01157	0.0000
RM^2	0.051453	0.004015	12.81543	0.0000	RM^2	0.017303	0.012330	1.403330	0.1607
R-squared	0.794442	Mean dependent var	0.703808		R-squared	0.415285	Mean dependent var	0.593163	
Adjusted R-squared	0.794238	S.D. dependent var	0.460399		Adjusted R-squared	0.414437	S.D. dependent var	0.300165	
S.E. of regression	0.208842	Akaike info criterion	-0.292987		S.E. of regression	0.229692	Akaike info criterion	-0.101983	
Sum squared resid	87.57887	Schwarz criterion	-0.284623		Sum squared resid	72.70125	Schwarz criterion	-0.090620	
Log likelihood	297.5984	Hannan-Quinn criter.	-0.289917		Log likelihood	73.41912	Hannan-Quinn criter.	-0.097732	
F-statistic	3880.272	Durbin-Watson stat	1.539602		F-statistic	489.3525	Durbin-Watson stat	1.140774	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## FRANCE

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:50 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:51 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.439631	0.007081	62.08349	0.0000	C	0.437016	0.007411	58.96825	0.0000
ABS(RM)	0.550771	0.023852	23.09165	0.0000	ABS(RM)	0.384580	0.019517	19.70515	0.0000
RM^2	0.001836	0.013464	0.136380	0.8915	RM^2	0.017318	0.007925	2.185140	0.0290
R-squared	0.583808	Mean dependent var	0.651193		R-squared	0.596031	Mean dependent var	0.614427	
Adjusted R-squared	0.583393	S.D. dependent var	0.277928		Adjusted R-squared	0.595445	S.D. dependent var	0.260380	
S.E. of regression	0.179389	Akaike info criterion	-0.597029		S.E. of regression	0.165614	Akaike info criterion	-0.756142	
Sum squared resid	64.61831	Schwarz criterion	-0.588665		Sum squared resid	37.79584	Schwarz criterion	-0.744780	
Log likelihood	603.3125	Hannan-Quinn criter.	-0.593959		Log likelihood	525.1162	Hannan-Quinn criter.	-0.751892	
F-statistic	1408.348	Durbin-Watson stat	1.009348		F-statistic	1016.576	Durbin-Watson stat	0.930716	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## GERMANY

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:53 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:54 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.538952	0.007072	76.20492	0.0000	C	0.519175	0.009192	56.47983	0.0000
ABS(RM)	0.568771	0.024804	22.93024	0.0000	ABS(RM)	0.398571	0.020560	19.38599	0.0000
RM^2	-0.023132	0.014813	-1.561580	0.1185	RM^2	0.069607	0.005960	11.67850	0.0000
R-squared	0.523797	Mean dependent var	0.736662		R-squared	0.615101	Mean dependent var	0.713043	
Adjusted R-squared	0.523323	S.D. dependent var	0.269280		Adjusted R-squared	0.614542	S.D. dependent var	0.364114	
S.E. of regression	0.185915	Akaike info criterion	-0.525558		S.E. of regression	0.226061	Akaike info criterion	-0.133853	
Sum squared resid	69.40565	Schwarz criterion	-0.517195		Sum squared resid	70.47197	Schwarz criterion	-0.122497	
Log likelihood	531.4490	Hannan-Quinn criter.	-0.522488		Log likelihood	95.49269	Hannan-Quinn criter.	-0.129606	
F-statistic	1104.346	Durbin-Watson stat	1.105294		F-statistic	1101.877	Durbin-Watson stat	1.191511	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## GREECE

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:55 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:55 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.434755	0.006515	66.72897	0.0000	C	0.679952	0.014752	46.09212	0.0000
ABS(RM)	0.378553	0.021891	17.29266	0.0000	ABS(RM)	0.389247	0.028806	13.51250	0.0000
RM^2	-0.048624	0.012604	-3.857834	0.0001	RM^2	-0.008920	0.010365	-0.860593	0.3896
R-squared	0.299725	Mean dependent var	0.559928		R-squared	0.375083	Mean dependent var	0.939519	
Adjusted R-squared	0.299028	S.D. dependent var	0.201886		Adjusted R-squared	0.374176	S.D. dependent var	0.387569	
S.E. of regression	0.169028	Akaike info criterion	-0.716019		S.E. of regression	0.306602	Akaike info criterion	0.475635	
Sum squared resid	57.36920	Schwarz criterion	-0.707656		Sum squared resid	129.6324	Schwarz criterion	0.486991	
Log likelihood	722.9573	Hannan-Quinn criter.	-0.712949		Log likelihood	-325.6636	Hannan-Quinn criter.	0.479883	
F-statistic	429.7233	Durbin-Watson stat	1.462033		F-statistic	413.8461	Durbin-Watson stat	1.229704	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## HONG KONG

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:57 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:57 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.543492	0.007569	71.80884	0.0000	C	0.493441	0.010596	46.56787	0.0000
ABS(RM)	0.446016	0.023093	19.31376	0.0000	ABS(RM)	0.439702	0.025945	16.94742	0.0000
RM^2	-0.056174	0.011906	-4.718041	0.0000	RM^2	0.003812	0.009148	0.416745	0.6769
R-squared	0.308510	Mean dependent var	0.693633		R-squared	0.448954	Mean dependent var	0.687922	
Adjusted R-squared	0.307821	S.D. dependent var	0.255956		Adjusted R-squared	0.448155	S.D. dependent var	0.339450	
S.E. of regression	0.212948	Akaike info criterion	-0.254042		S.E. of regression	0.252165	Akaike info criterion	0.084701	
Sum squared resid	91.05688	Schwarz criterion	-0.245679		Sum squared resid	87.68667	Schwarz criterion	0.096057	
Log likelihood	258.4396	Hannan-Quinn criter.	-0.250972		Log likelihood	-55.52872	Hannan-Quinn criter.	0.088949	
F-statistic	447.9366	Durbin-Watson stat	1.401159		F-statistic	561.7565	Durbin-Watson stat	1.402813	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## HUNGARY

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:59 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 15:59 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.736224	0.022075	33.35050	0.0000	C	0.886352	0.021391	41.43586	0.0000
ABS(RM)	0.590142	0.077432	7.621440	0.0000	ABS(RM)	0.570174	0.044190	12.90277	0.0000
RM^2	-0.099794	0.051319	-1.944605	0.0520	RM^2	-0.044790	0.013483	-3.322107	0.0009
R-squared	0.093279	Mean dependent var	0.948393		R-squared	0.227063	Mean dependent var	1.162902	
Adjusted R-squared	0.092376	S.D. dependent var	0.548495		Adjusted R-squared	0.225941	S.D. dependent var	0.558783	
S.E. of regression	0.522547	Akaike info criterion	1.541288		S.E. of regression	0.491621	Akaike info criterion	1.419951	
Sum squared resid	548.2959	Schwarz criterion	1.549652		Sum squared resid	333.0500	Schwarz criterion	1.431314	
Log likelihood	-1546.765	Hannan-Quinn criter.	1.544358		Log likelihood	-977.4763	Hannan-Quinn criter.	1.424202	
F-statistic	103.2871	Durbin-Watson stat	1.780726		F-statistic	202.4050	Durbin-Watson stat	1.547137	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## INDIA

<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:19 Sample: 1/01/2001 9/15/2008 Included observations: 2011</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.596194</td> <td>0.007703</td> <td>77.39355</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.361843</td> <td>0.018453</td> <td>19.60850</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>-0.011225</td> <td>0.006994</td> <td>-1.604951</td> <td>0.1087</td> </tr> </tbody> </table> <p>R-squared 0.386685 Mean dependent var 0.760806 Adjusted R-squared 0.386074 S.D. dependent var 0.270812 S.E. of regression 0.212190 Akaike info criterion -0.261175 Sum squared resid 90.40973 Schwarz criterion -0.252811 Log likelihood 265.6113 Hannan-Quinn criter. -0.258105 F-statistic 633.0064 Durbin-Watson stat 1.509804 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.596194	0.007703	77.39355	0.0000	ABS(RM)	0.361843	0.018453	19.60850	0.0000	RM^2	-0.011225	0.006994	-1.604951	0.1087	<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:19 Sample: 9/16/2008 12/31/2013 Included observations: 1381</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.460145</td> <td>0.008699</td> <td>52.89434</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.461836</td> <td>0.019969</td> <td>23.12738</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>-0.021139</td> <td>0.005930</td> <td>-3.564808</td> <td>0.0004</td> </tr> </tbody> </table> <p>R-squared 0.448859 Mean dependent var 0.642716 Adjusted R-squared 0.448059 S.D. dependent var 0.285264 S.E. of regression 0.211931 Akaike info criterion -0.262946 Sum squared resid 61.89230 Schwarz criterion -0.251583 Log likelihood 184.5640 Hannan-Quinn criter. -0.258695 F-statistic 561.1336 Durbin-Watson stat 1.579117 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.460145	0.008699	52.89434	0.0000	ABS(RM)	0.461836	0.019969	23.12738	0.0000	RM^2	-0.021139	0.005930	-3.564808	0.0004
Variable	Coefficient	Std. Error	t-Statistic	Prob.																																					
C	0.596194	0.007703	77.39355	0.0000																																					
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Variable	Coefficient	Std. Error	t-Statistic	Prob.																																					
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ABS(RM)	0.461836	0.019969	23.12738	0.0000																																					
RM^2	-0.021139	0.005930	-3.564808	0.0004																																					
<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:19 Sample: 9/15/2008 4/30/2010 Included observations: 425</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.536204</td> <td>0.021636</td> <td>24.78307</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.487997</td> <td>0.036835</td> <td>13.24825</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>-0.031026</td> <td>0.009325</td> <td>-3.327298</td> <td>0.0010</td> </tr> </tbody> </table> <p>R-squared 0.470643 Mean dependent var 0.807923 Adjusted R-squared 0.468134 S.D. dependent var 0.398381 S.E. of regression 0.290536 Akaike info criterion 0.372854 Sum squared resid 35.62147 Schwarz criterion 0.401457 Log likelihood -76.23149 Hannan-Quinn criter. 0.384154 F-statistic 187.5965 Durbin-Watson stat 1.628439 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.536204	0.021636	24.78307	0.0000	ABS(RM)	0.487997	0.036835	13.24825	0.0000	RM^2	-0.031026	0.009325	-3.327298	0.0010	<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:20 Sample: 5/03/2010 12/31/2013 Included observations: 957</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.444275</td> <td>0.009410</td> <td>47.21167</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.470661</td> <td>0.045687</td> <td>10.30186</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>-0.152921</td> <td>0.043029</td> <td>-3.553923</td> <td>0.0004</td> </tr> </tbody> </table> <p>R-squared 0.276500 Mean dependent var 0.569771 Adjusted R-squared 0.274983 S.D. dependent var 0.172596 S.E. of regression 0.146962 Akaike info criterion -0.994160 Sum squared resid 20.60423 Schwarz criterion -0.978913 Log likelihood 478.7057 Hannan-Quinn criter. -0.988353 F-statistic 182.2950 Durbin-Watson stat 1.626117 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.444275	0.009410	47.21167	0.0000	ABS(RM)	0.470661	0.045687	10.30186	0.0000	RM^2	-0.152921	0.043029	-3.553923	0.0004
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## INDONESIA

<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:23 Sample: 1/01/2001 9/15/2008 Included observations: 1991</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.669332</td> <td>0.014625</td> <td>45.76706</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.521023</td> <td>0.035294</td> <td>14.76240</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>-0.055960</td> <td>0.014524</td> <td>-3.852919</td> <td>0.0001</td> </tr> </tbody> </table> <p>R-squared 0.190915 Mean dependent var 0.887827 Adjusted R-squared 0.190101 S.D. dependent var 0.436583 S.E. of regression 0.392900 Akaike info criterion 0.970983 Sum squared resid 306.8884 Schwarz criterion 0.979415 Log likelihood -963.6132 Hannan-Quinn criter. 0.974080 F-statistic 234.5481 Durbin-Watson stat 1.177493 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.669332	0.014625	45.76706	0.0000	ABS(RM)	0.521023	0.035294	14.76240	0.0000	RM^2	-0.055960	0.014524	-3.852919	0.0001	<p>Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:23 Sample: 9/16/2008 12/31/2013 Included observations: 1366</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th>Variable</th> <th>Coefficient</th> <th>Std. Error</th> <th>t-Statistic</th> <th>Prob.</th> </tr> </thead> <tbody> <tr> <td>C</td> <td>0.535800</td> <td>0.012007</td> <td>44.62289</td> <td>0.0000</td> </tr> <tr> <td>ABS(RM)</td> <td>0.417526</td> <td>0.029386</td> <td>14.20812</td> <td>0.0000</td> </tr> <tr> <td>RM^2</td> <td>0.014224</td> <td>0.010034</td> <td>1.417521</td> <td>0.1566</td> </tr> </tbody> </table> <p>R-squared 0.417162 Mean dependent var 0.729065 Adjusted R-squared 0.416307 S.D. dependent var 0.365337 S.E. of regression 0.279116 Akaike info criterion 0.287818 Sum squared resid 106.1859 Schwarz criterion 0.299282 Log likelihood -193.5800 Hannan-Quinn criter. 0.292109 F-statistic 487.7793 Durbin-Watson stat 1.328018 Prob(F-statistic) 0.000000</p>	Variable	Coefficient	Std. Error	t-Statistic	Prob.	C	0.535800	0.012007	44.62289	0.0000	ABS(RM)	0.417526	0.029386	14.20812	0.0000	RM^2	0.014224	0.010034	1.417521	0.1566
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## IRELAND

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:25 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:26 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.809909	0.017701	45.75375	0.0000	C	0.926179	0.021715	42.65068	0.0000
ABS(RM)	0.661259	0.061382	10.77294	0.0000	ABS(RM)	0.736407	0.049925	14.75041	0.0000
RM^2	-0.055600	0.034137	-1.628706	0.1035	RM^2	-0.018769	0.016743	-1.121062	0.2625
R-squared	0.192450	Mean dependent var	1.039315		R-squared	0.345115	Mean dependent var	1.266249	
Adjusted R-squared	0.191645	S.D. dependent var	0.506729		Adjusted R-squared	0.344164	S.D. dependent var	0.620028	
S.E. of regression	0.455593	Akaike info criterion	1.267055		S.E. of regression	0.502122	Akaike info criterion	1.462222	
Sum squared resid	416.7897	Schwarz criterion	1.275419		Sum squared resid	347.4302	Schwarz criterion	1.473585	
Log likelihood	-1271.024	Hannan-Quinn criter.	1.270125		Log likelihood	-1006.664	Hannan-Quinn criter.	1.466473	
F-statistic	239.2659	Durbin-Watson stat	1.348211		F-statistic	363.0927	Durbin-Watson stat	1.317028	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## ISRAEL

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:27 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:27 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.437283	0.007852	55.68787	0.0000	C	0.423144	0.013466	31.42309	0.0000
ABS(RM)	0.489269	0.031409	15.57748	0.0000	ABS(RM)	0.516481	0.046558	11.09328	0.0000
RM^2	-0.128180	0.023307	-5.499595	0.0000	RM^2	0.003515	0.026734	0.131485	0.8954
R-squared	0.242362	Mean dependent var	0.577568		R-squared	0.295584	Mean dependent var	0.607299	
Adjusted R-squared	0.241607	S.D. dependent var	0.225594		Adjusted R-squared	0.294561	S.D. dependent var	0.354798	
S.E. of regression	0.196461	Akaike info criterion	-0.415220		S.E. of regression	0.297996	Akaike info criterion	0.418698	
Sum squared resid	77.50226	Schwarz criterion	-0.406856		Sum squared resid	122.3688	Schwarz criterion	0.430060	
Log likelihood	420.5033	Hannan-Quinn criter.	-0.412150		Log likelihood	-286.1109	Hannan-Quinn criter.	0.422948	
F-statistic	321.1708	Durbin-Watson stat	1.501798		F-statistic	289.1149	Durbin-Watson stat	1.127403	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## ITALY

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:30 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:30 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.397192	0.005283	75.18209	0.0000	C	0.479805	0.008829	54.34236	0.0000
ABS(RM)	0.423926	0.018871	22.46438	0.0000	ABS(RM)	0.337586	0.021008	16.06923	0.0000
RM^2	-0.009607	0.011214	-0.856752	0.3917	RM^2	0.010661	0.008335	1.279089	0.2011
R-squared	0.487693	Mean dependent var	0.534205		R-squared	0.501192	Mean dependent var	0.661239	
Adjusted R-squared	0.487182	S.D. dependent var	0.200577		Adjusted R-squared	0.500468	S.D. dependent var	0.266081	
S.E. of regression	0.143636	Akaike info criterion	-1.041584		S.E. of regression	0.188059	Akaike info criterion	-0.501949	
Sum squared resid	41.42743	Schwarz criterion	-1.033220		Sum squared resid	48.73475	Schwarz criterion	-0.490587	
Log likelihood	1050.312	Hannan-Quinn criter.	-1.038514		Log likelihood	349.5958	Hannan-Quinn criter.	-0.497699	
F-statistic	955.7613	Durbin-Watson stat	1.143974		F-statistic	692.2926	Durbin-Watson stat	0.981593	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			



## JAPAN

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:31 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:32 Sample: 9/15/2008 12/31/2013 Included observations: 1382				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.613888	0.010925	56.18919	0.0000	C	0.584439	0.016493	35.43531	0.0000
ABS(RM)	0.361097	0.037885	9.531472	0.0000	ABS(RM)	0.509333	0.037883	13.44488	0.0000
RM^2	0.102928	0.021070	4.885154	0.0000	RM^2	0.044056	0.012715	3.464912	0.0005
R-squared	0.352832	Mean dependent var	0.777618		R-squared	0.429950	Mean dependent var	0.848832	
Adjusted R-squared	0.352188	S.D. dependent var	0.349364		Adjusted R-squared	0.429123	S.D. dependent var	0.504928	
S.E. of regression	0.281192	Akaike info criterion	0.301934		S.E. of regression	0.381506	Akaike info criterion	0.912787	
Sum squared resid	158.7707	Schwarz criterion	0.310298		Sum squared resid	200.7088	Schwarz criterion	0.924143	
Log likelihood	-300.5949	Hannan-Quinn criter.	0.305004		Log likelihood	-627.7356	Hannan-Quinn criter.	0.917035	
F-statistic	547.3752	Durbin-Watson stat	1.521786		F-statistic	520.0425	Durbin-Watson stat	1.460911	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## KOREA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:33 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:33 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.609976	0.009020	67.62624	0.0000	C	0.529991	0.010090	52.52870	0.0000
ABS(RM)	0.354050	0.021267	16.64811	0.0000	ABS(RM)	0.395985	0.025113	15.76818	0.0000
RM^2	-0.033188	0.009154	-3.625461	0.0003	RM^2	-0.018694	0.008844	-2.113885	0.0347
R-squared	0.252810	Mean dependent var	0.769720		R-squared	0.351669	Mean dependent var	0.692875	
Adjusted R-squared	0.252066	S.D. dependent var	0.283988		Adjusted R-squared	0.350728	S.D. dependent var	0.295513	
S.E. of regression	0.245602	Akaike info criterion	0.031282		S.E. of regression	0.238117	Akaike info criterion	-0.029939	
Sum squared resid	121.1232	Schwarz criterion	0.039645		Sum squared resid	78.13225	Schwarz criterion	-0.018576	
Log likelihood	-28.45370	Hannan-Quinn criter.	0.034352		Log likelihood	23.67255	Hannan-Quinn criter.	-0.025688	
F-statistic	339.7012	Durbin-Watson stat	1.394851		F-statistic	373.7290	Durbin-Watson stat	1.384830	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## MALAYSIA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:36 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:36 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.401590	0.006033	66.56640	0.0000	C	0.298987	0.005952	50.23483	0.0000
ABS(RM)	0.522935	0.023096	22.64208	0.0000	ABS(RM)	0.581837	0.037217	15.63366	0.0000
RM^2	0.013540	0.011039	1.226626	0.2201	RM^2	-0.027781	0.036635	-0.758322	0.4484
R-squared	0.436734	Mean dependent var	0.532759		R-squared	0.442598	Mean dependent var	0.410429	
Adjusted R-squared	0.436173	S.D. dependent var	0.237389		Adjusted R-squared	0.441789	S.D. dependent var	0.177847	
S.E. of regression	0.178252	Akaike info criterion	-0.609749		S.E. of regression	0.132876	Akaike info criterion	-1.196631	
Sum squared resid	63.80159	Schwarz criterion	-0.601385		Sum squared resid	24.33002	Schwarz criterion	-1.185268	
Log likelihood	616.1023	Hannan-Quinn criter.	-0.606679		Log likelihood	829.2734	Hannan-Quinn criter.	-1.192380	
F-statistic	778.4608	Durbin-Watson stat	1.452104		F-statistic	547.0916	Durbin-Watson stat	1.564602	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## MEXICO

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:37 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:37 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.480554	0.008980	53.51394	0.0000	C	0.424252	0.011007	38.54514	0.0000
ABS(RM)	0.485367	0.036108	13.44195	0.0000	ABS(RM)	0.521361	0.037654	13.84627	0.0000
RM^2	-0.054710	0.025831	-2.117988	0.0343	RM^2	0.029270	0.018485	1.583441	0.1136
R-squared	0.252348	Mean dependent var	0.627979		R-squared	0.426236	Mean dependent var	0.604252	
Adjusted R-squared	0.251603	S.D. dependent var	0.255921		Adjusted R-squared	0.425403	S.D. dependent var	0.335950	
S.E. of regression	0.221397	Akaike info criterion	-0.176227		S.E. of regression	0.254658	Akaike info criterion	0.104377	
Sum squared resid	98.42550	Schwarz criterion	-0.167863		Sum squared resid	89.36401	Schwarz criterion	0.115739	
Log likelihood	180.1961	Hannan-Quinn criter.	-0.173157		Log likelihood	-69.07205	Hannan-Quinn criter.	0.108627	
F-statistic	338.8710	Durbin-Watson stat	1.324079		F-statistic	511.8422	Durbin-Watson stat	1.313626	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## NETHERLANDS

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:39 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:39 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.525170	0.008649	60.72121	0.0000	C	0.570925	0.010350	55.15949	0.0000
ABS(RM)	0.579424	0.028996	19.98321	0.0000	ABS(RM)	0.478097	0.027873	17.15297	0.0000
RM^2	0.010580	0.015677	0.674871	0.4998	RM^2	0.001085	0.010715	0.101239	0.9194
R-squared	0.530856	Mean dependent var	0.749327		R-squared	0.503618	Mean dependent var	0.776955	
Adjusted R-squared	0.530388	S.D. dependent var	0.326321		Adjusted R-squared	0.502897	S.D. dependent var	0.330877	
S.E. of regression	0.223622	Akaike info criterion	-0.156226		S.E. of regression	0.233286	Akaike info criterion	-0.070931	
Sum squared resid	100.4139	Schwarz criterion	-0.147863		Sum squared resid	74.99418	Schwarz criterion	-0.059568	
Log likelihood	160.0853	Hannan-Quinn criter.	-0.153156		Log likelihood	51.97779	Hannan-Quinn criter.	-0.066680	
F-statistic	1136.067	Durbin-Watson stat	1.051614		F-statistic	699.0433	Durbin-Watson stat	1.284736	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## NEW ZEALAND

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:41 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:41 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.415369	0.006745	61.57746	0.0000	C	0.384059	0.007781	49.35959	0.0000
ABS(RM)	0.473931	0.040843	11.60381	0.0000	ABS(RM)	0.672960	0.043111	15.60990	0.0000
RM^2	0.051156	0.045063	1.135216	0.2564	RM^2	-0.158116	0.034982	-4.519940	0.0000
R-squared	0.225517	Mean dependent var	0.511937		R-squared	0.274268	Mean dependent var	0.502552	
Adjusted R-squared	0.224746	S.D. dependent var	0.200476		Adjusted R-squared	0.273215	S.D. dependent var	0.206509	
S.E. of regression	0.176516	Akaike info criterion	-0.629316		S.E. of regression	0.176053	Akaike info criterion	-0.633898	
Sum squared resid	62.56529	Schwarz criterion	-0.620952		Sum squared resid	42.71045	Schwarz criterion	-0.622535	
Log likelihood	635.7773	Hannan-Quinn criter.	-0.626246		Log likelihood	440.7064	Hannan-Quinn criter.	-0.629647	
F-statistic	292.3486	Durbin-Watson stat	1.518189		F-statistic	260.3867	Durbin-Watson stat	1.453320	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:41 Sample: 9/15/2008 12/31/2013 Included observations: 1382					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:42 Sample: 5/03/2010 12/31/2013 Included observations: 957				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.384117	0.007776	49.39913	0.0000	C	0.371061	0.007467	49.69642	0.0000
ABS(RM)	0.672336	0.043046	15.61907	0.0000	ABS(RM)	0.558021	0.067527	8.263649	0.0000
RM^2	-0.157803	0.034954	-4.514525	0.0000	RM^2	-0.359710	0.114215	-3.149406	0.0017
R-squared	0.274479	Mean dependent var	0.502657		R-squared	0.153815	Mean dependent var	0.441874	
Adjusted R-squared	0.273427	S.D. dependent var	0.206471		Adjusted R-squared	0.152041	S.D. dependent var	0.131660	
S.E. of regression	0.175994	Akaike info criterion	-0.634560		S.E. of regression	0.121239	Akaike info criterion	-1.378975	
Sum squared resid	42.71320	Schwarz criterion	-0.623205		Sum squared resid	14.02277	Schwarz criterion	-1.363728	
Log likelihood	441.4813	Hannan-Quinn criter.	-0.630313		Log likelihood	662.8393	Hannan-Quinn criter.	-1.373167	
F-statistic	260.8516	Durbin-Watson stat	1.453183		F-statistic	86.70629	Durbin-Watson stat	1.466289	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## NORWAY

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:42 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:42 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.595784	0.010887	54.72616	0.0000	C	0.455768	0.010802	42.19133	0.0000
ABS(RM)	0.409857	0.033985	12.05989	0.0000	ABS(RM)	0.490291	0.025465	19.25342	0.0000
RM^2	-0.050026	0.019386	-2.580553	0.0099	RM^2	4.55E-05	0.008557	0.005322	0.9958
R-squared	0.183863	Mean dependent var	0.749732		R-squared	0.578404	Mean dependent var	0.702322	
Adjusted R-squared	0.183050	S.D. dependent var	0.296193		Adjusted R-squared	0.577792	S.D. dependent var	0.382755	
S.E. of regression	0.267715	Akaike info criterion	0.203702		S.E. of regression	0.248705	Akaike info criterion	0.057069	
Sum squared resid	143.9158	Schwarz criterion	0.212065		Sum squared resid	85.23485	Schwarz criterion	0.068432	
Log likelihood	-201.8220	Hannan-Quinn criter.	0.206772		Log likelihood	-36.40617	Hannan-Quinn criter.	0.061320	
F-statistic	226.1860	Durbin-Watson stat	1.110875		F-statistic	945.2669	Durbin-Watson stat	1.258161	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## PAKISTAN

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:44 Sample: 1/01/2001 9/15/2008 Included observations: 1995					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:44 Sample (adjusted): 12/15/2008 12/31/2013 Included observations: 1317 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.493005	0.008866	55.60933	0.0000	C	0.453777	0.011099	40.88480	0.0000
ABS(RM)	0.400061	0.022114	18.09108	0.0000	ABS(RM)	0.530595	0.042184	12.57807	0.0000
RM^2	-0.044395	0.009379	-4.733708	0.0000	RM^2	-0.092212	0.026000	-3.546663	0.0004
R-squared	0.312771	Mean dependent var	0.667919		R-squared	0.291738	Mean dependent var	0.616744	
Adjusted R-squared	0.312081	S.D. dependent var	0.291654		Adjusted R-squared	0.290660	S.D. dependent var	0.280969	
S.E. of regression	0.241900	Akaike info criterion	0.000920		S.E. of regression	0.236638	Akaike info criterion	-0.042291	
Sum squared resid	116.5633	Schwarz criterion	0.009339		Sum squared resid	73.58106	Schwarz criterion	-0.030485	
Log likelihood	2.082153	Hannan-Quinn criter.	0.004012		Log likelihood	30.84876	Hannan-Quinn criter.	-0.037864	
F-statistic	453.2980	Durbin-Watson stat	1.449290		F-statistic	270.6223	Durbin-Watson stat	1.322370	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:45 Sample: 9/15/2008 4/30/2010 Included observations: 361					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:45 Sample: 5/03/2010 12/31/2013 Included observations: 957				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.480138	0.033461	14.34931	0.0000	C	0.434513	0.009472	45.87486	0.0000
ABS(RM)	0.676730	0.101409	6.673243	0.0000	ABS(RM)	0.618762	0.047157	13.12136	0.0000
RM^2	-0.154655	0.053091	-2.912992	0.0038	RM^2	-0.288334	0.040886	-7.052214	0.0000
R-squared	0.276026	Mean dependent var	0.751073		R-squared	0.261431	Mean dependent var	0.565939	
Adjusted R-squared	0.271981	S.D. dependent var	0.411680		Adjusted R-squared	0.259882	S.D. dependent var	0.188333	
S.E. of regression	0.351262	Akaike info criterion	0.753708		S.E. of regression	0.162023	Akaike info criterion	-0.799028	
Sum squared resid	44.17186	Schwarz criterion	0.786025		Sum squared resid	25.04387	Schwarz criterion	-0.783781	
Log likelihood	-133.0442	Hannan-Quinn criter.	0.766556		Log likelihood	385.3347	Hannan-Quinn criter.	-0.793220	
F-statistic	68.24629	Durbin-Watson stat	1.326758		F-statistic	168.8433	Durbin-Watson stat	1.456908	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## PERU

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:46 Sample: 1/01/2001 9/15/2008 Included observations: 1894					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:46 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.738398	0.016590	44.50855	0.0000	C	0.408547	0.013954	29.27848	0.0000
ABS(RM)	0.549814	0.064640	8.505792	0.0000	ABS(RM)	0.728660	0.052593	13.85464	0.0000
RM^2	0.025973	0.033715	0.770368	0.4412	RM^2	-0.012240	0.027628	-0.443026	0.6578
R-squared	0.132922	Mean dependent var	0.887417		R-squared	0.337306	Mean dependent var	0.612149	
Adjusted R-squared	0.132004	S.D. dependent var	0.495377		Adjusted R-squared	0.336344	S.D. dependent var	0.414867	
S.E. of regression	0.461524	Akaike info criterion	1.293017		S.E. of regression	0.337971	Akaike info criterion	0.670459	
Sum squared resid	402.7914	Schwarz criterion	1.301803		Sum squared resid	157.4016	Schwarz criterion	0.681822	
Log likelihood	-1221.487	Hannan-Quinn criter.	1.296252		Log likelihood	-459.9522	Hannan-Quinn criter.	0.674710	
F-statistic	144.9434	Durbin-Watson stat	1.433458		F-statistic	350.6950	Durbin-Watson stat	1.707365	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## PHILIPPINES

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:48 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:48 Sample: 9/16/2008 12/31/2013 Included observations: 1374				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.644648	0.011253	57.28815	0.0000	C	0.525544	0.011503	45.68855	0.0000
ABS(RM)	0.421929	0.029433	14.33526	0.0000	ABS(RM)	0.520114	0.033793	15.39120	0.0000
RM^2	-0.014279	0.009944	-1.435970	0.1512	RM^2	-0.054361	0.014503	-3.748226	0.0002
R-squared	0.163759	Mean dependent var	0.788778		R-squared	0.259775	Mean dependent var	0.691240	
Adjusted R-squared	0.162926	S.D. dependent var	0.356845		Adjusted R-squared	0.258696	S.D. dependent var	0.318980	
S.E. of regression	0.326484	Akaike info criterion	0.600619		S.E. of regression	0.274639	Akaike info criterion	0.255461	
Sum squared resid	214.0363	Schwarz criterion	0.608982		Sum squared resid	103.4097	Schwarz criterion	0.266870	
Log likelihood	-600.9221	Hannan-Quinn criter.	0.603689		Log likelihood	-172.5017	Hannan-Quinn criter.	0.259730	
F-statistic	196.6105	Durbin-Watson stat	1.544774		F-statistic	240.5702	Durbin-Watson stat	1.363654	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:49 Sample: 9/15/2008 4/30/2010 Included observations: 418					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:49 Sample: 5/03/2010 12/31/2013 Included observations: 957				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.706974	0.024645	28.68591	0.0000	C	0.449914	0.012345	36.44544	0.0000
ABS(RM)	0.369635	0.058827	6.283381	0.0000	ABS(RM)	0.651611	0.048022	13.56906	0.0000
RM^2	-0.013108	0.019979	-0.656076	0.5121	RM^2	-0.166535	0.029722	-5.603109	0.0000
R-squared	0.211676	Mean dependent var	0.863967		R-squared	0.278340	Mean dependent var	0.616098	
Adjusted R-squared	0.207877	S.D. dependent var	0.350092		Adjusted R-squared	0.276827	S.D. dependent var	0.272137	
S.E. of regression	0.311586	Akaike info criterion	0.512869		S.E. of regression	0.231424	Akaike info criterion	-0.085998	
Sum squared resid	40.29066	Schwarz criterion	0.541832		Sum squared resid	51.09359	Schwarz criterion	-0.070751	
Log likelihood	-104.1897	Hannan-Quinn criter.	0.524319		Log likelihood	44.14993	Hannan-Quinn criter.	-0.080190	
F-statistic	55.71673	Durbin-Watson stat	1.510979		F-statistic	183.9761	Durbin-Watson stat	1.534581	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## PORTUGAL

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:50 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:50 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.460621	0.009948	46.30339	0.0000	C	0.787048	0.017584	44.75856	0.0000
ABS(RM)	0.652729	0.047560	13.72423	0.0000	ABS(RM)	0.573867	0.045359	12.65153	0.0000
RM^2	-0.084893	0.037083	-2.289236	0.0222	RM^2	-0.067297	0.017671	-3.808251	0.0001
R-squared	0.231716	Mean dependent var	0.612691		R-squared	0.190968	Mean dependent var	1.004840	
Adjusted R-squared	0.230951	S.D. dependent var	0.304746		Adjusted R-squared	0.189793	S.D. dependent var	0.431096	
S.E. of regression	0.267248	Akaike info criterion	0.200213		S.E. of regression	0.388036	Akaike info criterion	0.946730	
Sum squared resid	143.4145	Schwarz criterion	0.208576		Sum squared resid	207.4876	Schwarz criterion	0.958093	
Log likelihood	-198.3138	Hannan-Quinn criter.	0.203283		Log likelihood	-650.7172	Hannan-Quinn criter.	0.950981	
F-statistic	302.8080	Durbin-Watson stat	1.313969		F-statistic	162.6346	Durbin-Watson stat	1.446736	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## ROMANIA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:52 Sample: 1/01/2001 9/15/2008 Included observations: 1937					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:52 Sample: 9/16/2008 12/31/2013 Included observations: 1367				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.777143	0.014545	53.42870	0.0000	C	0.670358	0.014501	46.22944	0.0000
ABS(RM)	0.444440	0.033076	13.43695	0.0000	ABS(RM)	0.619943	0.030217	20.51645	0.0000
RM^2	0.019011	0.011965	1.588803	0.1123	RM^2	-0.066075	0.008508	-7.766540	0.0000
R-squared	0.349857	Mean dependent var	1.025877		R-squared	0.395088	Mean dependent var	0.951465	
Adjusted R-squared	0.349185	S.D. dependent var	0.467781		Adjusted R-squared	0.394201	S.D. dependent var	0.445543	
S.E. of regression	0.377374	Akaike info criterion	0.890387		S.E. of regression	0.346780	Akaike info criterion	0.721940	
Sum squared resid	275.4230	Schwarz criterion	0.899012		Sum squared resid	164.0297	Schwarz criterion	0.733397	
Log likelihood	-859.3400	Hannan-Quinn criter.	0.893559		Log likelihood	-490.4461	Hannan-Quinn criter.	0.726228	
F-statistic	520.3648	Durbin-Watson stat	1.284547		F-statistic	445.4368	Durbin-Watson stat	1.409065	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:52 Sample: 9/15/2008 4/30/2010 Included observations: 411					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:53 Sample: 5/03/2010 12/31/2013 Included observations: 957				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.877472	0.038129	23.01298	0.0000	C	0.630472	0.014244	44.26341	0.0000
ABS(RM)	0.470473	0.056622	8.309026	0.0000	ABS(RM)	0.597923	0.037479	15.95340	0.0000
RM^2	-0.040153	0.014117	-2.844294	0.0047	RM^2	-0.071424	0.012440	-5.741599	0.0000
R-squared	0.316709	Mean dependent var	1.230984		R-squared	0.313919	Mean dependent var	0.831745	
Adjusted R-squared	0.313359	S.D. dependent var	0.526656		Adjusted R-squared	0.312481	S.D. dependent var	0.341836	
S.E. of regression	0.436407	Akaike info criterion	1.186789		S.E. of regression	0.283439	Akaike info criterion	0.319492	
Sum squared resid	77.70401	Schwarz criterion	1.216122		Sum squared resid	76.64225	Schwarz criterion	0.334739	
Log likelihood	-240.8852	Hannan-Quinn criter.	1.198393		Log likelihood	-149.8768	Hannan-Quinn criter.	0.325299	
F-statistic	94.55489	Durbin-Watson stat	1.218199		F-statistic	218.2535	Durbin-Watson stat	1.671226	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## SINGAPORE

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:57 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:57 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.547479	0.007102	77.08657	0.0000	C	0.440512	0.009747	45.19237	0.0000
ABS(RM)	0.443637	0.028978	15.30966	0.0000	ABS(RM)	0.604758	0.033704	17.94301	0.0000
RM^2	0.025314	0.020440	1.238462	0.2157	RM^2	0.004742	0.016241	0.292016	0.7703
R-squared	0.418607	Mean dependent var	0.696352		R-squared	0.496291	Mean dependent var	0.632952	
Adjusted R-squared	0.418028	S.D. dependent var	0.232119		Adjusted R-squared	0.495560	S.D. dependent var	0.321618	
S.E. of regression	0.177077	Akaike info criterion	-0.622972		S.E. of regression	0.228425	Akaike info criterion	-0.113044	
Sum squared resid	62.96344	Schwarz criterion	-0.614609		Sum squared resid	71.90156	Schwarz criterion	-0.101681	
Log likelihood	629.3988	Hannan-Quinn criter.	-0.619902		Log likelihood	81.05654	Hannan-Quinn criter.	-0.108793	
F-statistic	722.8861	Durbin-Watson stat	1.435260		F-statistic	678.8528	Durbin-Watson stat	1.078465	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## SPAIN

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:58 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 16:58 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.422471	0.005444	77.60094	0.0000	C	0.626386	0.008411	74.47458	0.0000
ABS(RM)	0.475186	0.020518	23.15947	0.0000	ABS(RM)	0.338394	0.019399	17.44370	0.0000
RM^2	0.040162	0.013512	2.972256	0.0030	RM^2	0.060857	0.007507	8.106739	0.0000
R-squared	0.641595	Mean dependent var	0.600143		R-squared	0.637960	Mean dependent var	0.829760	
Adjusted R-squared	0.641238	S.D. dependent var	0.228858		Adjusted R-squared	0.637435	S.D. dependent var	0.303557	
S.E. of regression	0.137079	Akaike info criterion	-1.135031		S.E. of regression	0.182782	Akaike info criterion	-0.558875	
Sum squared resid	37.73151	Schwarz criterion	-1.126667		Sum squared resid	46.03797	Schwarz criterion	-0.547512	
Log likelihood	1144.274	Hannan-Quinn criter.	-1.131961		Log likelihood	388.9031	Hannan-Quinn criter.	-0.554624	
F-statistic	1797.300	Durbin-Watson stat	1.412474		F-statistic	1214.106	Durbin-Watson stat	1.503864	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## SWEDEN

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:00 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:00 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.394793	0.007315	53.96743	0.0000	C	0.354175	0.008935	39.63735	0.0000
ABS(RM)	0.418970	0.021055	19.89904	0.0000	ABS(RM)	0.296846	0.023259	12.76253	0.0000
RM^2	-0.011606	0.010612	-1.093607	0.2743	RM^2	0.006550	0.009496	0.689777	0.4905
R-squared	0.471854	Mean dependent var	0.579213		R-squared	0.398926	Mean dependent var	0.498777	
Adjusted R-squared	0.471328	S.D. dependent var	0.258024		Adjusted R-squared	0.398054	S.D. dependent var	0.258165	
S.E. of regression	0.187609	Akaike info criterion	-0.507420		S.E. of regression	0.200298	Akaike info criterion	-0.375855	
Sum squared resid	70.67604	Schwarz criterion	-0.499057		Sum squared resid	55.28415	Schwarz criterion	-0.364493	
Log likelihood	513.2109	Hannan-Quinn criter.	-0.504350		Log likelihood	262.5280	Hannan-Quinn criter.	-0.371605	
F-statistic	896.9881	Durbin-Watson stat	1.292605		F-statistic	457.2816	Durbin-Watson stat	0.995967	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## SWITZERLAND

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:01 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:02 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.376775	0.006388	58.97870	0.0000	C	0.370774	0.007256	51.10203	0.0000
ABS(RM)	0.587932	0.023893	24.60667	0.0000	ABS(RM)	0.523050	0.023826	21.95330	0.0000
RM^2	0.008773	0.014438	0.607656	0.5435	RM^2	0.006731	0.011070	0.608068	0.5432
R-squared	0.600825	Mean dependent var	0.571939		R-squared	0.581958	Mean dependent var	0.542767	
Adjusted R-squared	0.600427	S.D. dependent var	0.264766		Adjusted R-squared	0.581352	S.D. dependent var	0.268401	
S.E. of regression	0.167363	Akaike info criterion	-0.735813		S.E. of regression	0.173664	Akaike info criterion	-0.661220	
Sum squared resid	56.24482	Schwarz criterion	-0.727449		Sum squared resid	41.55929	Schwarz criterion	-0.649858	
Log likelihood	742.8597	Hannan-Quinn criter.	-0.732743		Log likelihood	459.5726	Hannan-Quinn criter.	-0.656970	
F-statistic	1511.186	Durbin-Watson stat	1.050425		F-statistic	959.1609	Durbin-Watson stat	0.964504	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## THAILAND

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:03 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:03 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.445280	0.007528	59.14649	0.0000	C	0.437380	0.008752	49.97534	0.0000
ABS(RM)	0.425295	0.015731	27.03528	0.0000	ABS(RM)	0.355761	0.020836	17.07470	0.0000
RM^2	-0.024622	0.004447	-5.536973	0.0000	RM^2	-0.001347	0.007442	-0.181029	0.8564
R-squared	0.370447	Mean dependent var	0.623480		R-squared	0.426929	Mean dependent var	0.598602	
Adjusted R-squared	0.369819	S.D. dependent var	0.273184		Adjusted R-squared	0.426097	S.D. dependent var	0.266429	
S.E. of regression	0.216864	Akaike info criterion	-0.217598		S.E. of regression	0.201837	Akaike info criterion	-0.360545	
Sum squared resid	94.43656	Schwarz criterion	-0.209235		Sum squared resid	56.13705	Schwarz criterion	-0.349183	
Log likelihood	221.7952	Hannan-Quinn criter.	-0.214528		Log likelihood	251.9566	Hannan-Quinn criter.	-0.356295	
F-statistic	590.7811	Durbin-Watson stat	1.607097		F-statistic	513.2938	Durbin-Watson stat	1.468359	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## TURKEY

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:10 Sample: 1/01/2001 9/15/2008 Included observations: 1990					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:10 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.554755	0.008829	62.83197	0.0000	C	0.464165	0.008854	52.42621	0.0000
ABS(RM)	0.301199	0.013469	22.36179	0.0000	ABS(RM)	0.302492	0.020125	15.03034	0.0000
RM^2	-0.024038	0.003251	-7.394061	0.0000	RM^2	-0.015145	0.007217	-2.098436	0.0360
R-squared	0.324979	Mean dependent var	0.747995		R-squared	0.337902	Mean dependent var	0.608588	
Adjusted R-squared	0.324299	S.D. dependent var	0.281798		Adjusted R-squared	0.336941	S.D. dependent var	0.242921	
S.E. of regression	0.231641	Akaike info criterion	-0.085749		S.E. of regression	0.197807	Akaike info criterion	-0.400881	
Sum squared resid	106.6177	Schwarz criterion	-0.077313		Sum squared resid	53.91778	Schwarz criterion	-0.389519	
Log likelihood	88.31980	Hannan-Quinn criter.	-0.082650		Log likelihood	279.8084	Hannan-Quinn criter.	-0.396631	
F-statistic	478.3054	Durbin-Watson stat	1.364551		F-statistic	351.6314	Durbin-Watson stat	1.259391	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## UK

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:12 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:12 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.370406	0.005737	64.56876	0.0000	C	0.430404	0.009611	44.78153	0.0000
ABS(RM)	0.522459	0.023232	22.48877	0.0000	ABS(RM)	0.434855	0.027467	15.83208	0.0000
RM^2	-0.023068	0.015521	-1.486267	0.1374	RM^2	0.010588	0.011330	0.934551	0.3502
R-squared	0.566984	Mean dependent var	0.537793		R-squared	0.463429	Mean dependent var	0.605949	
Adjusted R-squared	0.566553	S.D. dependent var	0.220580		Adjusted R-squared	0.462651	S.D. dependent var	0.298389	
S.E. of regression	0.145223	Akaike info criterion	-1.019603		S.E. of regression	0.218732	Akaike info criterion	-0.199772	
Sum squared resid	42.34811	Schwarz criterion	-1.011239		Sum squared resid	65.92844	Schwarz criterion	-0.188409	
Log likelihood	1028.211	Hannan-Quinn criter.	-1.016533		Log likelihood	140.9422	Hannan-Quinn criter.	-0.195521	
F-statistic	1314.622	Durbin-Watson stat	1.126571		F-statistic	595.0806	Durbin-Watson stat	0.847868	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			

## USA

Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:13 Sample: 1/01/2001 9/15/2008 Included observations: 2011					Dependent Variable: CSAD Method: Least Squares Date: 09/27/14 Time: 17:13 Sample: 9/16/2008 12/31/2013 Included observations: 1381				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.453679	0.007648	59.31907	0.0000	C	0.375241	0.009403	39.90555	0.0000
ABS(RM)	0.417944	0.030857	13.54468	0.0000	ABS(RM)	0.443694	0.024970	17.76926	0.0000
RM^2	0.021394	0.021690	0.986338	0.3241	RM^2	-0.004397	0.008985	-0.489426	0.6246
R-squared	0.354934	Mean dependent var	0.595438		R-squared	0.491354	Mean dependent var	0.556873	
Adjusted R-squared	0.354291	S.D. dependent var	0.245432		Adjusted R-squared	0.490616	S.D. dependent var	0.321265	
S.E. of regression	0.197219	Akaike info criterion	-0.407513		S.E. of regression	0.229290	Akaike info criterion	-0.105485	
Sum squared resid	78.10184	Schwarz criterion	-0.399150		Sum squared resid	72.44712	Schwarz criterion	-0.094122	
Log likelihood	412.7545	Hannan-Quinn criter.	-0.404443		Log likelihood	75.83707	Hannan-Quinn criter.	-0.101234	
F-statistic	552.4288	Durbin-Watson stat	1.075987		F-statistic	665.5773	Durbin-Watson stat	1.072894	
Prob(F-statistic)	0.000000				Prob(F-statistic)	0.000000			