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HERDING BEHAVIOR IN THE MAJOR LATIN AMERICAN STOCK MARKETS

Benedita de Freitas Vieira Giesteira de Almeida

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FACULDADE DE **ECONOMIA**

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ABSTRACT

This work applies the approach developed by Chang et al., (2000) – which measures the dispersion of returns around the "market consensus" – to test for the presence of herding behavior in the stock markets of major Latin American economies (Brazil, Chile, Colombia and Mexico) over the time period from 01/01/2013 to 12/31/2022. To this end, a survivor-bias-free dataset of daily and monthly returns of the stocks belonging to the most relevant equity index of each market was considered.

Further, we examine the potential impact of the recent COVID-19 pandemic on this irrational behavior, while also testing for eventual asymmetric herding effects contingent on the sign of the market portfolio return and market volatility levels.

As a distinctive feature, our study applies two novel tests, which, to the best of our knowledge, have never been conducted in the context of Latin American markets: first, we account for the influence of psychological, economic and global market factors on this bias; second, we examine whether the mimic instinct in one market is influenced by the trading activity in the other three economies.

Overall, our results provided no evidence of herding in Latin America, neither for the whole sample period nor for specific subperiods selected based on a Bai & Perron (2003) approach. Also, no herding activity seems to have been induced by the pandemic. However, we reported evidence of herding in Chile during rising markets and low volatility periods. Additionally, we found the herding activity in the Mexican stock market to be the most responsive to changes in macroeconomic and global market factors.

Finally, we provide strong evidence of cross-country herding effects connecting Latin American stock markets. Such a finding is of particular interest given its implications for the effectiveness of international portfolio diversification and the overall financial stability in the Latin American region.

RESUMO

Este trabalho utiliza a métrica desenvolvida por Chang et al., (2000) – que mede a dispersão dos retornos em torno do "consenso de mercado" – para estudar a presença de *herding* nos mercados de ações das principais economias Latino-Americanas (Brasil, Chile, Colômbia e México) entre 01/01/2013 e 31/12/2022. Para tal, foi considerado um conjunto de dados livre de *survivorship bias* consistindo nos retornos diários e mensais das ações pertences ao índice acionista mais relevante de cada mercado.

Ademais, é também examinado o potencial impacto da pandemia de COVID-19 neste comportamento irracional, ao mesmo tempo em que se estuda se este viés apresenta uma natureza assimétrica em função do sinal do retorno do portfólio de mercado e dos níveis de volatilidade.

Como característica distintiva, o nosso estudo aplica dois novos testes, que, até onde sabemos, nunca foram conduzidos no contexto latino-americano: em primeiro lugar, consideramos a influência de fatores psicológicos, económicos e de mercado global na intensidade de *herding*; em segundo lugar, é estudado se o instinto de imitação num determinado mercado é impactado pelo comportamento prevalecente nas demais economias.

Em geral, não foram encontradas evidências de *herding* na América Latina, nem quando todo o período temporal foi considerado, nem quando analisados apenas subperíodos específicos, selecionados com base na abordagem de Bai & Perron (2003). Além disto, este comportamento não parece ter sido intensificado em resposta à pandemia. Todavia, foram relatadas evidências de *herding* no Chile durante períodos de crescimento de mercado, tal como em períodos de baixa volatilidade. Adicionalmente, concluiu-se que o mercado de ações mexicano é o mais afetado pelo comportamento de importantes variáveis económicas, assim como de mercado global.

Finalmente, foram detetadas fortes evidências de *cross-herding* entre os países estudados. Tal descoberta é de particular interesse, dadas as suas implicações no que respeita à eficácia da diversificação internacional e à estabilidade financeira da região latino-americana.

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1. INTRODUCTION

Human beings are known to be influenced by their peers in their decision-making (Shiller & Pound, 1989; Devenow & Welch, 1996; Hong et al., 2005; Fenzi & Pelzmann, 2012). That is, even when confronted with simple decisions, such as selecting in which restaurant to have a meal, people tend to imitate the decisions of their predecessors, which leads them to frequently select the restaurant with the highest number of positive customer reviews or with the greatest number of clients, for example.

Indeed, it is now widely accepted that individuals are affected by psychological and behavioral biases which cause their decisions to often deviate from what is deemed "rational" (Hastrof et al., 1970; Tversky & Kahneman, 1973; Svenson, 1981; Shiller, 2000). Naturally, the same reasoning can be extended to financial markets, in the sense that, investors, as human beings, are likely to base their decisions not exclusively on the private information they may possess, but also on the paths followed by the other market participants.

In fact, several studies undertaken throughout the years have corroborated the idea that investors are undeniably impacted by the collective behavior observed in the market. In this sense, for instance, Hong et al., (2005) concluded that market participation is influenced by social interactions, suggesting that investors tend to find a market to be more attractive if their peers are also participating. Similarly, Shiller & Pound (1989) reported that both individual and institutional investors´ interest in a given stock is strongly influenced by their peers´ opinion about that stock. In the same line, more recently, Fenz & Pelzmann (2012) found evidence that investors tend to trade their stocks - buying or selling them - in reaction to the buying and selling decisions made by other market participants.

From the evidence presented above, it becomes evident that investors take into account their colleagues´ opinion when forming their investment decisions, which stands out the importance of analyzing the collective behavior - called herding - that may emerge in financial markets. Indeed, there are a series of reasons why herding is an issue worth studying. Concretely, from a regulatory perspective, correlated patterns of trades may undermine financial stability (Kutan & Demirer, 2006). In turn, for investors, an increase in the degree of co-movement among asset returns reduces the benefits of portfolio diversification. Hence, it may be necessary to hold a larger number of assets to achieve the desired reduction of idiosyncratic risk while, in the extreme case in which asset returns become almost perfectly correlated, risk reduction via diversification may not be attainable (Chang et al., 2000; Baur, 2006; Chiang & Zheng, 2010; Morelli, 2010). Moreover, mispricings resulting from this behavior reduce the effectiveness of the market mechanism to reveal assets "fair values", undermining the fundamental principle of market efficiency (Devenow & Welch, 1996) and potentially creating profitable trading opportunities (Hwang & Salmon, 2004; Tan et al., 2008). To the extent that these mispricings lead to suboptimal decision-making by investors, as well as erroneous reactions from policymakers, herding may cause a huge reduction on social welfare, which highlights the relevance of examining this behavior in detail.

The arguments presented in the previous paragraph leave no doubt about the relevance of studying the herding phenomenon by itself. However, examining such irrational behavior in the context of emerging economies is, according to existing literature, of particular interest (Bikhchandani & Sharma, 2000). In fact, these authors highlight the fact that the peculiar characteristics of this set of markets – such as their underdeveloped financial system or their exposure to highly volatile international capital flows – contribute to the creation of a scenario particularly favorable to the appearance of herding.

Based on this, the main purpose of the present work is to analyze the presence of such mimicking behavior among the market participants in four Latin American emerging markets: Brazil, Chile, Colombia and Mexico. Noteworthy, as it will be possible to conclude from the literature review presented in the next chapter, only very few studies have taken Latin American countries into account, representing a gap in existing literature we aim to fill.

Despite the lack of empirical evidence, studying investors´ behavior in this geographical area may be of great importance in light of the region´s relevance to the international economy. As a matter of fact, according to the World Bank, the countries included in our analysis, as the major economies of the region, represented, together, 64.41% of Latin America & Caribbean´s Gross Domestic Product (GDP) in 2021 and 94.22% of its total market capitalization as of 2020[1].

Apart from expanding the extant literature on herding behavior by focusing on a barely explored set of markets, our work also contributes to enrich the existent literature by addressing a series of issues scarcely examined before in the Latin-American context.

To begin with, taking into account the massive spike in uncertainty caused by the outbreak of the COVID-19 pandemic in 2020, as well as its unmeasurable impact on the global economy and capital markets, this work also accounts for the potential impact of the pandemic on investors´ mimic instinct. In fact, although the effects of the pandemic on stock markets have been a broadly studied topic since the beginning of 2020, most studies focused their attention on different sets of European and Asian markets (see, for instance, Bogdan

[1] At an individual level, according to the same source, in 2020, the market capitalization of public companies represented more than one third of each market´s GDP: Brazil (68.2%); Chile (73%); Colombia (39.3%) and Mexico (36.3%).

et al., 2022 and Jiang et al., 2022), whereas, to the best of our knowledge, no work to date has centered its attention on Latin American markets.

Second, we also examine the potential asymmetric nature of herding by analyzing the extent to which the mimic instinct of Latin American market players is impacted not only by different market conditions, but also by different psychological, economic and global market factors. Even though the issue of asymmetric herding contingent on domestic market conditions has already been widely investigated before (Chiang et al., 2000; Tan et al., 2008; Economou et al., 2011), little research has been conducted so far regarding the impact of psychological, economic and global market parameters on herding estimates.

Third, our work contributes to expand a rather under researched area in herding literature by exploring whether the mimicking activity in each of the four sample markets is motivated the trading dynamics in the remaining three economies. Although some authors have already considered the existence of cross-country herding effects (Economou et al., 2011; Mobarek et al., 2014), no research on this topic has been conducted in Latin American markets so far.

Finally, another distinctive factor of our analysis lies on the fact that, differently from most herding studies that apply only daily data, we considered two different data frequencies: daily and monthly. By adopting this approach, we also contribute to add value to existing literature by analyzing if this bias behaves differently in the short and long-terms.

In a nutshell, we found no evidence of herding in the four Latin American stock markets, neither for the whole sample period, nor when only specific subsamples were analyzed. Similarly, no herd formation seems to have been induced by the uncertain panorama created by the COVID-19 public health crisis. Nevertheless, our results reported the presence of mimicking activity among Chilean investors driven by rising markets and low volatility periods. In the remaining countries, different market conditions were observed as not fostering herding activity. On top of this, we also found the intensity of herd formation in the Mexican stock market to be strongly linked to different economic and global market factors. When it comes to the other three economies under study, the influence of external factors on investors´ behavior seems to diverge substantially across nations. At last, we documented strong cross-country herding forces connecting the four stock markets.

This dissertation will be structured as follows. In chapter 2, a brief literature review around the herding phenomena will be presented. In chapter 3, we will proceed with the formulation of the research questions, as well as with the presentation of the methodology employed. The results of the study will be presented and discussed in chapter 4 so that, in the 5th chapter, we can summarize the main conclusions obtained with this analysis.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

In his Efficient Market Hypothesis (EMH), Fama (1970) describes an ideal setting for financial markets, where investors always make rational decisions and share prices reflect all available information and stay unpredictable. However, in 1980s, several empirical findings started to show that these assumptions often fall in practice. In this sense, for instance, challenging the efficiency of security prices, Nicholson (1968) and Basu (1977) suggested that stocks with higher P/E ratios seemed to be overvalued, while the opposite was verified for those stocks with low values for the same ratio. Similarly, calendar effects have also been documented, with Keim (1983) finding evidence that daily abnormal return distributions in January had larger means when compared to the remaining eleven months of the year.

In light of this, in the recent years, it has been observed an increase in behavioral finance literature aiming at providing an explanation for these and other anomalies that take place in financial markets from a less rational standpoint, focusing on eventual psychological factors which may cause investors to act differently from what is predicted by traditional models. In fact, as stated by Baruch (1957, p. 85), "*above all else… stock market is people. It is people trying to read the future*". Hence, it can be argued that, when studying financial markets, one cannot neglect the human component that undeniably affects investors´ behavior, often leading to conflicting decisions.

As suggested by De Bondt et al., (2008), nowadays, understanding investors´ tendency to act as a group (i.e., herding) through the lenses of a behavioral finance approach is of heightened interest, which justifies the growing literature around herding behavior in financial markets. In our review of such literature, after presenting a concrete definition of this phenomenon, we will discuss some of the most cited causes behind it. In the sequence, we will then address some potential drivers of this bias, concluding with the exposure of several empirical studies already conducted in the field of herding around the world during different periods of time. To note that, as the present work is essentially focused on a set of emerging markets, a special emphasis will be given to those empirical studies that also included this group of economies, taking into consideration the Country Classification proposed by the MSCI Country Classification Standards as of August 2022[2].

[2] The MSCI Country Classification can be found at: https://www.msci.com/documents/1296102/1330218/MSCI-Country-Classification-Standard-cfs-en.pdf.

2.1 HERDING BEHAVIOR

In his influential article, Banerjee (1992, p. 798) defines herding as "*everyone doing what everyone else is doing, even when their private information suggests doing something quite different*". Extrapolating this general definition to the context of financial markets, herding, in finance, is generally understood as the phenomenon where investors tend to mimic trading activities from others who they believe are better informed, while their own intelligence is overlooked (Bikhchandani & Sharma, 2000).

This is often seen as a behavior that exacerbates volatility, destabilizes markets and increases the fragility of the overall financial system (Bikhchandani & Sharma, 2000). As such, it is frequently argued that financial crises are a result of a widespread herding among market participants (Chari & Kehoe, 2004).

The negative connotation associated with this mimicking behavior in financial lexicon naturally arouse the interest of many researchers to try to capture the causes behind such phenomenon. In this sense, according to Shiller (2000), investors´ tendency to mimic the behavior of their peers may be, at least in part, related to their reactions to public available information, although the author recognizes that this may not be the single reason behind this bias. Based on this idea, herding may be interpreted as an irrational behavior, where an investor simply follows his/her peers in a blind manner. Nonetheless, as defended by Tversky & Kahneman (1986), reactions induced behavior or psychological traits can also be consistent with a rational decision-making process.

This lack of consensus around the nature of herding led Devenow & Welch (1996) to defend the existence of two polar views of herding: irrational and rational. Irrational herding is related to psychology, suggesting that investors follow one another without any rational motivation. One practical example of this phenomenon could be investors that panic in a sudden market drop, choosing to sell their securities only to limit their losses. In this scenario, investors are neglecting their own information to simply follow the majority in a current market trend.

On the contrary, rational herding deals with the fact that optimal decision-making may be distorted by information difficulties or incentive issues. One of the explanations for the manifestation of rational herding behavior, initially proposed by Banerjee (1992), Bikhchandani et al., (1992) and Welch (1992), is the information-based herding. According to this theory, given that decisions are made in a sequential manner, an investor is able to observe the actions taken by his/her peers and, based on such decisions, infer if they have relevant information that must be included in his/her own decision. In this field of information-based herding, Froot et al., (1992) added that acquisition costs may play a role in why some investors tend to mimic others, especially when such costs are high for certain traders.

Another argument proposed to explain this phenomenon has to do with managers´ tendency to avoid reputation costs. That is, according to Bikhchandani & Sharma (2000), if a given manager is not sure about his ability, he will be keen to imitate what others are doing in order to maintain his reputation. In such circumstances, if the manager´s decision turns out being the right one, he will be seen as a good manager, while if, on the other hand, the decision proves to be the wrong one, the outcome will be simply attributed to bad luck, thereby not damaging the manager´s reputation. As a way of summarizing the existence of reputational incentives to herd, Keynes (1936, pp. 157-158) stated that "*it is better for reputation to fail conventionally than to succeed unconventionally*".

Finally, the last cause of rational herding behavior is related to compensation issues. In particular, if investors´ compensation is dependent on the comparison between their own performance and that of the overall market, they will have incentives to imitate other market participants (Bikhchandani & Sharma, 2000).

Based on what was stated in the previous paragraphs, one can argue that there is an extensive theoretical grounding trying to justify the manifestation of mimicking behavior among investors. However, to study the existence of such behavior empirically is not a simple task. In fact, when a group of investors is trading in the same direction, one is not able to know with certainty if they are doing so because they are simply imitating one another – thus engaging in intentional herding – or because the group had access to similar information, which led them to make similar decisions – in this case, we would be in the presence of spurious herding.

2.2 HERDING DRIVERS

The complexity associated with documenting herding in financial markets seems not to have stopped researchers from trying to extend their knowledge about this bias. Indeed, throughout the years, several studies have proved the existence of a link between this mimicking tendency among investors and several external factors, including market and economic conditions and even psychological factors.

Concretely, when it comes to market states, a factor that must be considered as having a strong influence on the intensity of herding is the level of volatility observed in the market. Specifically, Chiu et al., (2010) argued that volatility could represent an adequate proxy of information uncertainty which, in turn, could foster investors´ tendency to seek for the security of following the collective behavior. Supporting this line of reasoning, over the years, several empirical studies have reported that higher levels of volatility tend to lead to more pronounced levels of herding in equity markets (Butler & Joaquin, 2002; Forbes & Rigobon, 2002; Gleason et al., 2004; Corsetti et al., 2005). However, although most studies suggest the existence of a positive relationship between market volatility and herding, it is worth mentioning that, by contrast, the conclusions of an empirical study conducted by Lobão & Serra (2007) regarding the Portuguese market suggested that the level of mimicking behavior in this market is higher when lower levels of volatility are observed.

In a similar vein, the level of trading volume seems to also have an impact on the degree of herding observed in equity markets. Indeed, some authors argue that trading volume variables represent useful proxies for the quality of information (Blume et al., 1994; Suominen, 2001), a factor which naturally impacts the level of herding in financial markets, as investors are more likely to follow the majority behavior when their own private information is less reliable. Empirically, however, the conclusions obtained by different authors seem not to be consensual. In fact, whereas, for instance, Lan & Lai (2011) reported that higher levels of trading volume contribute to trigger herding in the Chinese stock market, Fu & Lin (2010) reached the opposite conclusion when analyzing the same market.

Adding to this, the impact of different market regimes on investors´ herding behavior has also been extensively studied throughout the years, with the reported findings being essentially mixed in nature. On the one hand, according to Tan et al., (2008), down markets may stimulate herding as investors tend to unload their positions as a way of avoiding additional losses in case the downturn period becomes prolonged. On the other hand, increased herding activity during up-market movements may be justified by investors´ intention to ride in what they believe to be an upward trend (Long et al., 1990).

Apart from market conditions, in the recent years it has been defended that the mimicking activity among investors may also be influenced by the prevalent economic panorama. Indeed, it can be argued that certain macroeconomic events, such as monetary policy announcements, may have an impact on investors´ tendency to herd, in the sense that such events elicit considerable public attention and are likely to affect public behavior. As such, and although empirical evidence addressing this issue is still considerably limited, some authors have already documented that rising interest rates tend to promote a more pronounced herding behavior among investors (Philippas et al., 2013; Gong & Dai, 2017). However, contrasting with this idea, some other studies have documented that, instead, monetary policy announcements exert an insignificant effect on the level of herd formation detected in certain stock markets (Wibowo, 2021).

Adding to interest rates, researchers have also explored the link between exchange rates and investors´ instinct of imitation. For instance, addressing this issue, Gong & Dai (2017) showed that a depreciation of the Chinese currency (CNY) induces a greater mimicking activity among Chinese market players. Similarly, Wibowo (2021) found that exchange rates exert a positive impact on the level of herd formation in a set of developed markets (UK, Canada, Japan, France and Germany), while a non-statistically significant relationship was found in the case of emerging economies (India, Indonesia, Brazil, Russia and China).

Moreover, after an extensive literature revealing that high levels of Economic Policy Uncertainty (EPU) are associated with adverse effects on all components of the economic system (Bloom, 2009; Kahle & Stulz, 2013; Jones & Olson, 2013), it seems reasonable to believe that such macroeconomic variable may also play a role on investors´ tendency to mimic other market participants. Concretely, Zhou & Anderson (2013) defend that the relationship between the level of EPU and herd formation is likely to be negative. The authors support their position by arguing that, as a way of dealing with the impact of policy uncertainty, investors will tend to make careful and rational investment decisions, therefore reducing their incentives to simply imitate the collective behavior in a blind reaction.

Although the relationship between this economic variable and the intensity of herding in the context of stock markets is a considerably understudied topic, some researchers have already conducted similar analyses in other relevant markets. For instance, Lin & Li (2019) reported that an increase in the U.S. EPU leads to a greater cross-sectional dispersion of returns - and, thus, to a weaker manifestation of mimicking activity - among U.S. investors in the housing market. On the contrary, Bouri et al., (2019), studying the U.S. market for cryptocurrencies, reached the exact opposite conclusion: a rise in the level of economic policy uncertainty in the North American market induces herd formation among market players.

Speaking of uncertainty, since the first oil crisis experienced in 1973, the impact of oil prices on the broad economy, including financial markets, has also been widely studied in the literature (e.g., Jones et al. 2004; Basher & Sadorsky, 2006; Kilian, 2008). In particular, from a behavioral perspective, some researchers have already shown that, in fact, the price of oil might be considered as one potential herding determinant, especially in the case of resource-exporting countries. As an example, Balcilar et al., (2014) found that the price of this commodity governs the transition to herding states in the Gulf Arab stock markets. In the same line, Demir & Solakoglu (2016) also showed that oil returns, as well as its volatility, drive herd formation in Qatar. In turn, contrasting with the previous studies, Economou et al. (2016) found that extreme movements in oil prices do not have a significant impact on the intensity of herding detected in the Nigerian and Moroccan equity markets. Interestingly, outside the Arabian Gulf region, Rahman & Ermawati (2020) concluded that oil prices do not foster herding, but rather promote anti-herd, among investors in the ASEAN-5 countries (Indonesia, Singapore, Malaysia, the Phillipines and Thailand).

In a similar vein, when uncertainty is the topic, one cannot leave the 2008 global financial crisis behind. Among other lessons, this turbulent period highlighted the increasing role played by investors´ sentiment on market efficiency. In light of this, even though market sentiment cannot be easily and accurately measured, recent studies have focused on analyzing its impact on the intensity of herding detected in stock markets by employing different proxies for this concept. Among the main indicators used to express market sentiment, the CBOE implied volatility index (VIX) - which expresses the expected future market volatility over the next 30 calendar days based on S&P500 options - is considered to be a primary measure of perceived stock market risk or uncertainty (Connolly et al., 2005). Although this indicator reflects essentially U.S. investors´ sentiment, its wide acknowledgement motivated researchers to apply this metric not only at a domestic level, but also in global studies. In concrete, among the studies incorporating this global risk metric in herding estimators, Philippas et al., (2013) found evidence that, when fear prevails in the U.S. REITs market, herding is more likely to occur. In turn, at an international level, Economou et al., (2019) showed that U.S. investors´ fear induces a greater herd formation in Romania, but not in the other three European markets under study (Bulgaria, Croatia and Slovenia). Finally, Chiang et al., (2013) reported a reduction in herding activity in the stock markets of the Pacific-Basin region during rising VIX days.

In spite of the global acceptance of the VIX index as the investors´ fear gauge (Whaley, 2000), several authors conducting studies outside the North American economy opted for either complementing or substituting this indicator with other proxies which better reflect local market sentiment. As an example, apart from showing that, in fact, the behavior of German and English market participants is influenced by the prevailing sentiment observed in the U.S. market, Economou et al. (2018) applied comparable domestic implied volatility indexes and concluded that these investors also herd when fear prevails in their home stock markets. Similarly, suggesting that the existence of herding around a "fear" indicator is not homogenous across the globe, Vieira & Pereira (2015) used a similar approach and showed that market sentiment exerts only weak influence over Portuguese investors´ propensity to herd. More interestingly, this time using trading volume as a proxy for overall stock market feeling, Bagh et al., (2023) documented the dominant sentiment among U.S. investors as being an imperative factor driving herd formation in this stock market.

Last but not least, the subprime crisis also left no doubt that the developments in the U.S. economy can potentially lead to major movements in developing and emerging stocks markets, either through contagion effects or through the activities of international investors. Such a conclusion motivated several authors to believe that herd behavior in global stock markets may be at least partially driven by the developments in the U.S. equity market. In this sense, an analysis conducted by Balcilar et al., (2014) showed that the U.S. stock market performance represented a significant factor governing the transition to herding states in a set of GCC stock markets (Abu Dubai, Dubai, Kuwait, Qatar and Saud Arabia). Analogously, studying two African frontier markets (Morocco and Nigeria), Economou (2016) also reported evidence that the cross-sectional dispersion of individual returns in Nigeria is reduced under conditions of extreme market returns in the U.S. market. Likewise, of special interest to our study, Chiang & Zheng (2010) reported that, while no herd formation was detected in the domestic stock markets of Latin American economies, Brazilian, Chilean and Mexican market participants were found to herd around the U.S. market. This peculiar finding let the authors to defend that, when studying the herding activity in this set of markets, one cannot rule out the role of the North American economy.

2.3 HERDING ACROSS THE GLOBE

Keynes (1936) published a pioneer study that lays the foundation in the field of herding behavior in the financial context, being then followed by several other authors that analyzed this phenomenon in different geographical areas (especially the U.S., along with European and Asian markets), during different periods of time and under divergent market conditions.

Naturally, the rise of several emerging economies in the Asian continent over the last decades have enhanced researchers´ interest in conducting studies in this set of countries. Particularly, under the scope of herding behavior, Demirer & Kutan (2006) investigated the presence of this anomaly in the Chinese market during the period from January 1999 to December 2002 and reported no evidence of such bias, which suggests that Chinese investors make rational decisions. By contrast, Tan et al., (2008) tested for the presence of herding in dual-listed Chinese A-share and B-share stocks employing daily stock data for the period from 1996 to 2003 and documented the presence of this bias in both markets. Additionally, the authors showed that this behavior occurred in both, rising and falling market conditions.

Besides China, other authors also analyzed the manifestation of herding in different Asian (emerging) markets. In the Indian context, for instance, Gupta & Kohli (2021) concluded that investors in the local stock market presented intensified herding activity during the subprime crisis and post-crisis periods, while no such behavior was found during the pre-crisis moments. In turn, studying the Taiwanese market, Demirer et al., (2010) reported evidence of this bias among market participants, adding that this behavior is particularly evident in days with large price movements.

At an American level, studying the Brazilian market during the time period from 2007 to 2016, Silva & Lucena (2019) concluded that, in moments of uncertainty, the greater insecurity experienced by investors leads them to act in accordance with the behavior of larger groups, thus herding. Similarly, Júnior et al., (2020) investigated the occurrence of herding in the Brazilian stock market from January 2004 to December 2017 for two groupings of companies: the IBOVESPA, comprising the largest companies by market capitalization and BOLSA, representing other companies. The findings of this study revealed high levels of herding in the Brazilian stock exchange, with only small differences observed between the two groups of companies.

Despite the fact that most existing studies involve one single market, some authors have extended their analyses to different groups of (emerging) markets. In this sense, it is worth mentioning the relevant contribution of Chang et al., (2000) who, while proposing a powerful measure to detect herding based on the behavior of equity returns - the Cross-Sectional Absolute Dispersion of Returns (CSAD) - tested for the presence of herding behavior in a set of developed (U.S., Hong Kong and Japan) and emerging markets (South Korea and Taiwan) in a time extensive study comprising data from 1963 to 1997. The authors reported evidence against herding for the U.S., Hong Kong and Japan, while, for both emerging markets, evidence of mimicking activity was observed during both up and down markets.

Also, responding to the lack of empirical studies on herding behavior involving African economies, Aawaar et al., (2020) examined the manifestation of this bias in this continent analyzing daily returns of 224 stocks traded in the stocks markets of five African economies (Egypt, Kenia, Morocco, Nigeria and South Africa). On the whole, the authors detected evidence of herding in Africa´s emerging markets (Egypt, Morocco and South Africa), although they concluded that this bias is less intense in South Africa, suggesting the presence of relatively greater informational efficiency in this market. Further, this study reported that, while for Egypt, Morocco and Nigeria this mimicking tendency was particularly pronounced under conditions of rising markets, low trading volume and low volatility periods, the opposite scenario was verified for the other two markets considered in the analysis (Kenia and South Africa).

Adding to this, a very comprehensive study was the one conducted by Chiang & Zheng (2010), which included 18 different markets, seven of which considered as advanced markets (Australia, France, Germany, Hong Kong, Japan, UK and U.S.), whereas the other 11 were classified as emerging economies (Argentina, Brazil, Chile, Mexico, China, Indonesia, Malaysia, Singapore, South Korea, Taiwan and Thailand). Their results documented evidence of herding in all the advanced markets (except for the U.S.) as well as in the Asian economies, while no evidence of such phenomenon was found for the Latin American countries.

Finally, studying specifically a set of Latin American economies (Argentina, Brazil, Chile and Mexico) along with the U.S. market from January 2000 to September 2010, Almeida et al., (2012) reported evidence of mimicking behavior solely in the Chilean economy, while reverse herding activity was detected in the other markets comprising the study. However, when studying this herd formation under different market conditions, the authors found evidence that low volatility levels tend to drive mimicking behavior in the stock markets of Argentina and Mexico. For the Chilean market, their results suggested that this bias is especially strong in up-market moments, as well as in high trading volume and low volatility days.

2.4 HERDING IN PERIODS OF CRISIS: THE COVID-19 PANDEMIC

A pandemic, as an unexpected event that substantially modifies the life and the routine of investors, may have a strong impact on their emotions, and therefore on their behavior, outside and inside financial markets. As such, since the beginning of 2020, several studies have already concluded that the pandemic had a massive effect on financial markets as well as in the broader economy by creating an unexpected level of uncertainty (Aslam et al., 2022). From a behavioral standpoint, a number of studies have documented the negative consequences of the COVID-19 outbreak on financial markets resulting from investors´ increased fear and anxiety (Lyócsa et al., 2020; Liu et al., 2020; Al-Awadhi et al., 2020; Zhang, et al., 2020). Considering this, it can be argued that, as a consequence of such increased fears, investors may be incentivized to suppress their own beliefs and follow market consensus, thus herding.

Under the scope of the impact of the pandemic on investors´ herding behavior, analyzing two developed European countries (Portugal and Spain) during the time period from January 2000 to May 2021, Ferreruela & Mallor (2021) concluded that this phenomenon occurs with greater intensity in pre-crisis periods, disappears during the crisis and reappears after the turbulent period, as their results reported no evidence of herding during the most critical period of the pandemic. By contrast, utilizing a larger sample of 15 developed, emerging and frontier European countries, Bogdan et al., (2022) found that, during the pandemic, herding behavior was indeed verified in emerging and frontier markets.

In turn, at an Asian setting, Jiang et al., (2022) tested for the presence of herding behavior in Japan, South Korea, China, Hong Kong, Singapore and Taiwan during the period from February 2020 to January 2021, reporting a sharp rise in the magnitude of the mimicking behavior observed among investors in these markets during the pandemic period. In the opposite direction, Warganegara & Warganegara (2022) concluded that Indonesian market participants were more reasonable in their investment decisions during the COVID-19 pandemic period, as their results showed no evidence of mimicking behavior.

At last, in a global study, Bouri et al., (2021) examined the impact of the pandemic on investors´ herding behavior in a set of 49 global stock markets, reporting a strong association between herd formation in stock markets and the COVID-19 pandemic induced market uncertainty. Concretely, the authors found that the herding effect of the COVID-19 induced market uncertainty was particularly strong for emerging stock markets, as well as for the European PIIGS (Portugal, Ireland, Italy, Greece and Spain).

From the evidence presented in the previous paragraphs, it becomes evident that existing literature on the impact of the pandemic on investors´ herding behavior seems to present mixed results. Nonetheless, given that the COVID-19 pandemic has had a strong territorial impact, as regions were not affected in the same way, one should expect its impact on investors´ behavior to also differ across countries, an idea defended by Sahabuddin et al., (2022). From here arises the relevance of conducting additional studies focused on the implications of the pandemic in terms of investors´ behavior in different geographical areas, as findings are likely to diverge.

The studies conducted so far under the scope of herding behavior that we just mentioned in the subchapters 2.3 and 2.4 are summarized in table 1.

TABLE 1: SUMMARY OF EMPIRICAL EVIDENCE ON HERDING

Author	Countries analyzed	Period of the study	Significant evidence of herding?
Demirer & Kutan (2006)	China	1999 - 2002	No
Tan et al., (2008)	China	1996-2003	Yes

Gupta & Kohli (2021)	India	2003-2017	Yes
Demirer et al., (2010)	Taiwan	1995 –2006	Yes
Silva & Lucena (2018)	Brazil	2007-2016	Yes
Júnior et al., (2020)	Brazil	2004-2017	Yes
Chang et al., (2000)	U.S., Hong Kong, South Korea and Japan	1963-1997	Yes: South Korea, Taiwan and Japan No: U.S. and Hong Kong
Awaar et al., (2020)	Egypt, Kenia, Morocco, Nigeria and South Africa	Non specified	Yes: Egypt, Morocco and South Africa No: Kenia, Nigeria
Chiang & Zheng (2010)	7 advanced (2 Asian and 4 European, in addition to the U.S.) and 11 emerging (7 Asian and 4 Latin American) markets	May 1988 – April 2009	Yes: for all advanced markets (except U.S.) and Asian markets. No: Latin American economies
Almeida et al., (2012)	Argentina, Brazil, Chile, Mexico and the U.S.	January 2000 – September 2010	Yes: Chile No: Argentina, Brazil, Mexico and the U.S.
Herding during the COVID-19 crisis			
Author	**Countries analyzed**	**Period of the study**	**Herding during the pandemic**
Ferruruela & Mallor (2021)	Portugal and Spain	January 2000-May 2021	No evidence
Bogdan et al., (2022)	15 developed, emerging and frontier European markets.	January 2018-January 2022	More pronounced (except for the advanced markets)
Jiang et al., (2022)	Japan, South Korea, China, Hong Kong, Singapore and Taiwan	February 2020-January 2021	More pronounced
Warganegara & Warganegara (2022)	Indonesia	March 2019-March 2021	No evidence
Bouri et al., (2021)	49 global markets	January 2019 – August 2021	More pronounced

3. RESEARCH QUESTIONS, DATA AND METHODOLOGY

In this chapter, at first, it will be presented the set of formulated research questions to be investigated in this study, with their relevance being justified either in a conceptual manner or based on empirical evidence. In the sequence, both the data used and the methodology employed to proceed with the analysis will be discussed.

3.1 RESEARCH QUESTIONS

As already previously mentioned, empirical evidence in the field of behavioral finance involving Latin American countries is still in its infancy. However, as we have discussed above, the substantial contribution of the markets under analysis to the economic wealth of the overall region highlights the relevance of studying investors´ behavior in the respective stock markets. In light of this, the first objective of the study is to analyze the presence of herding behavior among Brazilian, Chilean, Colombian and Mexican investors, which leads to the formulation of the following research question:

Q1.1*: Is there evidence of herding in the Latin American markets comprising the study during the time period analyzed?*

In spite of their undeniable relevance to the global economy, Latin American markets still present some important weaknesses. In fact, largely as a result of its considerable degree of social inequality, limited fiscal space and social protection, highly informal labor and its heterogenous productive structure, this region was, according to the Economic Commission for Latin America and the Caribbean (ECLAC, 2022), one of most affected by the COVID-19 pandemic, both in economic and social terms. As such, as an extension of the first goal of this analysis, we aim to understand the extent to which the COVID-19 pandemic impacted investors´ tendency to mimic the behavior of other market participants. From this objective, another research question arises, namely:

Q1.2*: Were there any changes observable in investors´ imitation behavior after the beginning of the COVID-19 pandemic?*

Naturally, as important as studying the presence or absence of mimicking behavior among investors is to understand the potential drivers of such tendency. Due to this, throughout the years, several authors have concluded that market conditions have an impact on the intensity of herding detected in financial markets, although the conclusions obtained by the different studies seem not be homogenous, as exposed in subchapters 2.3 and 2.4. In response to the ambiguous conclusions obtained by existing literature with regard to the existence of asymmetric herding behavior depending on market conditions, this work will examine if Latin American investors´ tendency to herd behaves differently in bear and bull market regimes, as well as in high and low volatility periods. This goal leads to the formulation of the following research questions:

Q2.1*: Are there any differences between days (months) with positive/negative returns in terms of investors´ herding behavior?*

Q2.2*: Are there any differences between days (months) with high/low volatility levels in terms of investors´ herding behavior?*

Apart from market conditions, we also aim to understand the extent to which certain external factors help explain herd formation in Latin American stock markets. As documented in subchapter 2.2, the level of fear experienced by investors seems to be one of the deterministic factors influencing the intensity of the mimicking activity observed in equity markets (see, for example, Economou et al., 2018). Beyond psychological factors, some relevant economic variables, such as interest rate levels, exchange rates with respect to the USD and the level of uncertainty around economic policies were also identified as important herding drivers (see, for instance, Philippas et al., 2013; Zhou & Anderson, 2013 and Balcilar et al., 2014).

In the context of our analysis, we believe that studying the extent to which the dominant investors´ feeling and the prevailing economic panorama help explaining herd formation in Latin American stock markets may be of particular interest. In fact, due to the non-sophisticated nature of investors in emerging markets, these may be seen as particularly likely to make irrational decisions in response to fear and economic stress conditions.[3]

In a similar vein, also following some previous literature (see, for instance, Chiang & Zheng, 2010; Economou et al., 2011; Economou 2018; Rahman & Ermawati, 2020), the present study will also analyze how the mimicking activity among Latin American investors is impacted by three global market factors: the U.S. market performance; the level of fear experienced in the North American stock market and the evolution of crude oil prices.

[3] This line of thinking is motivated by previous studies´ conclusions reporting that less-experienced investors are more sensitive to risk, that is, more risk averse than professional market participants (see, for instance, Dyer et al., 1989).

Noteworthy, the selection of these specific factors was not arbitrary. To begin with, in response to the deep ties connecting all corners of today´s world, it seems reasonable to expect investors to possibly exhibit herding behavior in response to major developments in the U.S. stock market, which still plays a dominant role in investors´ perception and was already documented as impacting stock markets at a global scale (Verma & Soydemir, 2006; Bathia et al., 2016). Indeed, as defended by Chiang & Zengh (2010), in an integrated global financial market facilitated by high-tech devices and efficient information processing, trades and investment activities are unlikely to be insulated from the rest of the globe.

Second, as a result of accounting for around one fifth of proven oil reserves worldwide and being home to net-oil exporters (Brazil, Colombia and Mexico included)[4], the economic activity, fiscal revenues and current account balances of Latin American countries tend to be highly sensitive to oil price shocks (IMF, 2019). Hence, our conjecture is that the volatilily of oil prices, which casts uncertainty around the future economic performance and the expected cash inflows of operating companies, may induce unsophisticated Latin American investors to follow the crowd instead of trying to see through the smoke screens of changes in fundamentals, thus herding.

Motivated by the previous arguments, our third research question addresses the topic of herding drivers by examining how the mimic instinct of Latin American investors is impacted by different psychological (local investors´ sentiment), macroeconomic (Central Banks´ policy rates, exchange rates and the level of EPU) and global market factors (U.S. investors´ fear, U.S. market performance and crude oil prices).

***Q3**: How does herding behavior in Latin American countries is influenced by psychological, economic and global market factors?*

Finally, taking into account that stock markets are more interconnected than ever before, the present study will follow the approach used by Economou et al., (2011) and analyze whether the cross-sectional dispersion of returns in one market is affected by the cross-sectional dispersion of returns in the other, which gives origin to the last research question:

***Q4**: Is there synchronicity in terms of herding intensity among the four markets under study?*

[4] According to the Economic Commission for Latin America and the Caribbean (ECLAC), in 2021 (2020), the percentage of the total production of crude oil destinated to exports was: 44.45% (47.65%) in Brazil; 60.05% (69.27%) in Colombia and 65.52% (72.10%) in Mexico.

3.2 DATA AND METHODOLOGY

3.2.1 DATA

The stock market data employed in this study were retrieved from Refinitiv DataStream and consists of the daily and monthly closing prices, together with the respective trading volumes, of all stocks listed on the Brazilian (IBOVESPA), Chilean (S&P CLX IPSA), Colombian (COLCAP) and Mexican (S&P/BVM IPC) indexes at any time during the period from 01/01/2013 to 12/31/2022. The selection of these specific indexes was based on their overall relevance: in fact, the chosen indexes measure the performance of the most relevant and liquid stocks listed on the main stock exchange of the respective country. That said, globally, our study considers a total of 252 stocks: 120 belonging to IBOVESPA, 55 to S&P CLX IPSA, 31 to COLCAP and 46 to S&P/BVM IPC.

To note that, in order to ensure that our dataset is totally free of the survivorship bias – known as a cognitive shortcut that occurs when a visible successful subgroup is mistaken as an entire group given that the unsuccessful group is not observable –, both active and dead stocks were included in the sample.

In turn, data concerning the evolution of the Central Banks´ policy rates and exchange rates (measured as domestic currency against USD) were obtained from the International Monetary Fund (IMF) database. The level of Economic Policy Uncertainty is represented by the EPU indexes developed by Baker et al., (2016) in the case of Brazil and Mexico, whereas for Chile and Colombia the indexes developed by Cerda et al., (2016) and Gil & Silva (2019) are used, respectively.[5] These indexes are essentially built based on future expectations around macro-level variables (e.g., the consumer price index and government expenditures), the newspaper coverage of topics related to governmental uncertainty and documents reporting new tax information. Finally, data around the evolution of VIX index returns and crude oil prices (represented by the West Texas Intermediate (WTI)) were retrieved from the Federal Reserve Economic Data (FRED) database.

The length of the time period defined for the study was not random. Indeed, this decision had into account the Christie & Huang (1995) suggestion that studies in the field of herding behavior should compare tranquil with crises periods, as these authors defend that investors tend to behave in accordance with traditional models during tranquil periods, while herding during periods of crises. In this case, the "crisis" period is represented by all the

[5] Data regarding the EPU index can be found at http://www.policyuncertainty.com/index.html.

trading days (months) that followed the COVID-19 pandemic outbreak, while the period before such happening is considered as "tranquil".

Similarly, the decision of using daily data reflects the fact that evidence on herding behavior is reported to be much stronger using high frequency data, suggesting the short-term nature of this phenomenon (Christie & Huang, 1995). Nevertheless, these authors also assert that daily data limits the manifestation of herding during periods of market stress. Motivated by this weakness, our study applies both daily and monthly data so that we can conduct a more comprehensive analysis of herd formation in the short but also in the long-term.

In order to examine market-wide herding through the study of the evolution of stocks´ returns with respect to the market consensus, there is the need to estimate the returns of the market portfolio. In this sense, following the approach adopted by Economou et al., (2011), market returns are computed employing an equally weighted market portfolio:

$$R_{m,t} = \frac{\sum_{i=1}^{N} R_{i,t}}{N} \qquad (3.1)$$

Where N represents the number of stocks and $R_{i,t}$ denotes each stock daily (monthly) return. Note that returns ($R_{i,t}$) are computed applying the formula used by Chiang & Zheng (2010), which is defined as follows:

$$R_t = 100 * (\log(P_t) - \log(P_{t-1})) \quad (3.2)$$

Where R_t represents the return of a stock at time *t*, P_t is the price of that stock at time *t* and P_{t-1} is the price of the stock at time *t-1*.

Still regarding stock returns, it is worth mentioning that, with the ultimate purpose of reaching powerful and unbiased conclusions, we excluded from our sample those individual returns equal to zero for four (or more) days in a row. This decision is justified in light of the conclusion obtained by Kallinterakis (2009), who defines thin trades stocks as securities that present an illiquid trading pattern over time, that stocks with this characteristic often lead to positive bias on model estimators. After this adjustment, the total number of individual stock returns considered in a given day *t* ranged from 55 to 89 for Brazil, from 27 to 43 in the Chilean market, from 14 to 24 in the case of Colombia and, finally, from 32 to 36 in Mexico.

3.2.2 METHODOLOGY

In what concerns the chosen methodology, the present study applies the measure of Cross-Sectional Absolute Dispersion of returns (CSAD) developed by Chang et al., (2000), which is widely regarded as one of the most appropriate approaches to be used in herding studies (Economou et al., 2011). This measure is defined as follows:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N} \quad (3.3)$$

Where $R_{i,t}$ is the observed return of the stock *i* at time *t*, N is the number of stocks in the market portfolio and $R_{m,t}$ is the cross-sectional average return of the market portfolio at time *t*.

The intuition behind this measure is straightforward: the low dispersion of returns around their cross-sectional average indicates that market participants ignore their prior heterogeneous beliefs and information to follow correlated trading patterns around the "market consensus".

Concretely, according to the developers of this metric, in the absence of herding, market returns and the CSAD measure should display a positive and linear relationship, as suggested by the Capital Asset Pricing Model (CAPM). However, when herding is detected, this relation is expected to become non-linear. Namely, if, in a given period, investors imitate each other, the CSAD should decrease, as securities are expected to cluster around the market portfolio return. Under such scenario, the relation between CSAD and the square of the market portfolio return will become negative, motivated by the fact that the cross-sectional dispersion of returns will decrease or increase to a lesser extent with the market return. This negative relation between CSAD and the square of market returns is, thereby, perceived as an indicator of herding behavior.

In other words, considering equation (3.4), if herding is observed, γ_2 is expected to assume a significant negative value. By contrast, in the absence of herding, we expect γ_1 to be positive and γ_2 to be statistically no different from zero. Finally, if anti-herding exists, γ_2 should, in turn, assume a positive and significant value.

$$CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t \quad (3.4)$$

This general model is the one to be implemented in order to simply test for the presence of herding in a given market, which is the purpose of our first research question (1.1).

However, once the general methodology is understood, it can be easily adapted so that we can effectively answer the other research questions of the proposed study. Particularly, addressing research question 1.2, which aims to analyze the impact of the COVID-19 pandemic on Latin American investors´ herding behavior, we argue that, under such extreme conditions of uncertainty, investors may be keen to seek for the feeling of security in following their peers, ignoring their own private information. Thus, we expect the pandemic to exert a positive impact on the intensity of herding. In order to assess such impact, in line with the work developed by Lobão (2022), the following equation will be tested:

$$CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \gamma_3 * COVID_t * R_{m,t}^2 + \varepsilon_t \quad (3.5)$$

Where $COVID_t$ is a dummy variable assuming the value of 1 on the trading days (months) during the pandemic period and 0 otherwise. Note that, as there is no consensus around the exact day that marked the beginning of the pandemic, this study assumed the day of January 30th, 2020 – the day in which the World Health Organization (WHO) declared a global public health emergency – as the first day of the pandemic period. Analogously, when estimating the regression model using monthly data, we considered February 2020-December 2022 as the crisis period.

In this scenario, a statistically significant and negative value of γ_3 would indicate that the presence of mimicking behavior was intensified during the pandemic period. On the contrary, a positive figure for this coefficient would suggest that the outbreak of the COVID-19 pandemic promoted anti-herd formation (or a less intense herding activity) in the Latin American markets.

In the sequence, based on the extensive empirical evidence suggesting the existence of asymmetric herding behavior depending on market conditions, we further aim to examine whether the dispersion of returns behaves differently in up and down markets, as well as in days (months) with high or low volatility levels. Particularly, to analyze the impact of different market regimes on herd formation, inspired by the steps of Lobão (2022) and Economou et al., (2011), the following model will be employed:

$$CSAD_t = \gamma_0 + \gamma_1 * D^{UP} * |R_{m,t}| + \gamma_2 * (1 - D^{UP}) * |R_{m,t}| + \gamma_3 * D^{UP} * R_{m,t}^2 + \gamma_4 * (1 - D^{UP}) * R_{m,t}^2 + \varepsilon_t \quad (3.6)$$

Where $D^{UP} = 1$ for periods with positive market returns ($R_{m,t} > 0$) and 0 otherwise.

In this case, significantly negative values observed for γ_3 (γ_4) would signal that herding is observed in days/months with positive (negative) market returns. By contrast, positive and significant values of γ_3 (γ_4) would imply that anti-herding is observed in days/months with positive (negative) market returns. In each case, if the relevant herding coefficients are found as being statistically different and $\gamma_3>\gamma_4$ (in absolute terms), one can conclude that these herding effects are more pronounced in moments with positive average market returns, with the opposite interpretation taking place if $\gamma_3<\gamma_4$.

Similarly, with the objective of testing for any differences in terms of herding behavior depending on the level of market volatility, a similar model, which once again comes in line with the one applied by Economou et al., (2011), will be used:

$$CSAD_t = \gamma_0 + \gamma_1 * D^{HVOL} * |R_{m,t}| + \gamma_2 * (1 - D^{HVOL}) * |R_{m,t}| + \gamma_3 * D^{HVOL} * R_{m,t}^2 + \gamma_4 * (1 - D^{HVOL}) * R_{m,t}^2 + \varepsilon_t \quad (3.7)$$

Here, D^{HVOL} is a binary variable taking the value of 1 on high volatility periods and zero otherwise. For this model, the interpretation of the obtained coefficients is similar to that described for model (3.6): significantly negative values observed for γ_3 (γ_4) would signal that herding is observed in days/months with high (low) volatility levels. By contrast, positive and significant values of γ_3 (γ_4) would suggest that anti-herding is detected in high (low) volatility periods.

Note that, following Tan et al., (2008), in this study, volatility on day *t* is calculated as the square of the market portfolio return ($R_{m,t}^2$) and it will be regarded as being high if it is greater than the previous 30 trading days moving average and low if this condition is not verified. Analogously, when applying monthly data, volatility on month *t* is computed in a similar way and it is perceived as being high if it exceeds the previous 3-month moving average.

The next research question attempts to uncover potential channels that could amplify the herd phenomenon, suggesting that this bias may be driven by certain external variables, including psychological, macroeconomic and global market factors. Concretely, from a psychological point of view, we analyze the extent to which investors´ feelings influence their tendency to imitate other market players. To this end, as there is no perfect indicator of market sentiment, we took into account Baker & Wurgler (2007) argument that trading volume, or more generally liquidity, can be viewed as an investor sentiment index[6] and used the percentage change in trading volume as a proxy for domestic stock market feeling. In particular, following the rationale defended by Lee & Swaminathan (2000) and Shiller (2000), our conjecture is that a positive change in trading volume is associated with greater levels of optimism among market players.

Adding to this, also following some earlier literature (for instance, Philippas et al., 2013; Gong & Dai, 2017), we decided to study how Latin American investors´ mimic instinct is influenced by relevant economic variables, such as interest rates (represented by the policy rate adopted by Central Banks), exchange rates (domestic currency against the USD) and the level of uncertainty around economic policies, as measured by the EPU index.

Finally, from a global standpoint, in the same spirit with Economou et al., (2011), Balcilar et al. (2014) and Economou et al., (2016), we also test the extent to which Latin American investors´ propensity to herd is influenced by three global market factors: the level of fear experienced in the North American stock market (represented by the VIX index), U.S. market returns and the volatility of crude oil prices.

To control for these external factors, adopting an approach similar to that used by Economou et al., (2011), Philippas et al., (2013), Economou et al., (2016) and Bagh et al., (2023), the following augmented version of the benchmark model (3.4) will be used:

$$CSAD_t = \gamma_0 + \gamma_1 * \left|R_{m,t}\right| + \gamma_2 * R_{m,t}^2 + \gamma_3 * \Delta TV_{m,t} + \gamma_4 * IR_{m,t} + \gamma_5 * ER_{m,t} + \gamma_6 * EPU_{m,t} + \gamma_7 * R_{VIX,t} + \gamma_8 * R_{U.S.,t}^2 + \gamma_9 * R_{OIL,t}^2 + \varepsilon_t \quad (3.8)$$

Where $\Delta TV_{m,t}$ represents the percentage change in the total trading volume of the stocks belonging to the chosen index for market *m* at time *t*; $IR_{m,t}$ represents Central Bank´s policy rate of market *m* at time *t;* $ER_{m,t}$ stands for the exchange rate of the domestic currency of country *m* against the USD at time *t;* $EPU_{m,t}$ reflects the Economic Policy Uncertainty index measure for country *m* at time *t*; $R_{VIX,t}$ stands for the logarithmic return of the VIX index at time *t;* and, finally, $R_{U.S.,t}^2$ and $R_{OIL,t}^2$ represent, respectively, the square of the logarithmic returns of the S&P 500 index and WTI crude oil prices at time *t*. For simplicity, a detailed presentation of these added variables can be found in Annex A3, while their descriptive statistics are presented in Annex A4.

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[6] Similarly, Gervais & Odean (2001) and Baker & Stein (2004) also defend that trading volume represents a good proxy for investor sentiment. In particular, in line with our conjecture, these authors argue that investors tend to trade more when they feel optimistic about the market. Thus, investors´ optimism (pessimism) would be reflected by ascending (descending) levels of trading volume.

In this model, a significant positive (negative) value obtained for coefficient γ_3 would be indicative that an increase in trading volume, understood as a greater level of optimism in the stock market, leads to a less (more) pronounced herd formation among investors. Likewise, a significant negative (positive) figure reported for γ_4 would be indicative that higher Central Bank policy rates induce a more (less) significant mimicking activity. A similar interpretation holds for coefficients γ_5, γ_6, γ_7, γ_8 and γ_9 with respect to the behavior of exchange rates, the level of EPU, U.S. investors´ fear, the volatility of U.S. market returns and extreme oil price movements, respectively.

Finally, our last research question aims to examine whether the cross-sectional returns´ dispersion in the four markets under analysis exhibit a certain degree of co-movement, suggesting the existence of cross-country effects in terms of herding behavior. Evidence in favor of this conjecture would provide support to the argument that herding effects may be synchronized across the four Latin American countries, which may prove catalytic in triggering a regional financial crisis. In order to test this hypothesis, adopting the same approach used by Economou et al., (2011), the following model will be estimated:

$$CSAD_t = \gamma_0 + \gamma_1 * \left|R_{m,t}\right| + \gamma_2 * R_{m,t}^2 + \sum_{j=1}^{3} \delta_j * CSAD_{j,t} + \varepsilon_t \quad (3.9)$$

Where, in comparison to the benchmark model, the cross-sectional dispersions of the other three markets ($CSAD_j, j = 1, 2, 3$) were added as explanatory variables.

Here, a positive and significant value observed for δ_j would suggest that a higher (lower) manifestation of herding in a particular market would be observed if also a higher (lower) manifestation of herding is detected in the other markets under analysis. Naturally, a negative figure for this variable would be interpreted in the opposite way.

Note that, as a way of ensuring the accuracy of the results obtained, and following the argument defended by Chang et al., (2000) and Mobarek et al., (2014) that standard errors of the estimated regressions should be adjusted for heteroscedasticity and autocorrelation, in all models of this empirical analysis we applied the estimator proposed by Newey & West (1987).

3.2.3 DESCRIPTIVE STATISTICS

Table 2 displays the descriptive statistics for the Cross-Sectional Absolute Dispersion of Returns measure ($CSAD_t$) and the market portfolio return ($R_{m,t}$) when the whole sample period is considered. Panel A contains the results for the case where daily data is applied, whereas Panel B reports the corresponding results using monthly data. All values, except for the number of observations, are expressed in percentage.

TABLE 2: DESCRIPTIVE STATISTICS

Panel A: daily data	**Brazil**		**Chile**		**Colombia**		**Mexico**	
	Rm	***CSAD***	***Rm***	***CSAD***	***Rm***	***CSAD***	***Rm***	***CSAD***
Mean	-0.00028	0.69890	-0.00206	0.48970	-0.01280	0.49120	-0.00093	0.53130
Median	0.02110	0.65350	0.01070	0.44870	-0.00075	0.42640	0.00243	0.49950
Maximum	4.87210	3.09320	4.32900	3.33910	5.13940	7.21040	2.06510	2.83390
Minimum	-7.65730	0.26380	-6.08860	0.18140	-6.60220	0.11300	-2.61670	0.19940
Std. Dev.	0.69470	0.2249	0.45900	0.20150	0.46650	0.31830	0.38990	0.17320
Observations	2475		2488		2436		2514	
Panel B: monthly data								
Mean	-0.03460	3.12160	-0.06460	2.23016	-0.24730	1.99220	-0.01650	2.31270
Median	-0.02340	3.01130	0.13370	2.03560	-0.05050	1.82710	0.28930	2.22980
Maximum	6.04790	8.09660	6.03560	5.73130	4.46504	8.18160	4.59160	8.29510
Minimum	-18.21930	1.88340	-8.79240	1.09840	-14.41540	0.54990	-10.56560	1.22690
Std. Dev.	3.15930	0.85460	2.28840	0.83760	2.38550	0.98670	1.90250	0.74600
Observations	120		120		120		120	

Notes: This table reports the descriptive statistics of the cross-sectional absolute deviation (CSAD) of individual stock returns and the market portfolio return (Rm) when the whole sample period is considered (1st January 2013-31st December 2022). The CSAD measure is defined as: $CSAD_t = \frac{\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|}{N}$, where $R_{i,t}$ is the daily (monthly) return of stock i, $R_{m,t}$ is the market return and N is the number of stocks in the market portfolio.

Through the analysis of the table above, one can notice that there are more than 2400 daily observations for each market, with Mexico being the economy presenting the highest number of trading days (2514). Worth of note, all the four markets under analysis presented a negative performance during the sample period, with the Colombian market standing out as the economy with the lowest mean daily and monthly returns (-0.01280% and -0.24730%, respectively). Apart from that, it is possible to observe that the Brazilian market experienced the most expressive minimum returns, irrespectively of the data frequency considered.

In turn, an analysis of the results for the CSAD metric allows us to conclude that the dispersion of returns is more pronounced in the Brazilian market, while it is significantly less evident in the case of the Chilean and Colombian economies.

4. DISCUSSION OF THE EMPIRICAL RESULTS

In this chapter, the results obtained from the application of the regression models described in the previous chapter are presented and discussed. As a matter of organization, the analysis and interpretation of the results will be divided in the following way: in a first moment, we analyze the outputs obtained with regard to the presence of herding in each market when the whole sample period is considered (4.1), as well as when only specific subperiods are studied (4.1.1). In the sequence, we present the conclusions concerning the impact of the pandemic on investors´ mimicking behavior (4.2). After this analysis, we address the issue of herding asymmetries depending on the sign of market portfolio returns (4.3.1) and volatility levels (4.3.2). Then, we discuss the role played by several psychological, economic and global market factors as potential drivers of herding behavior (4.4). Finally, in a last moment, we state and discuss the obtained conclusions with respect to any potential cross-country herding effects (4.5).

In each of the following tables (3-14), unless otherwise stated, both the regression coefficients obtained using daily and monthly data are presented.

4.1 PRESENCE OF HERDING

To test for the presence of herding formation in the four Latin American countries when the entire sample period is considered we applied the standard model (3.4), whose estimated coefficients are reported in table 3.

TABLE 3: HERDING ESTIMATES – MODEL (3.4)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$

	Brazil		Chile		Colombia		Mexico	
	Daily	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*
γ_0	***0.005795 (57.69)	***0.026435 (29.67)	***0.003866 (53.22)	***0.016974 (15.05)	***0.003320 (22.83)	***0.015914 (12.56)	***0.004543 (64.33)	***0.020650 (26.36)
γ_1	***0.230201 (8.34)	***0.179119 (2.96)	***0.360468 (12.85)	***0.312297 (3.14)	***0.550163 (7.08)	*0.173855 (1.81)	***0.216650 (6.37)	0.056684 (0.88)
γ_2	****1.691421** (2.48)	****0.718943** (2.27)	0.323852 (0.44)	0.860538 (0.59)	0.833177 (0.26)	*****2.028900** (3.37)	*****10.41094** (2.91)	*****4.749389** (7.99)
R^2 adj.	0.411147	0.474450	0.437254	0.368210	0.443446	0.468327	0.299357	0.601663

Notes: This table reports the estimated coefficients for the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return $R_{m,t}$ considering the whole sample period (January 1st 2013-December 31st 2022) The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

Analyzing the table, in a first moment, it is worth noting that the explanatory power of the models, measured by the adjusted R^2, is in line with that reported in similar studies, such as the one conducted by Chiang & Zheng (2010), which was already cited previously.

Concerning the results obtained for the estimated coefficients, some interesting conclusions can be taken. In the case of Brazil, the positive and statistically significant results obtained for γ_1 and γ_2, either for the daily or monthly frequency, suggest that no significant mimicking behavior was observed in this market during the sample period. In fact, on the contrary, the positive values of these coefficients indicate the prevalence of anti-herding behavior among Brazilian market participants.

In turn, the outputs obtained for the Chilean market suggest the absence of either herding or anti-herding in this economy. Indeed, the fact that, regardless of the data frequency used, γ_1 was found to be positive and significant, while, in turn, γ_2 was reported as being statistically no different from zero support the argument proposed by traditional asset pricing models around the linear relationship between CSAD metric and the average market return, thus indicating no herd formation in this market.

When it comes to the Colombian market, our findings also indicate that no significant levels of herding were detected in the market during the entire sample period. More importantly, the analysis of the regression results obtained for this country allows us to reach the interesting conclusion that, as already defended by some existing literature (Vo & Phan, 2017, Ali, 2022), the herding phenomena does not necessarily present an equivalent behavior in the short and long terms. Indeed, while when daily data was applied the herding coefficient (γ_2) was positive but not statistically significant, suggesting the absence of any herding effects in the short term, when monthly data was used this coefficient was found as being positive but no longer statistically insignificant, thus indicating the manifestation of anti-herding behavior among Colombian market participants in the long term.

Finally, in the case of Mexico, our findings are similar to those observed for Brazil: the positive and statistically significant γ_2 coefficient resulting from the application of both daily and monthly data indicates the presence of anti-herding behavior in the market in the short and long terms. However, a simple comparison between the magnitude of the herding coefficient in both markets makes it possible to conclude that this reverse herding phenomenon is much stronger among Mexican market players, since $\gamma_{2\ MEXICO} > \gamma_{2\ BRAZIL}$.

In a nutshell, this first analysis failed to detect herding behavior in the major stock markets of Latin America when the whole sample period was considered, irrespectively of the data frequency selected. Conversely, anti-herding behavior was reported in two of the analyzed markets (Brazil and Mexico) when daily data was applied and in three of them (Brazil, Colombia and Mexico) when, in turn, monthly returns were used.

According to Gębka & Wohar (2013), this reverse herding phenomenon may be understood as a reflection of investors´ tendency to overemphasize on their own view or focus excessively on the views of a subset of other market participants, which ultimately results in an increased cross-sectional dispersion of returns. As such, based on this idea, it can be argued that the manifestation of anti-herding behavior among investors in these Latin American markets may be justified in light of their excessive confidence, which causes them to overestimate their ability to make the right investment decisions and, as a result, ignore market signals.

Adding to the previous explanation, one can also argue that the lack of herding activity observed in Latin American markets may be justified by the potential existence of divergent opinions defended by different leading financial firms and the media, a setup which fosters the formation of divergent beliefs among investors. Such heterogeneity induces market participants to base their investment decisions on their own private information, reducing the likelihood of herding activity being detected in these markets.

That being said, it is of interest to mention that our results indicating no herd formation in Latin American markets, but rather suggesting the manifestation of anti-herding in some cases, are consistent with the findings obtained by other authors when studying a similar set of markets, such as those reported by Chiang & Zheng (2010) and Almeida et al., (2012). Nonetheless, they also differ from, for example, the results reported by Júnior et al., (2020), which suggested the presence of strong mimicking behavior in the Brazilian market. These distinct results may be explained by the fact that these authors, apart from studying a different time span (2004-2017), opted for using a different methodology: the state-space approach proposed by Hwang & Salmon (2004).

4.1.1 PRESENCE OF HERDING: IS THIS A TIME-VARYING PHENOMENON?

In the previous subchapter, we concluded that Latin American investors seem not to mimic their peers, as no evidence of herding was reported for any of the markets under study during our whole sample period. Nevertheless, it is important to mention that existing empirical evidence (Balcilar, et al., 2013; Bouri et al., 2019) suggests that this bias tends to present a time-varying dynamics[7]. In order to verify this line of reasoning, the powerful tests of Bai & Perron (2003) were applied to equation (3.4) to detect 1 to *M* structural breaks, while allowing for heterogenous error distributions across the breaks. Using only daily data for the sake of organization and simplicity, the breaks detected through the application of this test for each of the countries under analysis are summarized in table 4.

TABLE 4: STRUCTURAL BREAKS – BAI & PERRON (2003)

	Brazil	Chile	Colombia	Mexico
Break 1	23rd October 2014	2nd April 2018	22nd October 2014	13th March 2020
Break 2	9th August 2016	4th November 2019	20th June 2016	-
Break 3	18th April 2018	-	14th August 2018	-
Break 4	17th March 2020	-	2nd April 2020	-

Once the structural breaks are identified, we are able to test if, in fact, our data supports the argument that the imitation behavior among Latin American investors presents a time-varying nature by estimating the general model (3.4) for each subperiod. The results obtained with such procedure are described in the tables 5-8.

TABLE 5: HERDING ESTIMATES – SUBPERIOD ANALYSIS (BRAZIL)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$

	Brazil				
	1st subperiod (1/01/13-10/22/14)	**2nd subperiod (10/23/14-08/08/16)**	**3rd subperiod (08/09/16-04/17/18)**	**4th subperiod (04/18/18-03/18/20)**	**5th subperiod (03/19/20-12/31/22)**
$\boldsymbol{\gamma_0}$	***0.006070 (36.40)	***0.007500 (35.09)	***0.005254 (47.65)	***0.005502 (28.89)	***0.006396 (48.60)
$\boldsymbol{\gamma_1}$	-0.013042 (-0.24)	0.011592 (0.18)	***0.112308 (2.85)	***0.165312 (3.04)	***0.132655 (3.58)
$\boldsymbol{\gamma_2}$	*****16.99884** (3.90)	****11.86227** (2.48)	*****7.290298** (7.33)	*****2.336832** (2.61)	*****8.300040** (6.74)
$\boldsymbol{R^2}$ **adj.**	0.208856	0.208849	0.466973	0.702634	0.402699

Notes: This table reports the estimated coefficients for the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$) considering different sample periods, selected after applying the Bai & Perron (2003) test with purpose of identifying structural breaks in our data sample. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

With regard to the Brazilian market, the outputs documented above seem to be consistent with those previously obtained when considering the full sample period, as evidence of reverse herding phenomenon was detected in all the subperiods identified (γ_2>0

[7] To further explore this dynamic nature, we implemented a rolling window regression of model (3.4) – please see annexes A1 and A2 for the relevant graphical representations.

and significant in all cases). However, it is observable that the intensity of such anti-herding behavior showed a decreasing tendency along the first four subperiods (the relevant herding coefficient declined from 16.99 in the first subsample to 2.33 in the fourth), being especially pronounced during the first three years of our analysis (roughly comprised in the first two subsamples). In line with the argument presented in subchapter 4.1 when trying to justify the manifestation of such anti-herding phenomenon, one can state that, during this period, Brazilian investors seemed to strongly untrust the general behavior observed in financial markets, a sentiment which ultimately led them to ignore the collective behavior and focus on their own decision-making skills. In light of this evidence, it may be important to note that the 2013–2016-time interval was marked the by one of the worst recessions in the history of the Brazilian economy, motivated by a series of inconsistent macroeconomic policies implemented by Dilma Rousseff – President of the Brazilian economy at that time. Indeed, her administration´s decisions, among other effects, have reduced Brazil´s economic competitiveness, deteriorated fiscal outcomes and increased inflation, a conjunction of factors that, naturally, contributed to an overall decrease in the administration´s political credibility. Such a challenging political and economic environment may eventually be among the reasons that help explain why our results suggest that Brazilian investors seemed to be more cautious with respect to their investments, prioritizing independent decisions.

Analogously, even though a less intense presence of anti-herding behavior was reported in the fourth subperiod (April 18th, 2018- March 18th, 2020), a sharp increase in this reverse mimicking activity was observed after March 19th, 2020 - the herding coefficient (γ_2) increased from 2.33 to 8.30. Following the same line of reasoning presented previously when debating about the reasons behind the intensified anti-herd activity verified in the 2013-2016 period, this rise could potentially be attributed to the outbreak of the COVID-19 pandemic that happened close to this date and also caused an extreme economic slowdown.

TABLE 6: HERDING ESTIMATES – SUBPERIOD ANALYSIS (CHILE)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$

	Chile		
	1st subperiod (1/01/13-04/01/18)	**2nd subperiod (04/02/14-11/03/19)**	**3rd subperiod (11/04/19-12/31/22)**
γ_0	***0.003611 (82.77)	***0.003393 (42.10)	***0.005291 (41.28)
γ_1	***0.310452 (15.71)	***0.227711 (5.93)	***0.238057 (6.01)
γ_2	-0.539211 (-0.49)	2.433683 (1.06)	***2.243465** (2.84)
R^2_{adj}	0.311722	0.308398	0.430692

Notes: This table reports the estimated coefficients for the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return $(R_{m,t})$ considering different sample periods, selected after applying the Bai & Perron (2003) test with purpose of identifying structural breaks in our data sample. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any level), these are highlighted in **bold**.

TABLE 7: HERDING ESTIMATES – SUBPERIOD ANALYSIS (COLOMBIA)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$

	Colombia				
	1st subperiod (1/01/13-10/21/14)	**2nd subperiod (10/22/14-06/19/16)**	**3rd subperiod (06/21/16-08/13/18)**	**4th subperiod (08/14/18-04/01/20)**	**5th subperiod (04/02/20-12/31/22)**
γ_0	***0.003175 (25.50)	***0.004137 (24.17)	***0.002864 (32.98)	***0.003719 (15.41)	***0.004699 (16.74)
γ_1	***0.427987 (5.26)	***0.330143 (4.76)	***0.290995 (4.15)	***0.681013 (4.62)	0.069024 (0.70)
γ_2	-10.66902 (-1.10)	0.601752 (0.10)	12.56148 (1.08)	-3.680748 (-1.39)	***34.32979 (5.36)
R^2 adj.	0.235981	0.311048	0.270990	0.577131	0.558527

Notes: This table reports the estimated coefficients for the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return $(R_{m,t})$ considering different sample periods, selected after applying the Bai & Perron (2003) test with purpose of identifying structural breaks in our data sample. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

The results obtained in this subperiod analysis for the Chilean and Colombian markets are quite similar. In concrete, the obtained outputs indicate the manifestation of anti-herding behavior only in the last considered subperiod (4th November 2019-31st December 2022 in the case of Chile and 2nd April 2020-31st December 2022 for the Colombian economy). Such findings contrast with those obtained when the whole sample period was considered, which, when daily data was used, indicated the absence of any herding effects in these two economies. These divergent outputs support the argument that, in fact, the herding phenomena exhibit a time-varying dynamics.

TABLE 8: HERDING ESTIMATES – SUBPERIOD ANALYSIS (MEXICO)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$

	Mexico	
	1st subperiod (1/01/13-03/12/20)	**2nd subperiod (03/13/20-12/31/22)**
γ_0	***0.004412 (69.78)	***0.004969 (30.12)
γ_1	***0.207778 (8.20)	***0.233061 (3.26)
γ_2	***4.557118 (2.65)	***16.11717 (3.90)
$R^2{}_{adj}$	0.226166	0.405337

Notes: This table reports the estimated coefficients for the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return $(R_{m,t})$ considering different sample periods, selected after applying the Bai & Perron (2003) test with purpose of identifying structural breaks in our data sample. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

Conversely, the results for the Mexican economy are consistent with the findings reported when studying the whole sample period: the positive and statistically significant values obtained for the γ_2 coefficient indicate the manifestation of anti-herding during both subperiods analyzed. Even so, a simple comparison between the magnitude of the herding coefficients obtained for the different subsamples (4.56 in the first and 16.12 in the last) suggests that such reverse herding phenomenon was intensified after the last identified structural break, in this case starting in the second half of March 2020.

Globally, a common feature was verified in all the four countries comprising this study: an increased level of anti-herding behavior was detected during the period that followed the most recent structural break, which, in most cases, took place close to March 2020. Faced with this evidence, and taking into consideration the conclusion reported by Baker et al., (2020) that, as a result of the COVID-19 pandemic outbreak, uncertainty reached levels close to those reported during the great depression in the United States, one can state that these results may be indicative that Latin American investors tend to react to global instability by taking more careful and independent investment decisions – thus being less likely to engage in herd formation. Note that, to test the accuracy of this line of thinking, the following subchapter is entirely dedicated to the analysis of the impact of the pandemic on investors´ herding behavior.

4.2 HERDING DURING THE COVID-19 PANDEMIC CRISIS

After testing for the presence of herding effects among Latin American investors considering the whole and specific sample periods, the second goal of our analysis is to understand how the recent COVID-19 pandemic impacted investors´ tendency to follow the majority behavior. As such, model (3.5) was estimated for each market, with the respective results being displayed in table 9:

TABLE 9: HERDING ESTIMATES – MODEL (3.5)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R^2_{m,t} + \gamma_3 * COVID_t * R^2_{m,t} + \varepsilon_t$

	Brazil		Chile		Colombia		Mexico	
	Daily	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*
γ_0	***0.005772 (51.05)	***0.026738 (30.96)	***0.003843 (85.46)	***0.016114 (13.95)	***0.003200 (20.12)	***0.015418 (11.07)	***0.004478 (53.35)	***0.020246 (25.78)
γ_1	***0.243223 (6.32)	**0.139139 (2.52)	***0.378646 (26.50)	***0.491159 (5.11)	***0.672909 (6.76)	**0.307537 (2.00)	***0.278246 (6.00)	**0.151141 (2.08)

γ_2	0.083196 (0.03)	1.830530 (1.34)	***-3.391349 (-4.01)	***-7.871466 (-3.76)	***-24.90484 (-2.90)	-4.530795 (-1.12)	-3.078965 (-0.70)	-0.314753 (-0.16)
γ_3	1.448014 (0.68)	-0.908363 (-0.75)	***$\mathbf{3.729278}$ (4.97)	***$\mathbf{7.101985}$ (5.15)	***$\mathbf{23.54206}$ (3.39)	*$\mathbf{5.613057}$ (1.80)	***$\mathbf{14.88961}$ (4.13)	***$\mathbf{4.322548}$ (2.88)
R^2 adj.	0.411854	0.474203	0.442561	0.463435	0.462180	0.492277	0.325461	0.625112

Notes: This table reports the regression coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \gamma_3 * COVID_t * R_{m,t}^2 + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$) and $COVID_t$ is a binary variable assuming the value of 1 for those trading days (months) during the pandemic period (30 January 2020 – 31 December 2022) and zero otherwise. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

Some curious insights can be taken from the table above. In fact, one can observe that, regardless of the data frequency considered, no negative and statistically significant values for the γ_3 coefficient were reported, suggesting that the COVID-19 pandemic has not induced a greater herding activity among Latin American market players. Such a conclusion contrasts with the argument pointed out by some researchers (e.g., Ferreruela & Mallor, 2021) that the adverse conditions created by the pandemic could represent an incentive for investors to herd and make more irrational decisions as, among other effects, the cost and time of processing information during turbulent periods is higher than usual.

In detail, the lack of statistically significant figures obtained for the relevant herding coefficient in the Brazilian economy suggests that no herding effects (either herding or reverse herding) seem to have been induced by the pandemic outbreak. However, the scenario observed for the other three Latin American markets is quite different. Indeed, the positive and significant values documented for the γ_3 parameter (for both data frequencies) in the case of the Chilean, Colombian and Mexican economies indicate that the public health crisis promoted a greater anti-herd practice in these stock markets. Considering the challenging environment created by the COVID-19 pandemic, and in line with the argument proposed by Gębka & Wohar (2013), these results may be a reflection of a "flight to quality" strategy, where investors shift out of risky assets to safer alternatives (such as bonds) in an effort to mitigate potential losses. Such an event, that is most likely to occur during periods of uncertainty, generates large negative equity returns, which, as a consequence, lead to greater levels of returns´ dispersion.

Noteworthy, these findings are somehow consistent with those reported in subchapter 4.1.1, which also detected an intensified reverse herding activity in the last time-window analyzed - that, in all cases, comprised either the entire or the largest part of the COVID-19 period as we defined (30 January 2020-31 December 2022). A single exception was found in the Brazilian market, as the absence of any herding effects documented in this subchapter contrasts with the increased presence of anti-herding activity reported in the sequence of the most recent structural break (starting in March 2020). These heterogeneous results may be indicative that, differently from the other studied economies, the effects of the COVID-19 on Brazilian investors´ behavior only became significantly pronounced after the beginning of the third month of the 2020 year. Note that this conclusion is not totally surprising if we take into consideration that the first confirmed case of the disease in the Brazilian economy was reported close to this date, on February 26th, 2020.

That being said, it is relevant to mention that our conclusions with respect to the impact of the pandemic on investors´ tendency to mimic other market participants are similar to those obtained by Ferreruela & Mallor (2021) and Warganegara & Warganegara (2022), which also reported no evidence of an intensified herd formation in response to the public health crisis among European and Indonesian market players, respectively. Despite this, our findings contrast with those documented by, for example, Bouri et al., (2021) and Bogdan et al., (2022), which found evidence of a more pronounced herding activity motivated by the pandemic in several global markets. However, as already stated, given the fact that the public reaction to the COVID-19 pandemic, as well as the intensity of the disease, was not homogenous across the globe, it is not surprising that its impact on investors´ behavior also differs across regions.

Before going further, it may be of interest to note that, although not focusing specifically on the COVID-19 outbreak, Almeida et al., (2012) have also considered the impact of different crises on the intensity of herding activity observed in Latin American stock markets. In particular, these authors provided evidence that both the attacks of September 2001 and the subprime crisis have not triggered herding activity in the region, but rather promoted reverse herd formation in almost all the equity markets considered (Argentinean, Brazilian, Chilean and Mexican). Such a conclusion is, to some extent, in line with our findings, which also failed to document an increased herding activity in response to a different, but also relevant, turbulent period.

4.3 HERDING UNDER ASYMMETRIC MARKET CONDITIONS

As already previously discussed, adding to the intention of simply testing for the presence of herding among Latin American investors, we also aim to understand if such mimic instinct behaves differently depending on the prevailing market conditions. Hence, in this subchapter we start by discussing the results obtained with regard to the impact of different market regimes (up *vs* down markets), proceeding then with the influence of different volatility levels on the cross-sectional dispersion of returns observed in Latin American equity markets.

4.3.1 UP AND DOWN MARKETS

With the purpose of studying the impact of the different market states on investors´ mimicking instinct, model (3.6) was estimated for each market, with the respective results being displayed in table 10:

TABLE 10: HERDING ESTIMATES – MODEL (3.6)

Model: $CSAD_t = \gamma_0 + \gamma_1 * D^{UP} * |R_{m,t}| + \gamma_2 * (1 - D^{UP}) * |R_{m,t}| + \gamma_3 * D^{UP} * R^2_{m,t} + \gamma_4 * (1 - D^{UP}) * R^2_{m,t} + \varepsilon_t$

	Brazil		**Chile**		**Colombia**		**Mexico**	
	Daily	***Monthly***	***Daily***	***Monthly***	***Daily***	***Monthly***	***Daily***	***Monthly***
γ_0	***0.005878 (63.81)	***0.027588 (29.02)	***0.003848 (53.57)	***0.016019 (14.93)	***0.003344 (24.41)	***0.015369 (11.01)	***0.004548 (65.16)	***0.021118 (24.74)
γ_1	***0.201827 (6.58)	-0.104975 (-1.04)	***0.427712 (13.58)	***0.526509 (3.04)	***0.498985 (7.23)	0.267598 (1.22)	***0.221810 (5.91)	-0.056914 (-0.43)
γ_2	***0.187880 (7.99)	**0.162871 (2.51)	***0.312366 (10.03)	***0.349377 (4.06)	***0.572266 (7.08)	**0.275756 (2.14)	***0.201567 (5.27)	-0.003977 (-0.05)
γ_3	*****5.625671** (4.29)	*****6.600361** (3.36)	***-1.641406** (-1.86)	-4.958920 (-1.48)	***3.378537** (1.71)	-2.745634 (-0.55)	****11.05308** (2.19)	*****9.382056** (2.83)
γ_4	*****1.925504** (3.77)	****0.729568** (2.16)	1.264104 (1.61)	1.281609 (1.48)	0.000998 (0.00)	1.345140 (1.64)	*****10.89116** (2.95)	*****5.230138** (6.58)
R^2 adj.	0.427971	0.500712	0.444724	0.386379	0.444904	0.481389	0.299345	0.603660

Panel B: **Wald tests for equality of herding coefficients**								
H_0: $\gamma_3 = \gamma_4$								
γ_3-γ_4	3.700168	5.870793	-2.905510	-6.240530	3.377538	-4.090774	0.161925	4.151918
χ^2	***[0.0001]	***[0.0021]	***[0.0022]	**[0.0440]	[0.2796]	[0.3784]	[0.9732]	[0.2006]

Notes: This table reports the regression coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 * D^{UP} * |R_{m,t}| + \gamma_2 * (1 - D^{UP}) * |R_{m,t}| + \gamma_3 * D^{UP} * R^2_{m,t} + \gamma_4 * (1 - D^{UP}) * R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$) and D^{UP} is a binary variable assuming the value of 1 for those trading days (months) with positive average market returns ($R_{m,t}$>0) and zero otherwise. In Panel B, a Wald test was conducted with the aim of testing if the relevant herding coefficients (γ_3 and γ_4) were not statistically equal. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

From the table above one can observe that, in the case of the Brazilian market, as it happened when considering the whole sample, we continue to find a statistically significant and positive sign for the herding coefficients (γ_3 and γ_4), regardless of whether the market is rising or falling, which implies that reverse herding occurs in either regime. Nevertheless, one can notice that, irrespectively of the data frequency considered, the coefficient for bullish periods was found as being much larger than the one reported during bearish market trends, suggesting that the reported anti-herding activity seems to be stronger under up-market conditions. As a robustness check, an equality test was conducted by subtracting the respective coefficient on down markets to that observed under upward trends. The results of such an analysis, reported in Panel B, confirm the described asymmetry, as the estimated value is positive (implying that $\gamma_3 > \gamma_4$) and statistically significant. On the whole, these results suggest that up-market moments seem to drive up Brazilian investors´ overconfidence – a behavioral bias which makes them less likely to opt for mimicking the investment decisions of their peers – thus fostering the dispersion of individual returns.

A similar panorama was found for Mexico: the positive and statistically significant herding coefficients obtained confirm that the anti-herd phenomenon we documented previously in subchapter 4.1 takes place during both up and down-market periods. However, in contrast to what was observed for Brazil, the results of the Wald equality tests indicate that the respective herding parameters are not different under both market regimes, thereby we cannot conclude that this reserve herding formation presents an asymmetric nature during rising and falling market conditions.

Analogously, as far as the Colombian market is concerned, our results also indicate an absence of asymmetric herding, regardless of the data frequency considered. Such a conclusion derives from the fact that both Wald tests conducted for this market supported the null hypothesis around the equality of herding coefficients. Thus, one cannot conclude that the herding activity among Colombian investors behaves differently depending on the prevailing market regime.

At last, for the Chilean market, the reached results when applying daily are consistent with the herd behavior hypothesis during up-market regimes, since the respective γ_3 coefficient was found as being significantly negative. Following the rationale proposed by Long et al., (1990), these findings may be justified by arguing that Chilean investors are more likely to imitate other market participants when they perceive an upward trend in the market as a way of ensuring that they also take advantage of such positive market movements, along with the other market players. On the contrary, no herding effects seem to be present among Chilean market players during down-market moments, as γ_4 was reported to be statistically no different from zero. These results suggesting that the herding phenomena behaves differently depending on the prevailing market regime are supported by the equality test performed in Panel B, which indicates that, in fact, the herd activity in the Chilean economy presents an asymmetric component – the null hypothesis of equivalent herding coefficients was rejected.

In sum, our results for the daily data frequency suggest the existence of asymmetric herding effects depending on the market regime in the Brazilian and Chilean stock markets, although in opposite directions. In concrete, with regard to the former, we found up-market trends as inducing greater levels of reverse herding. In turn, in what concerns the latter, our results suggest that, conversely, these rising market moments trigger herding activity among Chilean market players. Instead, in the long run, asymmetric herding effects were solely found to take place in Brazil, where, once again, anti-herding was documented as being stronger during up-market trends.

On the whole, these findings go together with those reported by Almeida et al., (2012), which also documented that positive market returns drive increased reverse herding among Brazilian investors and herd formation in the Chilean stock market. Additionally, even though no asymmetric component was verified in the Mexican economy, our results indicating the prevalence of negative herding in this stock market during either rising or falling market trends are also in line with the conclusions obtained by these authors.

Beyond Latin American economies, evidence of intensified mimicking activity in up-market regimes was also detected by Tan et al. (2008) when studying the behavior of A-share investors in the Shanghai stock market. However, as we have seen previously in subchapter 2.3, evidence around the existence of asymmetric herding behavior depending on market states is essentially mixed in nature. Thus, not surprisingly, our findings contrast with several other studies which reported stronger herding activity during downward trends of the market, such as the one conducted by Lao & Singh (2011) also with respect to the Chinese equity market.

4.3.2 HIGH AND LOW VOLATILITY PERIODS

Once the analysis of the impact of different market regimes on Latin American investors´ mimicking activity is complete, we can proceed and test if, in a similar vein, any asymmetries in terms of herding behavior are observed depending on the level of market volatility. With this goal in mind, model (3.7) was run for each of the markets comprising this study, with the obtained regression coefficients being presented in table 11:

TABLE 11: HERDING ESTIMATES – MODEL (3.7)

Model: $CSAD_t = \gamma_0 + \gamma_1 * D^{HVOL} * |R_{m,t}| + \gamma_2 * (1 - D^{HVOL}) * |R_{m,t}| + \gamma_3 * D^{HVOL} * R_{m,t}^2 + \gamma_4 * (1 - D^{HVOL}) * R_{m,t}^2 + \varepsilon_t$

	Brazil		Chile		Colombia		Mexico	
	Daily	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*
$\boldsymbol{\gamma_0}$	***0.005697 (49.39)	***0.026809 (25.47)	***0.003651 (44.56)	***0.014527 (13.50)	***0.003019 (15.52)	***0.016030 (11.96)	***0.004489 (53.88)	***0.020181 (27.51)
$\boldsymbol{\gamma_1}$	***0.208205 (9.39)	**0.153478 (2.33)	***0.338223 (13.44)	***0.302355 (3.28)	***0.539582 (7.36)	0.058356 (0.95)	***0.187427 (5.10)	0.046991 (0.65)

γ_2	***0.262242 (4.96)	0.061718 (0.41)	***0.586963 (10.08)	***0.878177 (4.50)	***0.850951 (6.18)	0.089618 (0.51)	***0.222079 (3.33)	0.161078 (1.05)
γ_3	****1.981875** (3.20)	****0.851742** (2.57)	0.881194 (1.33)	1.302467 (0.98)	1.201405 (0.39)	****2.78310** (7.15)	****11.89146** (3.21)	****4.919076** (7.34)
γ_4	****11.33141** (2.87)	****5.905042** (2.05)	-4.458801 (-0.92)	***-6.764313** (-1.90)	-9.377610 (-1.19)	****16.33735** (4.93)	****37.38790** (3.01)	5.401972 (0.69)
R^2 adj.	0.442841	0.475880	0.464196	0.491684	0.456199	0.625233	0.316868	0.604983

Panel B: **Wald tests for equality of herding coefficients**								
H_0: γ_3= γ_4								
γ_3-γ_4	-9.349537	-5.053301	5.339995	8.066780	10.57902	-13.55504	-25.49644	-0.482896
χ^2	**[0.0161]	*[0.061]	[0.2634]	**[0.0275]	[0.2297]	***[0.0000]	**[0.0206]	[0.9497]

Notes: This table reports the regression coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 * D^{HVOL} * |R_{m,t}| + \gamma_2 * (1 - D^{HVOL}) * |R_{m,t}| + \gamma_3 * D^{HVOL} * R^2_{m,t} + \gamma_4 * (1 - D^{HVOL}) * R^2_{m,t} + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$) and D^{HVOL} is a binary variable assuming the value of 1 during high volatility days (months) and zero otherwise. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. In Panel B, a Wald test was conducted with the aim of testing if the relevant herding coefficients (γ_3 and γ_4) were not statistically equal. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

In line with the scenario observed when studying asymmetric herding effects depending on the sign of the market portfolio return, for the daily data frequency, positive and significant figures were obtained for both the γ_3 and γ_4 coefficients in the Brazilian and Mexican markets, indicating that the anti-herd phenomenon documented in subchapter 4.1 is detected regardless of the intensity of market volatility.

However, in both cases, the greater absolute value reported for the γ_4 coefficient in comparison to γ_3 leads us to believe that this reverse herding activity tends to be particularly strong under low volatility market conditions. Such an asymmetric behavior is confirmed by the results of the Wald test reported in Panel B: in fact, a highly negative and statistically significant value was obtained for the difference between the relevant herding coefficients (γ_3-γ_4<0), which implies that γ_4>γ_3.

Interestingly, when monthly returns were considered, an equivalent scenario was found in the case of the Brazilian market, but not in Mexico. Indeed, in what concerns the former, the results reported for the Wald equality test continue to indicate the existence of an asymmetric component in terms of herding phenomena, with anti-herding being much stronger during low volatility months (γ_3-γ_4<0 and statistically significant). However, on the contrary, the outputs of the same test ran for the Mexican market suggest an absence of asymmetric herding effects contingent on volatility levels in the long run - (γ_3-γ_4) is not statistically significant, which implies equivalent herding coefficients.

For the Colombian market, our results also indicate that the evidence of anti-herd formation in the long run documented when studying the whole sample period holds irrespectively of whether high or low volatility levels are experienced. Nevertheless, such reverse herding activity seems to be significantly more profound during low volatility months, as the Wald test led to the rejection of the null hypothesis, and we found that γ_3-γ_4<0 (implying that γ_4>γ_3). In turn, in line with our findings documented when the whole sample period was analyzed, we continue to find no herding effects affecting Colombian investors in the short term, regardless of volatility levels.

Finally, in the case of the Chilean economy, the negative and statistically significant coefficient γ_4 reported using monthly data is consistent with the herd hypothesis in the long term during low volatility periods. By contrast, no herding effects were detected during periods of high volatility, which suggests that, in Chile, such mimicking activity presents an asymmetric nature depending on volatility levels. Such line of reasoning is confirmed by means of an equality test, which reliably points towards the rejection of the hypothesis of equal herding coefficients during high and low volatility months, supporting the described asymmetry. In turn, the non-statistically significant herding coefficients reported for this stock market using daily data suggest that the short-term investment decisions of Chilean investors, at least in terms of herding, are not influenced by volatility levels.

Overall, our findings around the existence of asymmetric herding behavior depending on market volatility seem to challenge the idea defended by Gleason et al., (2004) and Tan et al., (2008) that investors are more likely to seek for the "comfort" of the collective behavior during periods of abnormal volatility. In fact, our results failed to provide any evidence of intensified mimicking activity in response to high volatility levels. Conversely, we found that, instead, low volatility periods tend to drive herd formation among Chilean investors, although solely in the long term. According to Holmes et al., (2013), low market volatility makes it easier for less informed market participants to monitor and follow the trades of the better-informed ones, thus fostering pronounced herding in the market.

Apart from suggesting the existence of herding in the Chilean stock market as driven by low volatility levels, our results deriving from the application of monthly data also reported asymmetric herding effects in the Colombian and Brazilian markets. Particularly, contrasting with the findings obtained for Chile, in both cases, low volatility periods were found as triggering not herding, but rather anti-herding among investors in these equity markets. Instead, using daily data, asymmetries in terms of herding effects driven by volatility levels were only detected in Brazil and Mexico: in each case, intensified reverse mimicking behavior was found during low volatility periods.

Despite not being consistent with the conclusions of several global studies suggesting greater herd formation driven by high volatility levels (Butler & Joaquin, 2002; Forbes & Rigobon, 2002; Gleason et al., 2004; Corsetti et al., 2005), it is interesting to note that our findings are somehow analogous to those reported by Almeida et al., (2012), which also documented low volatility as promoting a greater mimicking activity in the Chilean market.

All things considered, except for the Chilean economy, the absence of herd formation reported in this subchapter (4.3) indicates that Latin American investors seem not to follow the trend observed in other countries that led most empirical evidence to support the idea that investors´ mimicking activity is intensified under specific market conditions. Such a conclusion suggests that, overall, Brazilian, Colombian and Mexican market players prioritize making rational decisions even when the state of the market may be seen, according to existing literature, as propitious for them to herd.

On the contrary, as already stated, the herding evidence reported in the Chilean economy may be attributable to the presence of less experienced investors in this market, whose lack of analysis engine and evaluation ability represent an incentive for them to mimic their peers when certain market conditions are verified in a "flight to safety" strategy.

4.4 HERDING DRIVERS: THE INFLUENCE OF EXTERNAL FACTORS

In this subchapter, we extend our analysis by discussing the extent to which external factors may impact Latin American investors´ behavior. Precisely, following existing literature, we identified seven variables that we believe could potentially have a role in triggering herd behavior among market players, including psychological (local investors´ sentiment), economic (Central Banks´ policy rates, exchange rates and EPU) and global market factors (U.S. market performance, VIX returns and crude oil prices). These parameters were included as explanatory variables in model (3.8), whose results are displayed in table 12. Note that, due to the absence of daily updates around the evolution of the EPU index, as a matter of simplicity, in this subchapter only the results obtained using monthly stock market information are presented.

TABLE 12: HERDING ESTIMATES – MODEL (3.8)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \gamma_3 * \Delta TV_{m,t} + \gamma_4 * IR_{m,t} + \gamma_5 * ER_{m,t} + \gamma_6 * EPU_{m,t} + \gamma_7 * R_{VIX,t} + \gamma_8 * R_{U.S.,t}^2 + \gamma_9 * R_{OIL,t}^2 + \varepsilon_t$

	Brazil	Chile	Colombia	Mexico
γ_0	***0.025108 (9.63)	**0.013480 (2.03)	***0.016221 (4.14)	***0.030759 (6.51)
γ_1	**0.111971 (2.10)	0.158548 (1.45)	***0.216774 (3.56)	0.029014 (0.50)

γ_2	0.411695 (1.38)	1.654989 (0.66)	0.234031 (0.50)	***4.047332 (5.20)
γ_3	***0.008699 (3.17)	-0.000339 (-0.26)	0.001235 (0.82)	0.003011 (1.57)
γ_4	***0.066444 (3.62)	0.040457 (1.61)	0.017479 (0.38)	**-0.058998 (-2.64)
γ_5	-0.009923 (-1.33)	-1.572457 (-0.44)	-10.63778 (-1.64)	*-0.114128 (-1.72)
γ_6	-0.000006 (-0.86)	***0.000039 (4.07)	0.000013 (1.14)	-0.000016 (-1.35)
γ_7	-0.000116 (-0.02)	-0.005090 (-0.75)	0.007773 (1.48)	***-0.011054 (-2.64)
γ_8	1.117804 (1.00)	**-2.857340 (-1.98)	-0.711468 (-0.37)	*2.156002 (1.85)
γ_9	***0.209324 (4.81)	***0.220564 (2.91)	***0.474582 (6.12)	**0.148809 (2.61)
R^2 adj.	0.569202	0.601746	0.634809	0.674027

Notes: This table reports the regression coefficients of the model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R^2_{m,t} + \gamma_3 * \Delta TV_{m,t} + \gamma_4 * IR_{m,t} + \gamma_5 * ER_{m,t} + \gamma_6 * EPU_{m,t} + \gamma_7 * R_{VIX,t} + \gamma_8 * R^2_{U.S.,t} + \gamma_9 * R^2_{OIL,t} + \varepsilon_t$, where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$), $\Delta TV_{m,t}$ is defined as the percentage change in the trading volume of the stocks belonging to the reference index of market *m* at time *t* and is used as a proxy for local investors´ sentiment; $IR_{m,t}$ refers to the Central Bank´s policy rate of country *m* at time *t*; $ER_{m,t}$ is the exchange rate of the domestic currency of country *m* against the USD at time *t*; $EPU_{m,t}$ represents the level of Economic Policy Uncertainty in the respective country *m* at month *t*; $R_{VIX,t}$ is represented by the logarithmic return of the CBOE VIX index at time *t*; $R^2_{U.S.,t}$ is the logarithmic return squared of the S&P500 index and $R^2_{OIL,t}$ is the squared logarithmic return of WTI crude oil prices at time *t*. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

At a first sight, one can notice that the behavior of Mexican market players seems to be the most affected by external factors as, for this economy, most of the added explanatory variables (γ_3-γ_9) were found as being statistically significant. Even so, insightful findings were obtained for all the four markets, and thus are worth highlighting.

First centering our attention on the results around the influence of investors´ sentiment on their tendency to herd, we reached the interesting conclusion that the dominant feeling in the stock market does not influence the intensity of herd formation experienced among Chilean, Colombian and Mexican market players. However, this variable plays a role in explaining the level of herding activity observed in Brazil. Concretely, we reported a negative relationship between market sentiment and Brazilian investors´ tendency to herd (γ_3>0 and highly significant). In other words, we found that greater levels of optimism experienced in this stock market (reflected by an increase in the number of shares traded) promote a decrease in the level of herding activity detected among market participants. By contrast, when fear dominates, Brazilian investors are more likely to neglect their investment skills and simply imitate the majority behavior.

Noteworthy, similar mixed results around the influence of (domestic) market sentiment on the intensity of herd formation in stock markets have also been reported in earlier literature. As we have seen, while the findings of Economou et al. (2018) provided strong evidence of herding towards fear in the UK, U.S. and German stock markets, Vieira

& Pereira (2015) concluded that such a parameter exerts only a limited impact on the intensity of herding experienced in Portugal, for instance.

Apart from herding in response to fear, our findings indicate that the behavior of Brazilian investors is also impacted by the respective policy interest rates, a scenario that was also verified for the Mexican stock market. Such a conclusion comes from the fact that, in both cases, the relevant herding coefficient (γ_4) was found as being statistically significant. In detail, while in Brazil investors seem to herd as a response to a decline of interest rates (γ_4>0), Mexican investors were found as taking more irrational decisions (i.e., herding) when higher interest rates are experienced (γ_4<0). In turn, for the other two economies, benchmark interest rates seem not to have a significant influence over investors´ mimic instinct.

One possible explanation for these heterogeneous findings across the four markets may be related to the credibility and degree of transparency behind Central Bank announcements, factors which were already documented as playing a role in the relationship between monetary policy and herding behavior (Neuhierl & Weber, 2019). Particularly, considering the perspective defended by Bikhchandani & Sharma (2000) that asymmetric information drives herd formation, one could expect herding effects around monetary policy interest rates movements to be more pronounced in those economies characterized by more ambiguous Central Bank communications.

For this argument to be valid, then, the communications of the Chilean and Colombian monetary policy authorities should be considerably clearer than those of the other Latin American countries in which investors were found to herd around Central Banks´ policy rate levels (Brazil and Mexico). Interestingly, this is precisely the conclusion obtained by a recent study conducted by the IMF: whereas the Central Banks of Chile and Colombia seem to have improved the clarity of their communication over the years (2010-2017), the announcements of Brazilian and Mexican monetary policy authorities have become more complex and difficult to understand (IMF, 2018)[8].

In brief, our findings concerning the influence of (benchmark) interest rates on Latin American investors´ mimicking activity are not consensual. In fact, while this macroeconomic indicator helps explain the intensity of herd formation detected in Brazil and Mexico, it does not influence the herd behavior of the remaining Latin American

[8] To reach these conclusions, average reliability scores were attributed to Brazilian, Chilean, Colombian and Mexican Central Bank press releases, which were later put against benchmarks to compare the clarity of communication. The respective scores were computed based on the Flesch readability index, which is centered on two main factors: average sentence length and average number of syllables per word.

investors. Worth mentioning, similar mixed results were reported by previous researchers: in his study, Wibowo (2021) also documented that the mimicking activity among Brazilian investors is influenced by the country´s policy interest rate, while the same indicator exerts a non-significant influence over the behavior of Japanese investors, for example.

In turn, as far as exchange rates are concerned, our findings suggest that this macroeconomic parameter only has a significant impact on the behavior of Mexican market players, while not affecting the level of herd formation in the remaining Latin American stock markets. Such a conclusion that exchanges rates with respect to the U.S. dollar strongly impact the behavior of Mexican investors (while barely influencing other Latin American market players) is not totally surprising if we take into account that the connection between these economies go much beyond border sharing. Apart from extensive historical and cultural ties, the North American and Mexican markets also share a strong economic relationship, which, naturally, associates both stock markets. Indeed, as evidence of the deep bond connecting both economies, according to the Economic Commission for Latin America and the Caribbean (ECLAC), in 2021, the U.S. trade in goods with the Latin American region was, by far, dominated by the trade with Mexico, which represented around 80% of the total commercial activity between both regions. As a matter of comparison, the total trade with the remaining economies under study was far less expressive: Brazil (9.55%); Chile (3.96%); and Colombia (3.63%). These figures help illustrating that, even though the economic link connecting the overall Latin American region to the North American country is undeniable, such interconnection seems to be particularly strong with Mexico, which causes this country to be naturally more sensitive to exchange rate movements.

Particularly, we found that an appreciation of Mexico´s domestic currency over the USD tends to drive herd formation among Mexican market participants (γ_5<0 and significant). Among the reasons that could justify this finding lies the fact that a stronger Mexican peso may hurt the amount of export revenues entering the economy, as it makes imports less attractive (i.e., more expensive) from the perspective of U.S. consumers. To the extent that the Mexican economy relies heavily on exports for receipts (which represented over 41%[9] of the country´s GDP in 2021[10], according to the World Bank), such a scenario may decrease investors´ confidence on their own decision-making capabilities, causing them to seek for the security of following the crowd, thus herding.

[9] Comparatively, in the same year and according to the same source, the contribution of exports to the GDP of the remaining markets under study was not as significant: Brazil (20.1%); Chile (31.9%); Colombia (16.4%).
[10] It is worth noting that the overall contribution of exports to Mexican´s GDP has been showing an increasing tendency throughout the years. As a matter of comparison, in 2013 (the first year of our analysis), exports´ revenues represented 31.1% of the country´s GDP.

Altogether, with the exception of the findings for the Mexican economy, our results with regard to the influence of exchange rates on investors´ tendency to herd go together with those reported by Wibowo (2021), which also indicated a non-significant effect of exchange rates on the level of herding observed in the studied emerging markets.

A last (local) macroeconomic factor we decided to include in our analysis refers to the level of economic policy uncertainty. Concerning this, the outputs obtained for the relevant herding coefficient (γ_6) suggest that this indicator only impacts the level of mimicking activity observed in the Chilean stock market as, for all the other economies, this parameter was found as being non-statistically significant. In concrete, we found that, on average, the Chilean herding activity decreases as the EPU rises (γ_6 positive and significant). Such a finding indicates that investors in this stock market tend to make investment decisions more rationally and carefully to deal with the impact of policy uncertainties. As a matter of contextualization, it is worth referring that Lin & Li (2019) found that investors in the U.S. REITs market also handle the impact of economic uncertainty by taking more conscious trading decisions.

Moving forward, the role played by global market factors also seems to diverge across the studied nations. To begin with, our results around the influence of U.S. investors´ sentiment suggest that increased worry among North American market players results in a more correlated trading pattern in the Mexican stock market (γ_7 is statistically different from zero and negative), while it seems not to significantly influence the behavior of the remaining Latin American market players. Once more, Mexico´s greatest geographical proximity and close economic ties with the U.S. market may serve as reasons to justify the spillover of U.S. investors´ sentiment over the behavior of local market participants.

Taking earlier literature into account, our findings are somehow similar to those reported by Economou et al., (2019), which also concluded that, in a set of four European economies, the U.S. market sentiment only impacts the level of mimicking activity detected in Romania. Adopting an analogous rationale, these authors attributed such findings to Romania´s greater level of financial integration in the global financial system as well as to the strong commercial and cultural links connecting both countries.

In turn, extreme movements in U.S. market returns were found to influence not only the behavior of Mexican, but also of Chilean investors, although in opposite directions. On the one hand, higher levels of volatility in the U.S. stock market (as measured by $R^2_{U.S.,t}$) seem to drive Mexican investors to take more conscious and rational investment decisions, reducing the level of herd formation (γ_8>0 and highly significant); on the other hand, the same increased uncertainty around U.S. market returns seems to foster the mimicking behavior of Chilean investors (γ_8<0 and significant). By contrast, Brazilian and Colombian investors were found as not reacting significantly to the U.S. stock market volatility.

All in all, our conclusions deriving from the inclusion of the squared U.S. market return in the regression model seem to differ from those reported by Chiang & Zheng (2010), which conducted an equivalent analysis and took into consideration a similar set of Latin American equity markets. In fact, these authors documented a negative and statistically significant relationship between the U.S. stock market squared return and the level of returns´ dispersion observed for all the relevant markets. In our case, such a negative link was reported for the Chilean economy, but not for the other three countries. One potential reason for these divergent conclusions may lie on the fact that, compared to our study, these authors analyzed a totally different time span (1998-2008). Also, while our analysis was conducted using monthly data, Chiang & Zheng (2010) applied daily stock market information, a condition which may also help explaining the difference in the results.

Finally, while the influence of the remaining external factors seems to diverge across the four markets, the herding phenomena in all the studied Latin American stock markets were found to be sensitive to the volatility of crude oil prices. However, these extreme price movements were reported as not triggering herd formation. Instead, the positive and highly significant figures obtained for the γ_9 coefficient suggest that the volatility of oil prices tends to exert pressure over local market players to take more conscious investment decisions, decreasing the intensity of herding activity. Worth of note, these findings are in line with those reported by Economou et al. (2016), which also failed to document oil price volatility as a significant driver of herding in Nigeria and Morocco. Analogously, Rahman & Ermawati (2020) also found oil prices as fostering reverse herd in five Asian economies.

4.5 CROSS-COUNTRY HERDING EFFECTS

Finally, table 13 displays the results of our cross-country analysis, performed in order to examine if there is any synchronicity in terms of herding effects connecting the four Latin American stock markets under analysis.

TABLE 13: HERDING ESTIMATES – MODEL (3.9)

Model: $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \sum_{j=1}^{3} \delta_j * CSAD_{j,t} + \varepsilon_t$

	Brazil		Chile		Colombia		Mexico	
	Daily	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*	*Daily*	*Monthly*
γ_0	***0.003424 (13.53)	***0.017165 (7.75)	***0.001970 (7.77)	*0.006490 (1.94)	0.000463 (0.59)	0.006261 (1.05)	***0.002140 (8.05)	***0.012140 (5.43)

$\boldsymbol{\gamma_1}$	***0.179168 (10.75)	***0.186473 (2.99)	***0.279270 (12.03)	***0.497237 (6.05)	***0.416884 (5.52)	*0.158478 (1.90)	***0.221221 (6.96)	0.048979 (0.74)
$\boldsymbol{\gamma_2}$	**1.126670 (2.12)	-0.129464 (-0.39)	*1.078272 (1.85)	***-4.272224 (-2.70)	2.445744 (0.40)	1.197166 (1.22)	0.172908 (0.05)	***3.353616 (5.56)
$\boldsymbol{\delta_{BR}}$			** **0.069661** (2.22)	0.055225 (0.47)	** **0.107764** (2.00)	0.055933 (0.54)	*** **0.192843** (8.04)	*** **0.218239** (3.32)
$\boldsymbol{\delta_{CH}}$	*** **0.104087** (3.37)	0.003951 (0.04)			*** **0.235182** (3.64)	0.268124 (1.53)	*** **0.165180** (4.78)	0.049822 (0.94)
$\boldsymbol{\delta_{COL}}$	*** **0.095696** (3.74)	0.073535 (1.01)	** **0.104715** (2.50)	*** **0.311977** (4.16)			*** **0.085952** (3.19)	0.058050 (1.28)
$\boldsymbol{\delta_{MX}}$	*** **0.312727** (9.05)	*** **0.362610** (3.16)	*** **0.210803** (4.96)	0.082111 (0.71)	*** **0.242247** (3.23)	0.106470 (0.70)		
$\boldsymbol{R^2}$ **adj.**	0.507146	0.515139	0.506755	0.458392	0.499993	0.507979	0.457995	0.649914

Notes: This table reports the regression coefficients of the model:, $CSAD_t = \gamma_0 + \gamma_1 * |R_{m,t}| + \gamma_2 * R_{m,t}^2 + \sum_{j=1}^{3} \delta_j * CSAD_{j,t} + \varepsilon_t$ where $CSAD_t$ stands for the cross-sectional absolute dispersion of returns with respect to the market portfolio return ($R_{m,t}$) and $CSAD_{j,t}$ is represented by the Cross-Sectional Absolute Dispersion of Returns of country j (j = Brazil (BR), Chile (CH), Colombia (COL) or Mexico (MX)) at time *t*. The values in parenthesis represent the t-statistics, computed using the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Finally, ***, ** and * represent statistical significance at 1, 5 and 10% level, respectively. Whenever the relevant herding coefficients for the specific model present statistical significance (at any conventional level), these are highlighted in **bold**.

Overall, our findings provide robust evidence of cross-market herding, especially when considering daily data. Indeed, when applying this data frequency, we found a highly significant positive relationship connecting each market´s domestic CSAD measure and the equivalent measure of the three neighbor countries. Conversely, the results obtained using monthly returns were far less robust, suggesting that the synchronicity in terms of herding activity among Latin American market participants is much stronger over daily intervals.

In detail, our results obtained using daily stock market information suggest that the intensity of herd formation detected in each domestic market moves in line with the mimicking activity reported in all the other three economies. That conclusion comes from the fact that, for each country, positive and statistically significant figures were found for the herding coefficients corresponding to the returns´ dispersion measure of the neighbor equity markets.

Interestingly, a closer look at the magnitude of these herding parameters allows us to observe that the intensity of herding effects observed in the Brazilian, Chilean and Colombian stock markets is mostly influenced by the trading dynamics of Mexican market players. That is, a change in the CSAD metric of the Mexican stock market produces a greater impact on the domestic CSAD measures of the Brazilian, Chilean and Colombian equity markets in comparison to an equivalent variation in the respective measure of all the other non-domestic economies. Such a conclusion derives from the observation that, in each individual market, among all the relevant herding coefficients ($\delta_{BR}, \delta_{CH}, \delta_{COL,}\delta_{MX}$), δ_{MX} is the one presenting the highest absolute value. In turn, the cross-sectional dispersion of returns in the Mexican stock market is mainly impacted by changes in the equivalent Brazilian metric.

When it comes to the findings reported applying monthly data, as already stated, evidence of cross-country herding was significantly less expressive. Particularly, while in the short-term Brazilian investors were found to herd with all the remaining Latin American stock markets, in the long run such cross-herding activity was only found to happen with the Mexican economy. Noteworthy, the opposite was also verified: Mexican market players were found to herd exclusively with Brazilian investors in the long run. In turn, for this data frequency, our findings suggest that Chilean market players herd with the Colombian stock market, but not with the remaining economies. However, Colombian investors were found as not herding neither with Chilean nor with other neighbor investors in the long term.

All in all, our results showcase the presence of significant cross-market herding in the Latin American region, thus denoting that emerging markets are capable of motivating herding among themselves. More importantly, apart from confirming the conjecture of common "herding forces", these findings allow us to draw the relevant conclusion that, given the high degree of interdependence between Latin American stock markets, international diversification in this region may not be too beneficial.

The previous findings motivate us to confirm if, as expected, the CSAD metrics of all Latin American countries are highly correlated with each other. Thus, as a robustness check, table 14 contains the correlation matrix between the four CSAD measures.

TABLE 14: PAIRWISE CROSS-MARKET CORRELATIONS

Panel A: daily data	**Brazil**	**Chile**	**Colombia**	**Mexico**
Brazil	1.000000	0.407785	0.425028	0.506957
Chile	0.407785	1.000000	0.434169	0.457224
Colombia	0.425028	0.434169	1.000000	0.437892
Mexico	0.506957	0.457224	0.437892	1.000000
Panel B: monthly data				
Brazil	1.000000	0.334863	0.449022	0.637321
Chile	0.334863	1.000000	0.510149	0.405598
Colombia	0.449022	0.510149	1.000000	0.545577
Mexico	0.637321	0.405598	0.545577	1.000000

Notes: This table reports the pairwise correlation coefficients of the cross-sectional absolute deviation (CSAD) measures for the four countries under study considering the whole sample period. For the calculation of these correlations, we used only observations on the days that all four markets were open for trading, resulting in a total of 2253 daily observations. Panel A displays the results obtained using daily data, while Panel B reports the corresponding outputs reached using monthly stock market information.

Not surprisingly, the outputs reported above seem to be consistent with our conclusions. Indeed, focusing on Panel A, one can notice that the highest correlations are those connecting Mexico to the other economies, supporting our previous findings which indicate that the intensity of herding effects in Brazil, Chile and Colombia is mostly influenced by the dominant behavior of Mexican players. Similarly, turning our attention to Panel B, it is notable the high correlation between the Brazilian and Mexican stock markets, which also corroborates our conclusions that these investors herd exclusively with each other in the long run.

That said, taking into account earlier literature, our findings add to the previous results reported by Economou et al., (2011) and Mobarek et al., (2014), which also documented significant cross-country herding effects connecting the behavior of investors in different European stock markets. Also important, our results complement those of Heaney et al. (2002), which provided substantial evidence in favor of the equity market integration hypothesis within the Latin American region.

5. CONCLUSION AND FURTHER PERSPECTIVES

This work provides comprehensive evidence testing for the existence of herding effects in the Brazilian, Chilean, Colombian and Mexican markets. By virtue of being in budding stages of financial development, these countries are dominated by imperfect and non-smooth information flows spreading across a majority of non-sophisticated investors, factors which cause their equity markets to be particularly susceptible to the appearance of irrational behaviors, including herding. Despite this, the herding phenomena in Latin American stock markets is a topic that merits closer scrutiny, as most existing literature fails to take this set of economies into account.

Motivated by this weakness, we constructed a survivor-bias-free dataset consisting of daily and monthly returns for all the stocks listed on the most relevant equity index of each market at any time from 01/01/2013 to 12/31/2022. Then, calculating the commonly used CSAD measure that proxies for the cross-sectional dispersion of stock returns, it was conducted a battery of tests that help filling this gap and contribute to expand existing literature in several ways.

In concrete, apart from simply testing for the presence of herding among Latin American market players, we also examined the role played by the recent COVID-19 pandemic as a potential driver of this irrational behavior. On top of this, we analyzed the eventual asymmetric nature of this bias conditional on different market states and volatility levels.

Of special interest, we devised two analyses which, as far as we are concerned, have never been conducted before in the Latin-American context: at first, we studied the extent to which psychological, economic and global market factors contribute to the emergence of herd behavior; second, we accounted for the existence of potential cross-country herding effects linking the four neighbor stock markets.

Our results can be summarized as follows. First, irrespectively of the data frequency considered, we detected no significant signs of herding in any of the Latin American stock markets, neither in our full sample period nor when we applied the structural break model proposed by Bai & Perron (2003) to divide the sample into several smaller time-periods. Second, no mimicking activity seems to have been promoted by the COVID-19 pandemic.

Third, we found the behavior of the majority of Latin American investors in terms of herding as not being significantly sensitive to market conditions, since we continued to report no evidence of herding when rising and falling markets (as well as when high and low volatility periods) were analyzed separately. A single exception was the Chilean economy: in this stock market, investors seem to herd during up-market trends and when low volatility levels are experienced.

Fourth, we reached the interesting conclusion that the mimicking activity in the Mexican stock market is not influenced by local investors´ sentiment, although it is tightly linked to macroeconomic and global market factors. In what concerns the other three economies, our findings suggest that the influence of external factors on investors´ herding behavior, in spite of being less expressive, is also significant.

At last, our study reported significant cross-country herding effects connecting the four Latin American stock markets. Such evidence suggests that including these markets´ stocks in a portfolio is bound to generate reduced diversification benefits and raises the possibility of contagion across the region´s economies, thus rendering destabilization potentially more likely in the event of an international crisis. In light of these implications, we consider this finding to be of major interest for both foreign investors and policymakers.

Nonetheless, despite comprehensive, as any other research, our study has its limitations. To begin with, due to time and space constraints, our analysis was restricted to the application of one single herding measure. Following previous authors which supported their conclusions using more than one approach (e.g., Chen, 2013; Lobão, 2022), it would be of interest to verify the robustness of our findings across different methodologies.

In a similar vein, we also limited our analysis to only two frequencies of data: daily and monthly. However, taking into account the short-term nature of this phenomenon defended in the literature (e.g., Christie & Huang, 1995), complementing the study using intradaily data could have been valuable.

Last but not the least, in response to the findings reported by Chang et al., (2000) indicating that macroeconomic parameters tend to have a more significant impact over investors´ behavior when compared to firm-specific information, we prioritized using economic over firm-related variables (e.g., P/E and BTM ratios) when addressing the topic of potential herding determinants. Even so, previous researchers have already documented these factors as also capable of explaining the intensity of herd formation detected in global stock markets (e.g., Tan et al., 2008)[11].

Herding has become a psychological phenomenon in our society. In fact, this is an issue potentially affecting every sphere of an individual´s life, as it is part of the human nature to act as a group and follow socioeconomic norms. For this reason, we recommend the

[11] Using the same approach applied in our study, these authors controlled for the influence of each firm´s earnings yield and reported a significantly negative relationship between this variable and the level of returns´ dispersion in the Chinese stock market.

scientific community to deepen the exploration of the herding phenomena not only in Latin America, but also in other global regions. In particular, considering the aforementioned limitations, further opportunities for research may include studying this anomaly considering alternative estimating techniques (e.g., the metric proposed by Huang & Salmon (2004), quantile regressions…) and data frequencies. Besides this, based on our findings, examining a larger scope of potential herding determinants may also contribute to add value to existing literature. Finally, faced with today´s increasingly integrated financial markets, where cross-herding stands a greater chance, we strongly suggest future international studies to consider testing for the existence of co-movements in the cross-sectional dispersion of returns.

REFERENCES

Aawaar, G., Boamah, N. A., & Akotey, J. O. (2020). Investor herd behaviour in Africa's emerging and frontier markets. *International Journal of Economics and Financial Issues, 10*(6), pp. 194-205. https://doi.org/10.32479/ijefi.10709

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & S. A. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance, 27*. https://doi.org/10.1016/j.jbef.2020.100326

Ali, S. R. (2022). Herding in different states and terms: evidence from the cryptocurrency market. *Journal of Asset Management, 23*, pp. 322-336. https://doi.org/10.1057/s41260-022-00265-1

Almeida, R. P., Costa, H. C., & Jr., N. C. (2012). Herd Behavior in Latin American Stock Markets. *Latin America Business Review, 13*(2), pp. 81-102. https://doi.org/10.1080/10978526.2012.700271

Aslam, F., Ferreira, P., & Ali, H. (2022). Analysis of the Impact of COVID-19 Pandemic on the Intraday Efficiency of Agricultural Futures Markets. *Journal of Risk and Financial Management, 15*(12), p. 607. https://doi.org/10.3390/jrfm15120607

Bagh, T., Fenyves, V., Oláh, J., & Khan, M. A. (2023). Asymmetric Effect of Investors Sentiments on Herding Behavior and Stock Returns: Pre and Post Covid-19 Analysis. *Montenegrin Journal of Economics, 19*(1), pp. 43-55. http://dx.doi.org/10.14254/1800-5845/2023.19-1.4

Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. *The Econometrics Journal, 6*(1), pp. 72-78. https://doi.org/10.1111/1368-423X.00102

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets, 7*(3), pp. 271-299. https://doi.org/10.1016/j.finmar.2003.11.005

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *The Journal of Economic Perspectives, 21*(2), pp. 129-151. https://www.jstor.org/stable/30033721

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *Covid-Induced economic uncertainty* (Working Paper No. 26983; Working Paper Series). Cambridge: National Bureau of Economic Research. https://doi.org/10.3386/w26983

Baker, S., Bloom, N., & Davis, S. (2016). Measuring Economic Policy Uncertainty. *The Quartely Journal of Economics, 131*(4), pp. 1593-1636. https://doi.org/10.1093/qje/qjw024

Balcilar, M., Demirer, R., & Hammoudeh, S. (2014). What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors. *The North American Journal of Economics and Finance, 29*, pp. 418-440. https://doi.org/10.1016/j.najef.2014.06.009

Balcilar, M., Demirer, R., & Hammoudeh, S. M. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. *Journal of International Financial Markets, Institutions and Money, 23*, pp. 295-321. https://doi.org/10.1016/j.intfin.2012.09.007

Balcilar, M., Gupta, R., Kyei, C. K., & Wohar, M. E. (2019). The role of economic policy uncertainties in predicting stock returns and their volatility for Hong Kong, Malaysia and South Korea. *International Review of Economics and Finance , 59*(C), pp. 150-163. https://doi.org/10.1016/j.iref.2018.08.016

Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics, 107*(3), pp. 797-817. https://doi.org/10.2307/2118364

Baruch, B. M. (1957). *Baruch: My own story. A Confederate surgeon.* United States : Henry Holt.

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global Finance Journal, 17*(2), pp. 224-251. https://doi.org/10.1016/j.gfj.2006.04.001

Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance, 32*(3), pp. 663-682. https://doi.org/10.2307/2326304

Bathia, D., Bredin, D., & Nitzsche, D. (2016). International Sentiment Spillovers in Equity Returns. *International Journal of Finance & Economics, 21*(4), pp. 332-359. https://doi.org/10.1002/ijfe.1549

Baur, D. (2006). Multivariate market association and its extremes. *Journal of International Financial Markets, Institutions and Money, 16*(4), pp. 355-369. https://doi.org/10.1016/j.intfin.2005.05.006

Bikhchandani, S., & Sharma, S. (2000). Herd Behavior in Financial Markets. *IMF Economic Review, 47*, pp. 279-310.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica, 77*(3), pp. 623-685. https://www.jstor.org/stable/40263840

Blume, L., Easley, D., & O'Hara, M. (1994). Market Statistics and Technical Analysis: The Role of Volume. *Journal of Finance, 49*(1), pp. 153-181. https://doi.org/10.2307/2329139

Bogdan, S., Suštar, N., & Drazenovic, B. O. (2022). Herding Behavior in Developed, Emerging, and Frontier European Stock Markets during COVID-19 Pandemic. *Journal of Risk and Financial Management, 15*(9), p. 400. https://doi.org/10.3390/jrfm15090400

Bouri, E. I., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letter, 29*, pp. 216-221. https://doi.org/10.1016/j.frl.2018.07.008

Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). COVID-19 Pandemic and Investor Herding in International Stock Markets. *Risks, 9*(9), p. 168. https://doi.org/10.3390/risks9090168

Butler, K. C., & Joaquin, D. C. (2002). Are the gains from international portfolio diversification exaggerated? The influence of downside risk in bear markets. *Journal of International Money and Finance, 21*(7), pp. 981-1011. https://doi.org/10.1016/S0261-5606(02)00048-7

Cerda, R., Silva, Á., & Lacerda, J. T. (2016). Economic Policy Uncertainty Indices for Chile. *Economic Policy Uncertainty*

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance, 24*(10), pp. 1651-1679. https://doi.org/10.1016/S0378-4266(99)00096-5

Chari, V., & Kehoe, P. J. (2004). Financial crises as herds: overturning the critiques. *Journal of Economic Theory, 119*(1), pp. 128-150. https://doi.org/10.1016/S0022-0531(03)00225-4

Chen, T. (2013). Do Investors Herd in Global Stock Markets? *Journal of Behavioral Finance, 14*(3), pp. 230-239. https://doi.org/10.1080/15427560.2013.819804

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance, 34*(8), pp. 1911-1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Chiang, T., Tan, L., Li, J., & Nelling, E. (2013). Dynamic Herding Behavior in Pacific-Basin Markets: Evidence and Implications. *Multinational Finance Journal, 17*(3/4), pp. 165-200. https://doi.org/10.17578/17-3/4-3

Chiu, A. C., Titman, S., & Wei, K. J. (2010). Individualism and Momentum around the World. *The Journal of Finance, 65*(1), pp. 361-392. https://doi.org/10.1111/j.1540-6261.2009.01532.x

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal, 51*(4), pp. 31-37. https://doi.org/10.2469/faj.v51.n4.1918

Connolly, R., Stivers, C., & Sun, L. (2005). Stock Market Uncertainty and the Stock-Bond Return Relation. *The Journal of Financial and Quantitative Analysis, 40*(1), pp. 161-194. https://www.jstor.org/stable/27647190

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance, 24*(8), pp. 1177-1199. https://doi.org/10.1016/j.jimonfin.2005.08.012

Coskun, E. A., Lau, C. Z., & Kahyaoglu, H. (2020). Uncertainty and Herding Behavior: evidence from cryptocurrencies. *Research in International Business and Finance, 54*. https://doi.org/10.1016/j.ribaf.2020.101284

De Bondt, W. F., Muradoglu, Y. G., & Staikouras, H. S. (2008). Behavioral Finance: Quo Vadis? *Journal of Applied Finance (Formerly Financial Practice and Education), 18*(2). https://ssrn.com/abstract=2698614

Demir, N., & Solakoglu, M. N. (2016). Herding in Middle Eastern Frontier Markets: Are Local and Global Factors Important? In P. Andrikopoulos, G. Gregoriou, & V. Kallinterakis, *Handbook of Frontier Markets: Evidence from Asia and International*

Comparative Studies (pp. 3-17). Elsevier Inc. https://doi.org/10.1016/B978-0-12-809200-2.00001-4

Demirer, R., Kutan, A. M., & Chen, C.-D. (2010). Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. *Journal of Economic Behavior & Organization, 76*(2), pp. 283-295. https://doi.org/10.1016/j.jebo.2010.06.013

Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Research, 40*, pp. 603-615. https://doi.org/10.1016/0014-2921(95)00073-9

Dyer, D., Kagel, J. H., & Levin, D. (1989). A Comparison of Naive and Experienced Bidders in Common Value Offer Auctions: A Laboratory Analysis. *The Economic Journal, 99*(394), pp. 108-115. https://doi.org/10.2307/2234207

Economic Commission for Latin America and the Caribbean. (2022). *The sociodemographic impacts of the COVID-19 pandemic in Latin America and the Caribbean.* Santiago: ECLAC.

Economic Commission for Latin America and the Caribbean. (2022). *United States-Latin America and the Caribbean Trade Developments.* Santiago.

Economou, F. (2016). Herding Behavior in Frontier Markets: Evidence from Nigeria and Morocco. In P. Andrikopoulos, G. N. Gregoriou, & V. B. Kallinterakis, *Handbook of Frontier Markets* (Vol. 1, pp. 55-68). Academic Press. https://doi.org/10.1016/B978-0-12-803776-8.00004-5

Economou, F. (2019). Herding in frontier markets: evidence from the Balkan region. *Review of Behavioral Finance, 12*(2), pp. 119-135. http://dx.doi.org/10.1108/RBF-08-2018-0090

Economou, F., Gavriilidis, K., Goyal, A., & Kallinterakis, V. (2015). Herding dynamics in exchange groups: Evidence from Euronext. *Journal of International Financial Markets, Institutions and Money, 34*, pp. 228-244. https://doi.org/10.1016/j.intfin.2014.11.013

Economou, F., Kostakis, A., & Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money, 21*(3), pp. 443-460. https://doi.org/10.1016/j.intfin.2011.01.005

Economou, F., Hassapis, C., & Philippas, N. (2018). Investors' fear and herding in the stock market. *Applied Economics, 50*(34-35), pp. 3654-3663. https://doi.org/10.1080/00036846.2018.1436145

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25*(2), pp. 383-417. https://doi.org/10.2307/2325486

Fenzi, T., & Pelzmann, L. (2012). Psychological and Social Forces Behind Aggregate Financial Market Behavior. *Journal of Behavioral Finance, 13*(1), pp. 56-65. https://doi.org/10.1080/15427560.2012.655383

Ferreruela, S., & Mallor, T. (2021). Herding in the bad times: The 2008 and COVID-19 crises. *The North American Journal of Economics and Finance, 58*. https://doi.org/10.1016/j.najef.2021.101531

Forbes, K. J., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance, 57*(5), pp. 2223-2261. https://doi.org/10.1111/0022-1082.00494

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation. *The Journal of Finance, 47*(4), pp. 1461-1484. https://doi.org/10.2307/2328947

Fu, T., & Lin, M. (2010). Herding in China Equity Market. *International Journal of Economics and Finance, 2*(2), p. 148-156. https://doi.org/10.5539/ijef.v2n2p148

Gervais, S., & Odean, T. (2001). Learning to be Overconfident. *The Review of Financial Studies, 14*(1), pp. 1-27. https://doi.org/10.1093/rfs/14.1.1

Gil, M., & Silva, D. (2019). Índice de incertidumbre de política económica (EPU) para Colombia, 2000-2017. *Ensayos de Economía, 29*(55), pp. 37-56. https://doi.org/10.15446/ede.v29n55.76224

Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. *Journal of Empirical Finance, 11*(5), pp. 681-694. https://doi.org/10.1016/j.jempfin.2003.06.003

Gong, P., & Dai, J. (2017). Monetary policy, exchange rate fluctuation, and herding behavior in the stock market. *Journal of Business Research, 76*, pp. 34-43. https://doi.org/10.1016/j.jbusres.2017.02.018

Gupta, P., & Kohli, B. (2021). Herding Behavior in the Indian Stock Market : An Empirical Study. *Indian Journal of Finance, 15*(5-7). http://dx.doi.org/10.17010/ijf%2F2021%2Fv15i5-7%2F164495

Gębka, B., & Wohar, M. E. (2013). International herding: Does it differ across sectors? *Journal of International Financial Markets, Institutions and Money, 23*, pp. 55-84. https://doi.org/10.1016/j.intfin.2012.09.003

Hastrof, A. H., Schneider, D. J., & Polefka, J. (1970). *Person Perception* . Addision-Wesley.

Heaney, R., Hopper, V. J., & Jaugietis, M. (2002). Regional Integration of Stock Markets in Latin America. *Journal of Economic Integration, 17*(4), pp. 745-760. https://dx.doi.org/10.2139/ssrn.251967

Holmes, P., Kallinterakis, V., & Ferreira, M. P. (2013). Herding in a Concentrated Market: a Question of Intent. *Journal of European Financial Management, 19*(3), pp. 497-520. https://doi.org/10.1111/j.1468-036X.2010.00592.x

Hong, H., Kubik, J. D., & Stein, J. C. (2005). Social Interaction and Stock-Market Participation. *The Journal of Finance, 59*(1), pp. 137-163. https://doi.org/10.1155/2014/906564

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance, 11*(4), pp. 585-616. https://doi.org/10.1016/j.jempfin.2004.04.003

IMF. (2018). Credibility, Communication, and Monetary Policy Procyclicality in Latin America . In I. M. Debt, *Regional Economic Outlook, April 2018, Western Hemisphere Department* (pp. 53-70). International Monetary Fund.

IMF. (2019). *The Challenge of Moderate Commodity Prices in Latin America*. Retrieved May de 2023, from IMF Blog: https://www.imf.org/en/Blogs/Articles/2019/03/25/10841

Júnior, G. D., Klotzle, M. C., Pinto, A. C., & Leite, A. L. (2020). Political risk, fear, and herding on the Brazilian stock exchange. *Applied Economics Letters, 27*(9), pp. 759-763. https://doi.org/10.1080/13504851.2019.1645271

Jiang, R., Wen, C., Zhang, R., & Cui, Y. (2022). Investor's herding behavior in Asian equity markets during COVID-19 period. *Pacific-Basin Finance Journal, 73*. https://doi.org/10.1016/j.pacfin.2022.101771

Jones, D. W., Leiby, P. N., & Paik, I. K. (2004). Oil Price Shocks and the Macroeconomy: What Has Been Learned Since 1996. *The Energy Journal, 25*(2), pp. 1-32. https://www.jstor.org/stable/41323029

Jones, P. M., & Olson, E. (2013). The time-varying correlation between uncertainty, output, and inflation: Evidence from a DCC-GARCH model. *Economic Letters, 118*(1), pp. 33-37. https://doi.org/10.1016/j.econlet.2012.09.012

Kahle, K. M., & Stulz, R. M. (2013). Access to capital, investment, and the financial crisis. *Journal of Financial Economics, 110*(2), pp. 280-299. https://doi.org/10.1016/j.jfineco.2013.02.014

Kallinterakis, V. (2009). Herding and the Thin Trading Bias in a Start-Up Market: Evidence from Vietnam. *SSRN Electronic Journal, 6*(2), pp. 7-27. http://dx.doi.org/10.2139/ssrn.1105976

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics, 12*(1), pp. 13-32. https://doi.org/10.1016/0304-405X(83)90025-9

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money.* Palgrave Macmillan.

Kilian, L. (2008). The Economic Effects of Energy Price Shocks. *Journal of Economic Literature, 46*(4), pp. 871-909. https://www.jstor.org/stable/27647084

Kutan, A. M., & Demirer, R. (2006). Does herding behavior exist in Chinese stock markets? *Journal of International Financial Markets Institutions and Money, 16(2)*, pp. 123-142. https://doi.org/10.1016/j.intfin.2005.01.002

Lan, Q. Q., & Lai, R. N. (2011). Herding and Trading Volume. *SSRN Eletronic Journal* . http://dx.doi.org/10.2139/ssrn.1914208

Lao, P., & Singh, H. (2011). Herding Behaviour in the Chinese and Indian stock markets. *Journal of Asian Economics, 22*(6), pp. 495-506. https://doi.org/10.1016/j.asieco.2011.08.001

Lee, C. M., & Swaminathan, B. (2000). Price Momentum and Trading Volume. *The Journal of Finance, 55*(5), pp. 2017-2069. https://doi.org/10.1111/0022-1082.00280

Lin, W., & Li, Y. (2019). Economic Policy Uncertainty and U.S. REITs Herding Behaviors. *2019 Annual Conference of the Society for Management and Economics* . *4*, pp. 24-49. China: North China Electric Power University. https://doi.org/10.35532/JSSS.V4.005.

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environmental Research and Public Health, 17*(8), p. 2800. https://doi.org/10.3390/ijerph17082800

Lobão, J. (2022). Herding Behavior in the Market for Green Cryptocurrencies: Evidence from CSSD and CSAD Approaches. *Sustainability, 14*(19). https://doi.org/10.3390/su141912542

Lobão, J., & Serra, A. P. (2007). Herding Behavior: Evidence From Portuguese Mutual Funds. In G. N. Gregoriou, *Diversification and Portfolio Management of Mutual Funds* (pp. 167-197). Palgrave Macmillan. http://dx.doi.org/10.1057/9780230626508_8

Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy, 98*(4), pp. 703-738. https://www.jstor.org/stable/2937765

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters, 36*. https://doi.org/10.1016/j.frl.2020.101735

Mobarek, A., Mollah, S., & Keasey, K. (2014). A cross-country analysis of herd behavior in Europe. *Journal of International Financial Markets, Institutions and Money, 32*(C), pp. 107-127. https://doi.org/10.1016/j.intfin.2014.05.008

Morelli, D. (2010). European capital market integration: An empirical study based on a European asset pricing model. *Journal of International Financial Markets, Institutions and Money, 20*(4), pp. 363-375. https://doi.org/10.1016/j.intfin.2010.03.007

Neuhierl, A., & Weber, M. (2019). Monetary policy communication, policy slope, and the stock market. *Journal of Monetary Economics, 108*(C), pp. 140-155. https://doi.org/10.1016/j.jmoneco.2019.08.005

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), pp. 703-708. https://doi.org/10.2307/1913610

Nicholson, S. F. (1968). Price Ratios in Relation to Investment Results. *Financial Analysts Journal, 24*(1), pp. 105-109. https://www.jstor.org/stable/4470287

Philippas, N., Economou, F., Babalos, V., & Kostakis, A. (2013). Herding behavior in REITs: Novel tests and the role of financial crisis. *International Review of Financial Analysis, 29*, pp. 166-174. https://doi.org/10.1016/j.irfa.2013.01.004

Rahman, R. E., & Ermawati. (2020). An Analysis Of Herding Behavior In The Stock Market: A Case Study Of The Asean-5 And The United States. *Bulletin of Monetary Economics and Banking, 23*(3), pp. 297-318. https://doi.org/10.21098/bemp.v23i3.1362

Sahabuddin, M., Islam, M. A., Tabash, M. I., Anagreh, S., Akter, R., & Raham, M. M. (2022). Co-Movement, Portfolio Diversification, Investors' Behavior and Psychology: Evidence from Developed and Emerging Countries' Stock Markets. *Journal of Risk and Financial Management, 15*(8), p. 319. https://doi.org/10.3390/jrfm15080319

Shiller, R. J. (2000). *Irrational Exuberance.* New Jersey: Princeton University Press.

Shiller, R. J., & Pound, J. (1989). Survey evidence on diffusion of interest and information among investors. *Journal of Economic Behavior & Organization, 12*(1), pp. 47-66. https://doi.org/10.1016/0167-2681(89)90076-0

Silva, V. M., & Lucena, W. G. (2019). Finanças comportamentais: análise dos fatores do efeito manada em empresas listadas na [B]³. *Revista Catarinense da Ciência Contábil, 18*. https://doi.org/10.16930/2237-766220192730

Suominen, M. (2001). Trading Volume and Information Revelation in Stock Market. *Journal of Financial and Quantitative Analysis, 36*(4), pp. 545-565. https://doi.org/10.2307/2676224

Svenson, O. (1981). Are we all less risky and more skillful than our fellow drivers? *Acta Psychologica, 47*(2), pp. 143-148. https://doi.org/10.1016/0001-6918(81)90005-6

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal Vol. 16* , pp. 61-77. https://doi.org/10.1016/j.pacfin.2007.04.004

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology, 5*(2), pp. 207-232. https://doi.org/10.1016/0010-0285(73)90033-9

Tversky, A., & Kahneman, D. (1986). Rational Choice and the Framing of Decisions. *The Journal of Business, 59*(4), pp. S251-S278. https://www.jstor.org/stable/2352759

Verma, R., & Soydemir, G. (2006). The Impact of U.S. Individual and Institutional Investor Sentiment on Foreign Stock Markets. *Journal of Behavioral Finance, 7*(3), pp. 128-144. https://doi.org/10.1207/s15427579jpfm0703_2

Vieira, E. F., & Pereira, M. S. (2015). Herding behaviour and sentiment: Evidence in a small European market. *Revista de Contabilidad, 18*(1), pp. 78-86. https://doi.org/10.1016/j.rcsar.2014.06.003

Vo, X. V., & Phan, D. B. (2017). Further evidence on the herd behavior in Vietnam stock market. *Journal of Behavioral and Experimental Finance, 13*, pp. 33-41. https://doi.org/10.1016/j.jbef.2017.02.003

Warganegara, S. F., & Warganegara, e. L. (2022). Herding behavior in the indonesia stock exchange around the covid-19 pandemic. *Fair Value: Jurnal Ilmiah Akuntansi dan Keuangan, 4*(11). https://doi.org/10.32670/fairvalue.v4i11.1822

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *The Journal of Finance, 47*(2), pp. 695-732. https://doi.org/10.2307/2329120

Whaley, R. (2000). The Investor Fear Gauge. *The Journal of Portfolio Management, 26*(3), pp. 12-17. https://doi.org/10.3905/jpm.2000.319728

Wibowo, B. (2021). Monetary Policy and Herding Behavior Developed market and Emerging market comparison. *Economic Journal Trikonomika, 20*(1), pp. 11-16 https://doi.org/10.23969/trikonomika.v20i1.1579

World Bank. (2020). *Market capitalization of listed domestic companies (current US$) - Latin America and Caribbean*. Retrieved May 2023, from The World Bank: https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=ZJ

World Bank. (2021). *Exports of Goods and Services (% GDP) - Mexico*. Retrieved May 2023, from The World Bank: https://data.worldbank.org/indicator/NE.EXP.GNFS.ZS?locations=MX

World Bank. (2021). *GDP (current US$) - Latin America & Caribbean*. Retrieved May 2023, from The World Bank: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=ZJ

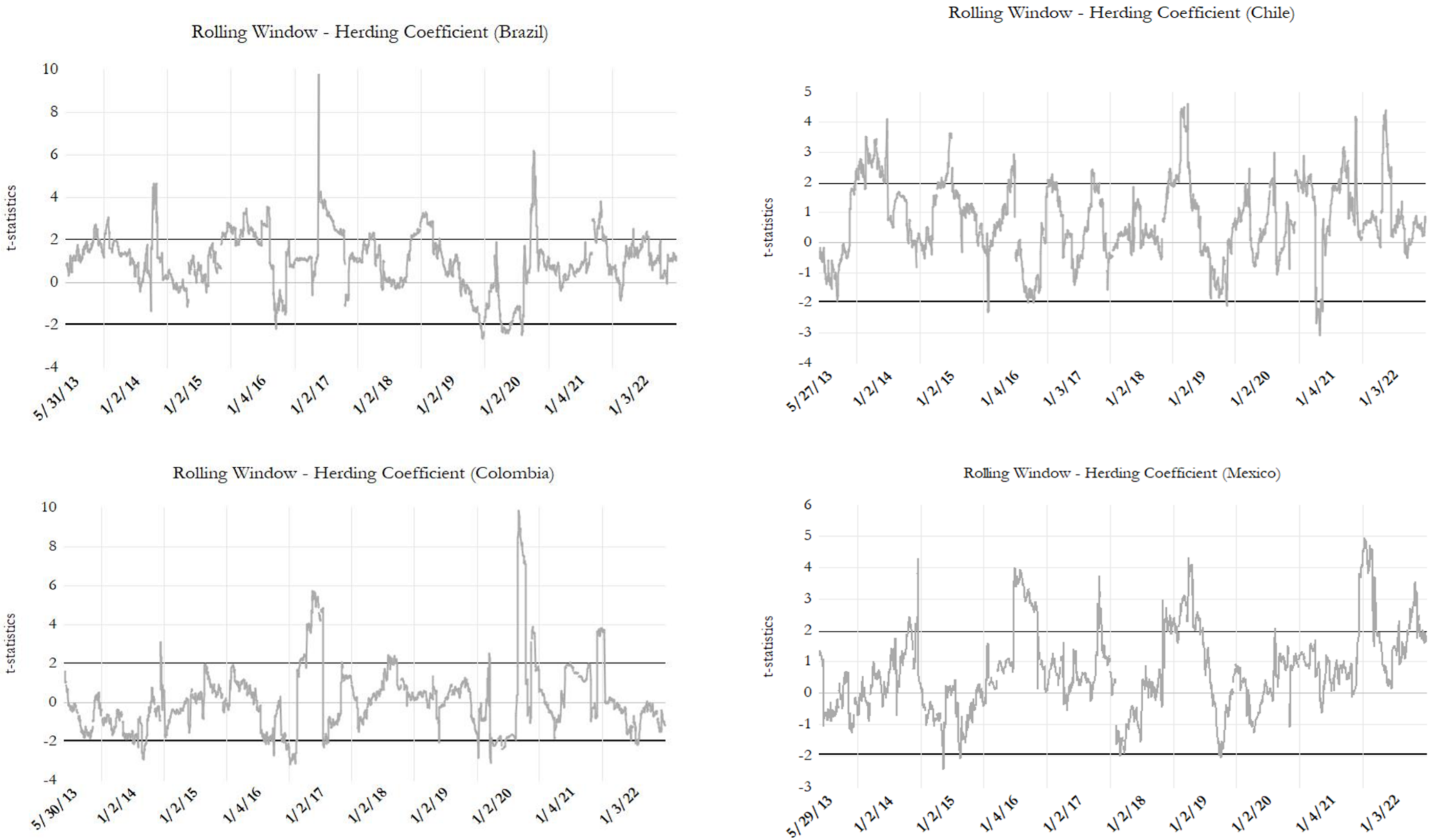
Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36*. https://doi.org/10.1016/j.frl.2020.101528

Zhou, J., & Anderson, R. (2013). An Empirical Investigation of Herding Behavior in the U.S. REIT Market. *The Journal of Real Estate Finance and Economics, 47*(1), pp. 83-108. http://dx.doi.org/10.1007/s11146-011-9352-x

ANNEXES

A1. ROLLING T-STATISTICS FOR THE λ_2 PARAMETER (EQUATION 3.4, <u>DAILY DATA</u>)

FIGURE 1: ROLLING T-STATISTICS - MODEL (3.4), DAILY DATA



Notes: This figure displays the rolling t-statistics based on a rolling-window estimation of the benchmark CSAD model (3.4) using windows of 100 observations with a step of one observation. The horizontal lines represent the critical values of 5%, which correspond to a t-statistics of -1.96 and +1.96. **All data points surpassing the top horizontal line indicate the prevalence of <u>anti-herding</u> behavior; conversely, all data points surpassing the bottom horizontal line are indicative of <u>herding behavior</u>.**

A2. ROLLING T-STATISTICS FOR THE λ_2 PARAMETER (EQUATION 3.4, <u>MONTHLY DATA</u>)

FIGURE 2: ROLLING T-STATISTICS - MODEL (3.4), MONTHLY DATA

Notes: This figure displays the rolling t-statistics based on a rolling-window estimation of the benchmark CSAD model (3.4) using windows of 10 observations with a step of one observation. The horizontal lines represent the critical values of 5%, which correspond to a t-statistics of -1.96 and +1.96. **All data points surpassing the top horizontal line indicate the prevalence of <u>anti-herding</u> behavior; conversely, all data points surpassing the bottom horizontal line are indicative of <u>herding behavior</u>.**

A3. VARIABLES DESCRIPTION – HERDING DRIVERS (MODEL 3.8)

TABLE 15: DESCRIPTION OF IDENTIFIED HERDING DRIVERS

Variable	Identification	Description	Previous similar studies
Trading Volume (as a proxy for local investors´ sentiment)	ΔTV	Percentage change in the monthly trading volume of the stocks belonging to the respective equity index.	Bagh et al., (2023).
Interest rates	IR	Central Bank monthly policy rate.	Rahman & Ermawati (2020).
Exchange rates	ER	The average value of the monthly exchange rate (domestic currency against USD).	Balcilar et al., (2014); Gong & Dai (2017); Rahman & Ermawati (2020); Wibowo (2021).
Economic Policy Uncertainty	EPU	The monthly value respecting to the EPU index for each market.	Bouri et al., (2019); Coskun et al., (2020).
VIX (as a proxy for U.S. investors´ fear)	R_{VIX}	The average value of the monthly CBOE Volatility Index (VIX).	Balcilar et al., (2014); Economou et al., (2016); Economou et al. (2018).
U.S. market volatility	$R_{U.S.}^2$	Monthly return of the S&P 500 index squared.	Economou et al., (2011); Chiang & Zengh (2010); Economou et al. (2016).
Oil price volatility	R_{OIL}^2	Monthly return of WTI crude oil squared.	Balcilar et al. (2014); Economou et al., (2016); Demir & Solakoglu (2016).

A4. DESCRIPTIVE STATISTICS – HERDING DRIVERS

TABLE 16: DESCRIPTIVE STATISTICS - HERDING DRIVERS

BRAZIL							
	ΔTV	IR	ER	EPU	R_{VIX}	$R_{U.S.}^2$	R_{OIL}^2
Mean	0.036805	0.089896	0.289379	215.481500	0.000975	0.000354	0.002895
Median	0.006347	0.091250	0.269353	188.113400	-0.004146	0.000142	0.000589
Maximum	1.088945	0.142500	0.504872	676.955000	0.468556	0.003370	0.060892
Minimum	-0.458588	0.020000	0.173274	62.591000	-0.161944	0.000000	0.000000
Std. Dev	0.226862	0.039111	0.092764	101.604600	0.085468	0.000555	0.009179
Observations	120	120	120	120	120	120	120

CHILE							
	ΔTV	IR	ER	EPU	R_{VIX}	$R_{U.S.}^2$	R_{OIL}^2
Mean	0.062309	0.033792	0.001501	184.5286	0.000975	0.000354	0.002895
Median	-0.038360	0.030000	0.001483	146.8111	-0.004146	0.000142	0.000589
Maximum	1.617875	0.112500	0.002121	454.5794	0.468556	0.003370	0.060892
Minimum	-0.615340	0.005000	0.001035	68.93858	-0.161944	0.000000	0.000000
Std. Dev	0.409358	0.022959	0.000248	96.26163	0.085468	0.000555	0.009179
Observations	120	120	120	120	120	120	120

COLOMBIA

	ΔTV	IR	ER	EPU	R_{VIX}	$R^2_{U.S.}$	R^2_{OIL}
Mean	0.053133	0.046063	0.000347	134.4738	0.000975	0.000354	0.002895
Median	-0.022584	0.042500	0.000327	132.5300	-0.004146	0.000142	0.000589
Maximum	2.364217	0.127500	0.000564	376.8400	0.468556	0.003370	0.060892
Minimum	-0.488633	0.017500	0.000207	48.97000	-0.161944	0.000000	0.000000
Std. Dev	0.380604	0.020726	0.000095	52.40022	0.085468	0.000555	0.009179
Observations	120	120	120	120	120	120	120

MEXICO							
	ΔTV	IR	ER	EPU	R_{VIX}	$R^2_{U.S.}$	R^2_{OIL}
Mean	0.017214	0.054000	0.057184	62.000000	0.000975	0.000354	0.002895
Median	-0.008623	0.047500	0.052836	58.000000	-0.004146	0.000142	0.000589
Maximum	0.767921	0.100000	0.082271	161.000000	0.468556	0.003370	0.060892
Minimum	-0.405670	0.030000	0.041003	12.000000	-0.161944	0.000000	0.000000
Std. Dev	0.212639	0.019431	0.010789	31.734450	0.085468	0.000555	0.009179
Observations	120	120	120	120	120	120	120