Investor Attention and Volatility Asymmetry in BRICS Stock Markets

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Abstract

We verified the effect of the attention of retail and professional investors on the asymmetry of the stock and index price volatility of emerging markets (namely Brazil, Russia, India and South Africa). We estimated time series of the asymmetry parameter of a variance model using moving windows and tested its relationship with the dynamics of Google and Bloomberg user activity indices, which are proxies of retail and professional investor attention. Using data from 2004 to 2023, we found that the average asymmetry in moments of higher retail attention is four times higher than the one in moments of lower attention. This result is contrary to the idea of preponderance of the ostricht effect, which is a market avoidance by investors during bad times. We also found evidence that size and book-to-market determine higher volatility asymmetry as well, but we did not evidence an influence of leverage or professional attention on volatility asymmetry. Our findings are robust to different specifications and control variables, and show the influence of an important market attribute on a stock volatility stylized fact.
Keywords: Volatility asymmetry, investor attention, BRICS, stock market, Google search volume, Bloomberg search volume.

1 Introduction

Volatility fluctuations are very notable in capital markets. The existence of clusters, for instance, has implications on pricing, risk management and market efficiency tests, being considered in several studies and models.

These fluctuations bring significant effects in required returns, which adjust current prices. They help to explain stylized facts, such as more common negative than positive returns (return asymmetry), more frequency of extreme returns than would be expected in a normal distribution, and higher volatility after falling than after rising prices.

This last evidence, called volatility asymmetry, was firstly addressed by Black (1976). While upward trends are typically more gradual, downward ones are notably steeper. The author argued that this asymmetry is a result of a higher leverage that occurs when prices fall. When the firm value decreases, the equity becomes riskier, which increases volatility. Schwert (1989) argued that the operational leverage also increases the intensity of this negative relationship between returns and volatility in bad times. Besides, an increase in stock trading leverage may lead to margin calls and forced selling, pushing prices down.

Other authors, however, verified that the magnitude of this effect is too limited to explain this negative correlation between current returns and future volatility. A second hypothesis was raised (or emphasized) by Pindyck (1984), French et al. (1987) and Campbell and Hentschel (1991). According to them, this anticipated increase in the volatility raises the expected equity return, causing an immediate decline in its price. In other words, they argued that the effect of prices coming from changes in volatility is more expressive than the impact in the opposite direction.

Campbell and Hentschel (1991) described how the volatility asymmetry can be explained by a feedback effect, based on future dividend shocks. Since positive shocks tend to be accompanied by other positive shocks, the first one generates an expectation of increase in volatility, driving an increase in the expected return, hence reducing the stock price, mitigating the positive impact of the price. If there is a negative shock, however, the price also decreases due to an expectation of an increase in volatility, but in this case this effect amplifies the negative impact of the shock. This amplification generates an excess of kurtosis and then extremely negative returns become more common than extremely positive ones. The authors represented this feedback effect using a variance model that helps to explain these asymmetry and kurtosis patterns of daily and monthly returns of United States (US) stocks over 63 years.

This hypothesis that the volatility asymmetry occurs due to fluctuations in expected returns takes as assumption a positive correlation between expected return and volatility, However, an opposite relationship was identified by Breen et al. (1989). Besides, it is reasonable to consider that, among volatility asymmetry determinants, there are market (systematic) factors as well as specific (idiosyncratic) factors of individual assets.

Identifying the determinants of volatility asymmetry is even more controversial in daily frequencies. Avramov et al. (2006) showed that the leverage effect might occur only in lower frequencies, since daily changes in leverage are transient and of smaller magnitude. Also, deviations in expected returns due to economic cycles are barely noticeable in daily series, when returns tend to be more unpredictable (Cochrane, 2001; Lehmann, 1990; Sims, 1984).

In this context, Avramov et al. (2006) studied the impact of trading operations on the daily volatility of stock prices. The authors verified that the activity of contrarian investors (who the authors considered as informed ones) reduces the volatility after a decrease in prices. On the other hand, herd behavior among investors, which results in less informed and liquidity-driven trading, increases volatility in this situation. This robust effect found in the relationship between volatility and lagged returns indicates that the two classical hypotheses might not be enough to explain the phenomenon of volatility asymmetry in daily returns.

Besides herd behavior, other behavioral aspects related to finance might be associated with daily volatility asymmetry. Some types of behavior create a feedback that induces decisions such as panic selling. Loss aversion (prefer avoiding losses to conquering equivalent gains) and endowment effect (tendency to hold losing stocks for a long time and sell winning stocks too soon) generate emotionally charged attitudes, illogical from a financial point of view and that may bias risk and probability assessments (Tversky & Kahneman, 1979).

It is known that the attention of investors fluctuates over time (Da et al., 2011) and by itself determines an increase in volatility (Dimpfl & Jank, 2016). Would the intensity of investor attention have the power to accentuate or mitigate the perceived difference between volatility levels over good and bad times? This is the question we want to answer in this chapter.

Few studies addressed the impact of attention on volatility asymmetry. In a cross-country investigation, Talpsepp and Rieger (2010) verified that economic development and market efficiency reduce volatility asymmetry, while analyst coverage has a positive influence. Dzieliński et al. (2018) did a similar research, using a large sample of monthly returns, from 1989 to 2007, of US stocks. The number of analysts following a specific firm was adopted as attention measure. The asymmetry parameter was obtained through an Asymmetric Power Autoregressive Conditional Heteroskedasticity (APARCH) model. The results of the cross-section analysis showed that stocks with higher analyst coverage (and with larger dispersion among the forecasts) presented higher asymmetry. These results were expressive for stocks with low share of institutional investors and high idiosyncratic volatility. The leverage effect, documented by seminal papers, was not found to be significant.

The authors associated this finding with an attention asymmetry that would be supposedly in the same direction of the volatility asymmetry. In other words, they assumed that investors become more attentive in bad times. According to them, this can be verified by the negative correlation between Google searches and returns, and by the surprising finding that hospitals attend more patients during bear markets (Engelberg & Parsons, 2016). Besides, due to the relationship between attention and volatility described by Andrei and Hasler (2015), attention is even more asymmetrical for companies that receive a higher level of it.

Recently, analyses based on information released over the Internet contributed to the identification of two different behavioral patterns that may explain how attention reacts to positive and negative news. One of these patterns, evidenced by Karlsson et al. (2009), is that individual investors tend to login less on their online accounts during bear markets. Kaustia and Knüpfer (2012), moreover, states that people are reluctant to share the results of bad investments with others (although it does not mean that they are less attentive). This phenomenon was named ostrich effect, an allusion to the legend that ostriches hide their heads in a hole when they are afraid. Gherzi et al. (2014), on the other hand, attest that the volume of logins raises both in good and bad times, suggesting that the investor behaves in a more vigilant way, analogous to that of a meerkat.

In this context, and trying to solve this controversy, the goal of this study is to investigate the longitudinal impact that fluctuations in the attention levels of investors induce in the volatility asymmetry of returns. Our conjecture is that, although the investor becomes more vigilant when markets become both better and worse, higher retail attention induces higher volatility asymmetry. While in good times retail attention is a mere indicator of vigilance, in bad times it means more noise trading. Hence, retail attention increases the difference in market volatility levels in good and bad times. As pointed by Sicherman et al. (2016), logins that result in trades are more common during bad times.

We used for the analysis the returns of the most relevant stock indices of BRICS markets, as well as the stocks that constitute it. The BRICS countries have been playing an increasingly important role in the world economy. China, India, Brazil, Russia and South Africa rank in 2nd, 5th, 9th, 11th and 40th economies in 2023, respectively. While few studies analyzed investor attention in developed markets, it is even more scarce in emerging ones. Moreover, we performed the analysis in daily frequency since it is less vulnerable to economic cycles and leverage effects. Last but not least, we adopted as attention measures two aggregate variables that represent different types of investors: the amount of search queries performed at Google, commonly used by non-sophisticated (retail) investors, and the user activity at Bloomberg terminals, usually preferred by professional investors.

Our results confirm that more retail attention significantly increases the asymmetry level of the market volatility, measured by an APARCH model. This outcome persists in the presence of control variables or the attention of professional investors.

Our approach contributes to a better understanding of the drivers of volatility asymmetry, a notable phenomenon in the stock market. In this sense, our purpose is to address the problem of the controversy of the identification of these drivers. Besides, it helps to analyze the fluctuations in the attention of investors and their effects on asset prices. Certainly, there is no consensus on whether attention is a cyclical or countercyclical variable, and our investigation helps to reach a conclusion.

Understanding the determinants of asymmetry levels and the implications of the dynamics of the agents' attention is useful, from the perspective of investors, in asset pricing and risk management. From the side of corporations, it aids in managing information releases and planning public offers. The relevance of this study is justified because our findings have the potential to increase the effectiveness of those processes.

In the next section, we present the most relevant references related to volatility asymmetry and to the dynamics between attention and asset prices. After that, we describe the research hypothesis, the sample, variables of interest and modeling decisions regarding both volatility asymmetry and the relationship between attention and asymmetry. The empirical results are then presented and discussed. In the end, we make final considerations.

2 Literature Review

In this section, we present one of the most relevant references used as theoretical and empirical background of this study. Firstly, we analyze papers that focus on volatility asymmetry and its determinants. After that, we expose studies and conjectures about the influence of the attention on the dynamics of asset prices.

2.1 Volatility Asymmetry

Due to the relevance that volatility asymmetry has in markets, some studies tried to investigate the major factors that determine it. One of those that gained higher prominence was Bekaert and Wu (2000), which developed a framework and an empirical approach to examine the asymmetry both at firm and market levels.

As major hypotheses for the asymmetry, the study mentions the leverage effect, presented and explained in the seminal papers of Black (1976) and Christie (1982). It shows that the increase in volatility when markets are bearish arises from an increment in the risk due to a decrease in equity values, and consequently a growth in firms leverage. Christie (1982) and Schwert (1989) evidenced this effect but recognize that it cannot be the only determinant for such high asymmetry patterns.

The volatility feedback is also considered, supported by the works of Pindyck (1984), French et al. (1987) and Campbell and Hentschel (1991). This phenomenon was described based on the idea that deviations on risk premiums naturally have an impact on the asymmetric profile of the volatility. The causality would be, in this case, in the opposite direction compared to the one of the leverage effect: an anticipated increase in volatility raises the expected returns on equity, when prices fall.

These patterns are supported by the idea that volatility is persistent, so shocks (both positive and negative) increase future and current volatility. Besides, it is based in an intertemporal relationship between expected return and conditional variance.

Considering these dynamics, French et al. (1987) and Campbell and Hentschel (1991) found a direct relationship between volatility and expected return. However, Turner et al. (1989), Glosten et al. (1993) and Nelson (1991) detected a correlation in the opposite direction. Other studies found a non-significant relationship. Besides that, according to what the Capital Asset Pricing Model (CAPM) determines, a condition for this hypothesis to hold at the firm level, it would be necessary that the market portfolio covariance respond positively to volatility increase.

The most important contribution of Bekaert and Wu (2000) is the test of these relevant hypotheses at the market and firm levels. The authors pointed out that the previous studies generally test the leverage effect at the firm (or portfolio) level, while the volatility feedback is tested using aggregate market data. Besides, Bekaert and Wu (2000) evidenced the influence of covariance asymmetry on the volatility asymmetry. When the covariance between market and stock returns increases in bad times, the feedback effect gets stronger.

The authors assume in the model that conditional volatility is persistent and that the conditional version of the CAPM holds. This means that the return excess of the market portfolio is the product of the price of risk and the market conditional variance, and the the stock return excess of any firm is the price of risk multiplied by the conditional covariance between firm and market return.

The model considers the (simultaneous) effects of leverage and volatility feedback, among the mechanisms that induce asymmetry, coming both at market and firm levels. Therefore, if bad news at market level appears, two effects take place. Firstly, while news are an evidence of higher market volatility, investors will probably also revise conditional volatility given its persistence. This upward revision of the market variance has to be compensated by a higher expected return, leading to reductions on prices and market values. This negative shock in the return generates an increase in the conditional variance. Besides that, it results in a higher general market leverage, and, consequently, in higher volatility. This means that in this case the leverage effect increases the volatility feedback effect.

At the same time, the resulting impact arising from the release of good news is not so clear. In this situation, there will be an increase in the current volatility and an upward revision in conditional volatility. This increment requires a higher expected return, resulting in a reduction in prices, which can cancel the initial positive shock. Hence, in this case, the feedback effect diminishes the initial effect of the volatility. Besides that, this positive shock elevates prices, reducing the general leverage and the conditional variance at the market level.

At the firm level, these dynamics of the initial impact of news is basically the same. However, the volatility feedback effect shows differences. The existence of this effect depends on an increase in the covariance between the stock and the market returns, in response to market shocks. If the shock is totally idiosyncratic, only the leverage effect generates asymmetry, because the covariance does not change, neither does the expected risk premium.

This impact on the unconditional covariance typically appears among firms. The higher the firm systemic risk, the higher should be the increment in the conditional covariance of its stocks due to market shocks. This leads to an increase in the required return, completing the feedback cycle of the volatility, which is also positively influenced by the firm leverage ratio.

The most relevant proposition of Bekaert and Wu (2000) is that the covariance asymmetry accentuates the volatility feedback effect. The authors argue that the covariance asymmetry was not properly investigated by previous studies. The proposed model, therefore, specifies this asymmetry arising both from the leverage and volatility feedback effects, given their impact on the variance asymmetry at the market and firm levels. The beta asymmetry is also considered in their framework, although this circumstance is less salient (generated by idiosyncratic shocks, but not so by systemic shocks) and is rarely treated in the models.

The authors adopted the conditional CAPM to investigate the interactions between expected values and variances of the stocks and the market, and built portfolios grouping firms with similar leverage ratios. The price of risk was defined according to the CAPM at the firm (and not the equity) level. The CAPM parameters were defined using a multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model, specifying a variance-covariance matrix from a asymmetric version of the Baba-Engle-Kraft-Kroner (BEKK) model. The model at the firm level allows a clear segregation of the leverage and the volatility feedback impacts. This setup results in a large number of parameters, but some constraints significantly reduce this amount.

This specification leads to variances and covariances exactly the way the Christie (1982) model describes with riskless debt in the case with constant firm variances. Fluctuations in those variances impact the deviations in the stock volatility when leverage is also higher.

At the market level, the volatility follows an univariate asymmetric GARCH model, adjusted by leverage. In addition to the same mechanism of Christie (1982) model, the influence of the leverage ratio in the conditional variance model occurs in two ways: through shocks of similar firms, which generate volatility effects when leverage increases, and through a leverage growth in the previous moment, which elevates the GARCH effect.

At the portfolio level, volatility unfolds in three components: one that adjusts the AutoRegressive Conditional Heteroskedasticity (ARCH) factor upwards only when the current leverage of the portfolio is higher than the previous one of the market; and other two ones that involve past idiosyncratic covariance and variance that adjust similarly.

The generalized BEKK model accounts for covariance dynamics with: a constant term that represents the leverage effects of Christie (1982); an autoregressive variance term, influenced by leverage; a term that represents the covariance persistence; and shock components, whose effects depend on the combination of individual and market shocks. The generalization imposes non-linear restrictions in the parameters and, consequently, in the particular magnitude of the responses, as well as implies that variances and covariances are defined by the same parameters.

After verifying that the model is well specified, the authors obtained for the empirical approach daily data from 1985 to 1994 of the prices and market capitalizations of 172 firms that comprise the Nikkei 225 index, as well as biannual data of the book value of their debt.

Three portfolios with five stocks each were built according to the leverage, excluding financial institutions. Despite measurement errors, the portfolios show very distinct proportions over the period. The one-month Gensaki was used as short-term interest rate.

The authors used likelihood ratio tests in order to verify the potential validity of models that are more restrictive than that one that simultaneously considers the presence of leverage factors, asymmetric shocks and volatility persistence. The results indicated that the leverage measure is not determined solely by the behavior of the volatility of the Japanese stock returns. Even removing leverage effects, the asymmetric volatility holds.

The volatility feedback can be generated by the dependency that firm covariance and volatility have over market shocks. The results suggested that the asymmetry effects are wider than simply feedback dynamics, or merely indicate correlation between market and firm shocks.

The parameter estimates of the model indicated a relevant persistence in the conditional volatility, at the market and portfolio levels. At the market level, return shocks show expressive effect over volatility asymmetry. The asymmetry is caused substantially by portfolio shocks in the low leverage portfolio, though this asymmetry is not very significant. Medium and large leverage portfolios exhibit an asymmetry of higher magnitude caused by market shocks. Impact curves indicate that the leverage effect accentuates the asymmetry, but the influence is secondary when compared to the feedback effect.

As stated by the time-varying risk premium theory, the conditional covariance has an important role in determining the expected excess return and the volatility feedback. Therefore, the authors verified whether negative shocks at the market level lead to an increase in the covariance between the market and the portfolios, particularly the medium and high leverage ones.

In general, the results showed a persistence in the covariances. More important, the high leverage portfolio showed an elevated covariance asymmetry. The high leverage portfolio covariances increase only when the market and portfolio shocks are of the same sign (and increase substantially when both are negative), while, in the medium leverage portfolio, they increase only when the portfolio shock is positive and the market one is negative.

The authors evidenced that the volatility asymmetry of high and medium leverage portfolios are in fact related to the asymmetric response of the covariance due to market shocks, and these effects are elevated by leverage.

The analysis of the beta responses to the shocks indicates similar patterns only in the medium and high leverage portfolios. Portfolio and market shocks of the same sign increase betas, but different patterns were found in the low leverage portfolio. The results suggest a leverage effect in this portfolio beta, but this occurs solely due to a lack of a relevant volatility feedback effect. In general, the authors conclude that the feedback effect is the one that determines the beta dynamics.

The economic significance of the variance asymmetry was assessed by analyzing the effect of the shocks on the series average values. Regarding the volatility, portfolio shocks generate strong asymmetry in the low leverage portfolio, but total volatility asymmetry remains low. Still, the difference between the effects of positive and negative combined shocks is 45 basis points. In the high and medium leverage portfolios, the difference is 96 and 153 basis points, respectively.

With respect to covariances, the effect is clearer because portfolio shocks typically generate an expressive asymmetry in all the portfolios. Adopting a measure of unconditional price of risk, the risk premiums range from 12 to 55 basis points for market and portfolio shocks combined, which is relevant given the average return excess of 1.73% per year in the sample of Japanese firms.

The volatility feedback induces return shocks high enough to compensate the new expected return, which is even higher for negative shocks after normalizing shocks of different signs. In percentage points, the difference is still more visible and is irrespective of the price of risk. An increase in volatility raises by 16% the expected return due to bad news and by 5% due to good news. When the higher level of uncertainty is priced and there is an increase in the covariances, combined negative shocks generate an increase of 17% in the risk premiums, while positive shocks increase only from 5% to 8%. With respect to betas, the simulations did not find evidence of asymmetry, except for lower magnitudes in the high and medium leverage portfolios.

The analysis using impact curves shows similar results. For equivalent shocks, the low leverage portfolio presents a volatility asymmetry much higher. This occurs because its firm shocks are much higher than the ones of the other portfolios. The fact that the shocks maintain high asymmetry corroborates with the reasoning that feedback effect dominates the leverage one.

An additional test was performed by the authors to verify whether size influences the results. They divide the sample in three groups based on market capitalization. The stock portfolios of higher and lower value were then subdivided according to the leverage ratio. The test steps were similar to the previous analysis. Specification tests did not reject the new model and the conclusions remained, showing that a strong volatility asymmetry is still present after removing the leverage effect. The effects found were economically significant, and the covariance asymmetry presented a direct and relevant influence in the risk premiums among all the portfolios. The beta asymmetry was not identified or was too weak. Besides that, they did not find evidence that confirm the findings of Cheung and Ng (1992) in the US market, that the volatility asymmetry is higher for stocks of small firms.

The findings of Bekaert and Wu (2000) were striking because they evidenced the feedback effect in the variance asymmetry and refuted the hypothesis that the leverage effect is preponderant for this phenomenon. However, the authors made clear that other factors should also determine this asymmetry. Our work intends to verify the contribution of investor attention for these dynamics. In the next section, previous studies with related approaches are presented.

2.2 Attention Reaction to Asset Prices

The model of Andrei and Hasler (2015) associates attention with market variables (returns, volatility and risk premium) to understand its role in determining prices. Besides evidencing that investor attention is very sensitive to recent experiences, the parameter estimates indicated that attention is high in bad times. They interpreted this finding supposing that investors do not have incentives to make efforts to learning during an expansionary economy. During a recession, the perspective of a reduction in future consumption captures more investor attention to estimate more accurately changes in fundamentals.

However, the authors recognize that this evidence is not conclusive when the results of other studies are taken into account. While Patton and Timmermann (2008), Da et al. (2014) and Garcia (2013) indicate that forecasts are more accurate during crises, the findings of Van Nieuwerburgh and Veldkamp (2006) indicated the opposite. Besides that, there are periods of economic expansion, such as the end of the 1990s, when the high level of media coverage suggests exalted investor attention.

Another important evidence of attention cyclicality is the model of Karlsson et al. (2009), which describes interactions between stock market variables and the attention level of investors. Their novel approach allows connecting an observable behavior (the decision about obtaining information) to internal psychological variables. These variables are not observable, but are of great importance in the fluctuation of the investors' preferences in good and bad times. The model extrapolates the investment environment, fitting any situation in which people care about information but have some ability to protect from them.

As in previous studies (Backus et al., 2004; Barberis et al., 2001), they propose a model that incorporates psychological aspects in price variations. However, a new data source is used, corroborating with the idea that people derive their utility directly from information about wealth changes. The idea is to investigate how investors carried with emotions and limited in the assimilation capacity process released information.

In the model, a sole investor is represented with some level of control between the timing to access specific information about their wealth and the effect of this information in their utility. The investor correctly interprets any information he accesses and accurately evaluates the impact of potential information in this sentiment.

In other words, the investor decides whether he awakens his attention or not to obtain more precise information about the position of his investments, conditioned to the general previous market news that he naturally receives. This awakening contemplates both the psychological processes and the necessary behavior for that.

The authors define two effects of selective attention on utility. The first one, named impact effect, corresponds to an increase in the psychological impact of the information on the utility. This effect is based on the prospect theory, which determines that the utility depends on how the results deviate from a pre-specified reference point. Among other factors already documented in previous studies, they argue that attention amplifies the marginal impact, both of losses and gains, in the utility.

The second effect of the attention is on the reference point update. The more attentive, the faster the investor updates this benchmark. This effect is supported by previous studies that indicated, for instance, that the reference points are more responsive to deterministic than to probabilistic information. Accessing more precise and specific information about this wealth would have, according to the authors, similar impact.

With this, the decision making model developed by the authors presents two moments of time. In the first one, there is a shock in the investor wealth. This shock consists of a component about which the investor learns automatically (having, good, bad or neutral content), and another one about which he can decide to learn (with no cost) or not. This discretionary component can assume a good or bad state with respect to the automatic component. At time 2, there is an additional shock in the final wealth of the investor, which can be a good or bad change in relation to the wealth at the first moment.

Deciding not to learn about the discretionary component at time 1 means burying the head under the ground (hence the name ostrich effect) and waiting to be aware of the content of this component only in the second moment. If he does that, his perceived wealth may not be equal to the actual position of his net worth.

The model relies on some assumptions that simplify reality. For instance, in the second moment, when the investor is psychologically attentive, his perceived wealth is always equal to the actual one. Besides that, the investor is risk averse in these preferences with respect to information about his wealth, and his utility at each time is centered at the level of the exact previous moment. The utility is then disturbed by the deviation of this perceived wealth compared to a previously determined reference point.

The basic premise of the model is that the investor conditions his decision of when to learn about the discretionary component to what he learns automatically about his wealth. If the automatic component has a good content, this decision is a trade-off between the advantages of receiving expected good news and the advantages of a more slow update of the reference point at the second moment, reducing the chances of disappointments. In this case, the investor will be attentive if the utility difference (between being and not being attentive) is sufficiently large and if the benchmark revision is significant enough. If the impact effect is equivalent to the effect of a slower update of the reference point, the investor chooses to be psychologically attentive if his degree of risk aversion is not very high.

Another possible scenario is the natural absorption of information of neutral content. In this case, comparing the value functions of an attentive and an inattentive investor , it is always more advantageous being inattentive in the first moment, due to his loss aversion. The change in expected utility at the second time will be identical, regardless of the investor being attentive or not in the first moment.

Lastly, when the automatic information has a negative content, the impact effect favors being inattentive while the updating effect of the benchmark justifies being attentive (in order to have a lower benchmark in the second instant). Hence, the investor will not be attentive if the impact effect is higher enough and if the reference update when inattentive does not take too long. If both effects are equivalent, the optimal solution is being always attentive to the discretionary component in this type of situation.

Regardless of that, the authors recognize that there is an indirect demand for information that serves as fundamental input for the buy and sell decisions by the investors. They take into account the expected utility of this demand to analyze the combined expected utility of checking the portfolio in the first instant. In other words, checking the value of the personal portfolio in bad times has psychological costs that makes it less probable, but can be justifiable in some cases, especially due to the heterogeneity of the investors.

Improvements in the model include a higher number of instants, time discounting the wealth value and relaxing the assumption that the investor is always attentive at the second moment. The authors argue that these adjustments to the model, in general, would increase the benefit of not being attentive to the information in bad times compared to regular times, corroborating even more with the ostrich effect.

Selective attention is, according to the authors, a rational mechanism given that investors are psychologically affected by assessed information. Schneider (2001) claims that less accurate information is perceived as less salient or vivid, having more room for self-manipulation of expectations with respect to knowledge. In other words, the authors consider that there are multiple ways to experiment with information.

The authors analyzed three different samples of Scandinavian countries to verify whether empirical data confirm the model outcomes: one with the amount of accesses to online accounts by investors from October 2003 to January 2004 in a large financial services company in Norway; another one with the quantity of investors logins on the funds investment position section in a large Swedish bank from June to October 2003; and a last one with the volume of accesses to the pages that inform the personal investments position in pension funds, at the pension Swedish authority, from January 2002 to October 2004.

The authors regressed the number of logins on the value of relevant stock indices (the current position and the average value of the last six days), as well as variables to control for alternative explanations. Deviations on the stock indices values were considered as a proxy for public (or automatically perceived) news.

The regressions with different databases indicate statistically and economically significant values for the coefficients that indicate the relationship between the indices values and the number of accesses. This pattern remains with subdivisions of the sample and the inclusion for day of the week and other variables to indicate logins that are merely to pay bills or accesses solely to the main page, as well as to indicate the number of transactions (removing the effect of an indirect information demand). The amount of accesses after bad news were higher than after news with neutral content only in the mutual funds database. The results were strongly in line with the ostrich effect suggested in the model.

Karlsson et al. (2009) argued that the results they found cannot be attributed solely to the fact that the investors are consuming the utility of good news. Based on evidence that results that do not reach expectations evoke disappointment (Bell, 1985; Gul, 1991; Loomes & Sugden, 1986; Zeelenberg et al., 2000), the authors argued that, after consuming good news about some wealth that will be realized in the future, people alter their expectations about this future wealth.

The media coverage asymmetry also may not totally explain the results, since the model compares the index value with its average in the week before and part of this asymmetry can be explained precisely by the ostrich effect in information consumers.

Another possible justification is the fact that investors are more prone to access the information providers when they want to buy stocks, and this aggregate effect would lead to an elevation in prices. The authors dismiss this argument when they show in one of the samples that the correlation between transactions and the index value (controlled by the number of accesses) is very weak compared to the correlation between accesses and the index value (controlled by the number of transactions).

The model of Karlsson et al. (2009) implies that the reference point of loss aversion should vary more (in module) in up than in down markets, leading to also asymmetry dynamics in the market risk premium. This effect helps to explain the pattern found by Griffin et al. (2004). They evidenced that positive returns lead to significant increases in the trading volume ten weeks after, in a relevant sample of countries. This notable phenomenon cannot be completely explained by liquidity effects, overconfidence and endowment effect. The drastic reduction in liquidity during crises are also supported by the ostrich effect, which determines that investors ignore the market in these moments to avoid having to mentally deal with painful losses. The positive asymmetry of attention can also be one of the reasons why there are subtle fluctuations in social transmissions of information, exacerbating crises in bad times or creating bubbles in good ones.

Although the ostrich effect seems reasonable, it may not be preponderant in explaining the relationship between attention and volatility asymmetry. Previous studies (Barber & Odean, 2008; Dimpfl & Jank, 2016) state that the attention of retail (non-professional) investors induces most of the non-fundamental volatility due to noise trading. The ostrich effect may make people check their portfolio less frequently in bad times. However, noise trading is more common in bad times and induces incremental volatility. Hence, even though there is information aversion when the market is bullish, the attention of retail investors results in more volatile trading in bad times than in good times.

Attention induces an increase in volatility, but investors become more attentive in both good and bad times. Since volatility has a notably countercyclical pattern (higher in bad times), we hypothesize that, due to noise trading, retail attention accentuates volatility asymmetry. In other words, when retail investors are more attentive, there is a higher imbalance between volatility levels that occur in economic movements of contraction and expansion. In bad times, volatility raises more than it does in equivalent good times, specially when retail investors are more attentive.

In more favorable periods, although attention increases, noise trading arising from retail attention is less influential to increased volatility. Hence, our main research hypothesis is the following:

H_1: An increase in retail attention leads to more positive volatility asymmetry (higher in bad times)

We describe in the next section the methods performed and decisions made to test our hypothesis, as well as the time series that are part of the sample.

3 Research Design

We obtained, from the Bloomberg terminal, daily close prices for the Bovespa Index (Ibovespa) (Brazil), the Moscow Exchange Index (IMOEX) (Russia), the Stock Exchange Sensitive Index (SENSEX) (India), the Shangai Composite Index (SHCOMP) (China), and the FTSE/JSE SA All Share Index (JALSH) (South Africa), as well as the stocks that form each of these indices (as from November, 2023): 87 stocks from the Ibovespa, 47 from IMOEX, 31 from SENSEX, 938 from SHCOMP, and 128 from JALSH. Our dataset ranges from 27 December 2004 to 17 November 2023.

Besides close prices, we obtained time series of News Heat – Daily Max Readership, an index for each stock that combines the number of times related articles were read by users with the number of searches about the stock, both in Bloomberg terminals. This is our measure for professional attention, since Bloomberg is mainly used by professional, institutional and more sophisticated investors. We refer to this measure as Bloomberg Search Volume (BSV). The News Heat is available only for individual stocks, so we calculated the value-weighted mean for those forming each index to gauge a professional attention measure for them.

Regarding retail investors' attention, we gathered time series of the index that represents the number of Google search queries that users performed using the stock or index ticker as keyword. We refer to this measure as Google Search Volume (GSV). We could only gather data on the indices from the Google Trends website[1] so we could not get Google attention time series for the individual stocks.

[1]Due to limitations in the R package gtrends (https://github.com/PMassicotte/gtrendsR).

We originally intended to use data of all five original BRICS countries (five other countries were admitted as new member in September, 2023), namely Brazil, Russia, India, China and South Africa. However, we found that information on both Google and Bloomberg searches is virtually non-existent for China, so data from China is excluded from our main analyses.

Using the studies from Dzieliński et al. (2018) and Talpsepp and Rieger (2010), we estimate volatility asymmetry for the stocks and indices' returns through an APARCH model, developed by Ding et al. (1993). The APARCH is a variance model that presents some stylized properties of financial time series. The unconditional distribution has excess kurtosis and the model features volatility clusters and long memory in the returns. As the name says, this model (as well as other GARCH variations) captures the volatility asymmetry, meaning that it assumes that the variance is higher when returns are negative, in comparison to when they are positive and equivalent in magnitude (Campbell & Hentschel, 1991).

Equations (1), (2), and (3) describe a general Autoregressive–Moving-Average (ARMA) model for the expected returnsr_t, and a general APARCH model for the variance σ_t^2.

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{i=1}^{q} \theta_i a_{t-i} + a_t; \tag{1}$$

$$a_t = \sigma_t \varepsilon_t; \tag{2}$$

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{s} \alpha_i (|a_{t-i}| - \gamma_i a_{t-1})^\delta + \sum_{i=1}^{m} \beta_i \sigma_{t-i}^\delta. \tag{3}$$

The model for the expected returns (1) includes shocks a_t in each period t, with finite unconditional variance, and a constant term μ. The model's order is defined by q autoregressive components, $\phi_i r_{t-i}$, and q moving average components, $\theta_i a_{t-i}$. Besides the order, the model parameters are μ, ϕ_i and θ_i. The term ε_t is an i.i.d. variable with zero mean and unitary variance, representing the distribution of the errors. In our main analysis, the ARMA order is automatically chosen according to the Akaike information criteria.

The variance model (3) includes a positive constant term α_0, an also positive power term δ, and the components $\alpha_i(|a_{t-i}| - \gamma_i a_{t-1})^\delta$ and $\beta_i \sigma_{t-i}^\delta$. Besides the parameters s and m, which define the orders, the constant term, α_i, β_i (both non-negative), δ and γ_i characterize the model. The component γ_i represents the asymmetry level of the model, assuming values from -1 to 1. In the APARCH model, it is our variable of interest.

Depending on the values of δ and γ_i, the APARCH model reduces itself to more simplified models, such as the GARCH one, proposed by Engle (1982) and generalized by Bollerslev (1986) and Taylor (1986), the TS-GARCH one, from Taylor (1986) and Schwert (1990), the GJR-GARCH one, from Glosten et al. (1993), the T-GARCH one, from Zakoian (1994), the N-GARCH one, from Higgins and Bera (1992), and the Log-ARCH one, from Geweke (1986) and Pentula (1986) (Gasparini et al., 2013).

To obtain the time series of the volatility asymmetry parameter γ, we estimate the APARCH model using daily log-returns inside quarterly periods, yielding a quarterly series of γ for each index and stock of the sample. Therefore, the γ are estimated using 60 to 66 observations (we excluded the estimations performed using less than 60 observations). Each sample of returns is winsorized at five percent.

Next, we average the daily measures of BSV and the monthly measures of GSV over each quarter, to match the quarterly series of γ, and estimate different versions for the following general model:

$$\gamma_{it} = \beta_{0i} + \beta_1 SV_{it} + \beta_2 Size_{it} + \beta_3 Momentum_{it} + \beta_4 PTB_{it} + \beta_5 DTE_{it} + \eta_z + \varepsilon_{it}, \tag{4}$$

where i represents the individual level (either stocks or indices), t represents quarters, and z represents years. In Equation (4), we control the relationship between volatility asymmetry (γ) and attention (BSV and GSV) by individual fixed effects (β_{0i}) and year fixed effects η_z, in addition to stocks or indices' size (natural logarithm of market capitalization), momentum (last 12 months accumulated returns, including the current quarter), Price-to-Book (PTB), and Debt-to-Equity (DTE). The data for the control variables also come from Bloomberg.

Following previous studies, we expected that moments of lower market capitalization and higher leverage (DTE) lead to higher variance asymmetry. The same is expected for moments of lower momentum and higher price-to-book ratios (Black, 1976; Christie, 1982; Dzieliński et al., 2018).

4 Empirical Results

Table 1 shows the descriptive statistics for the Bloomberg (BSV) and Google (GSV) search volume, capturing professional and non-professional investor attention, respectively. BSV ranges from zero to four, while GSV ranges from zero to 100 and is only available for the indices. The country with higher stock attention is Brazil, which may indicate Bloomberg is more popular in Brazil than in other countries. The country with higher GSV is India, followed by Brazil.

Figure 1 shows different patterns from professional and non-professional attention. For instance, in Brazil, Russia, and India, the GSV peaked during the pandemic, but that did not seem to happen with professional attention. South Africa presents some particular pattern. First Google attention is very low and sparse there, indicating Google is not commonly used to search for the JALSH index, and Bloomberg usage is also lower compared to Brazil and Russia. In India, though Google seems to be popular to look for the Sensex index, Bloomberg only started to be used in 2020.

Table 2 shows the descriptive statistics for the daily returns of the stocks (equity) and index series, separated for each country. Each series' length is 4,925 observations, which, for estimat-

Table 1: Search volume's descriptive statistics from 2005 to 2023 (non winsorized)

Country	Type	Variable	N	Mean	SD	Max	Min
Brazil	Equity	BSV	3,904	0.896	1.205	4	0
	Index	BSV	56	1.292	0.164	1.754	1.013
	Index	GSV	72	7.771	11.132	49.667	0
India	Equity	BSV	536	0.239	0.284	1.439	0
	Index	BSV	19	0.329	0.162	0.561	0.033
	Index	GSV	76	21.046	14.729	61.333	5
Russia	Equity	BSV	1,781	0.796	0.942	4	0
	Index	BSV	56	1.219	0.450	1.909	0.114
	Index	GSV	76	3.147	6.555	33.333	0
South Africa	Equity	BSV	4,945	0.446	0.918	4	0
	Index	BSV	56	0.701	0.174	1.077	0.171
	Index	GSV	76	0.697	3.964	33.333	0

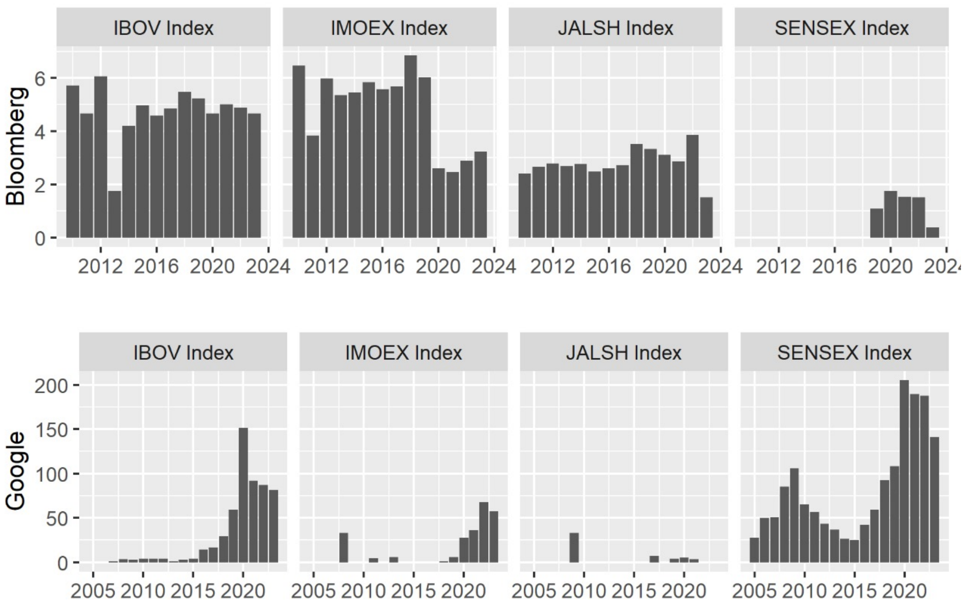

Figure 1: Search volumes for the indices (non-winsorized)

ing the γ are splitted into 77 quarters comprising circa 64 observations each. The daily average returns are close to zero, but the standard deviations are high. IMOEX (Russian index) has the higher standard deviation (3.567%) and the most dramatic minimum value (1,025.9%). South Africa's index JALSH has the lowest standard deviation.

Table 2: Daily returns' descriptive statistics from 2005 to 2023 (non winsorized)

Country	Type	N	Mean	SD	Max	Min
Brazil	Index	4,925	0.032	1.665	13.678	−15.994
	Equity	321,004	0.034	2.671	93.095	−45.994
India	Index	4,925	0.047	1.326	15.990	−14.102
	Equity	145,713	0.069	2.149	66.034	−32.869
Russia	Index	4,925	0.036	1.908	25.226	−40.467
	Equity	140,748	−0.001	3.567	55.207	−1,025.931
South Africa	Index	4,925	0.036	1.191	7.261	−10.227
	Equity	490,158	0.038	2.256	60.609	−133.011

Table 3 shows the descriptive statistics for the estimated γ parameter from Equation (3), which captures returns' volatility asymmetry, that is, the extent to which volatility is different after decreasing prices (negative returns) and after increasing prices (positive returns). Positive γ shows volatility is higher after negative returns while negative γ show volatility is higher after positive returns. Since the sample size for estimating the γ is short (around 64), in several cases the models did not converge and no reliable γ could be estimated. We eliminated such cases, resulting in only few valid observations for the indices, as Table 3 shows. Consequently, in the next estimations, we focused only on the stocks data.

Table 3: Volatility asymmetry's descriptive statistics from 2005 to 2023 (non winsorized)

Country	Type	N	Mean	SD	Max	Min
Brazil	Equity	974	0.029	0.530	0.900	−0.900
	Index	8	−0.023	0.452	0.832	−0.794
India	Equity	410	0.027	0.521	0.896	−0.900
	Index	5	−0.012	0.661	0.766	−0.752
Russia	Equity	330	0.048	0.548	0.895	−0.897
	Index	17	0.101	0.602	0.890	−0.823
South Africa	Equity	1,646	0.001	0.501	0.899	−0.900
	Index	22	−0.004	0.569	0.895	−0.884

Table 4 shows the descriptive statistics for the (winsorized) control variables. Brazil and India are the countries with higher leverage (DTE) and higher PTB ratios. India has the larger momentum returns for both the SENSEX and the individual stocks. The largest average firm size is from India and Russia.

Table 5 shows the estimation results of Equation (4) for the individual stocks. Since estimated γ availability for the indices is very low (see Table 3), we do not present Equation (4) using

Table 4: Control variables' descriptive statistics from 2005 to 2023 (winsorized)

Country	Type	Variable	N	Mean	SD	Max	Min
Brazil	Equity	DTE	5,390	118.475	109.933	361.077	10.144
		Momentum	4,881	0.093	0.307	0.573	−0.420
		PTB	4,874	2.068	1.683	5.668	0.421
		Size	5,205	9.582	1.170	11.541	7.790
	Index	DTE	76	127.506	33.974	158.871	72.009
		Momentum	73	0.081	0.190	0.382	−0.199
		PTB	76	1.843	0.615	3.233	0.965
		Size	76	14.555	0.308	15.224	14.329
India	Equity	DTE	1,992	81.269	72.546	203.194	0.708
		Momentum	2,169	0.177	0.261	0.590	−0.242
		PTB	1,989	4.683	3.687	12.950	1.154
		Size	2,250	13.592	1.046	14.993	11.707
	Index	DTE	76	112.133	14.720	138.588	78.025
		Momentum	73	0.123	0.168	0.382	−0.199
		PTB	76	3.021	0.255	3.233	2.267
		Size	76	17.266	0.484	17.655	15.800
Russia	Equity	DTE	2,424	88.090	88.456	277.056	4.677
		Momentum	2,144	0.022	0.195	0.403	−0.329
		PTB	1,696	1.742	1.508	5.229	0.350
		Size	2,217	9.411	1.044	11.142	7.890
	Index	DTE	76	56.527	11.537	99.399	46.756
		Momentum	73	0.103	0.183	0.382	−0.199
		PTB	76	0.659	0.102	0.956	0.592
		Size	76	16.931	0.573	17.655	15.042
South Africa	Equity	DTE	7,831	52.676	46.807	153.141	2.342
		Momentum	7,387	0.104	0.252	0.486	−0.317
		PTB	6,805	1.807	1.313	4.554	0.477
		Size	7,654	9.976	1.265	12.043	8.178
	Index	DTE	76	54.904	6.897	90.247	46.756
		Momentum	73	0.096	0.142	0.382	−0.199
		PTB	76	2.148	0.425	3.233	1.467
		Size	76	15.883	0.608	16.826	14.561

indices as the i level. Therefore, the models in Table 5 show the relationship between individual stocks' volatility asymmetry and professional attention (BSV).

In Table 5, when considering all countries together (Model 1), no statistically significant relationship is found, but different patterns emerge when considering countries separately. For Brazil (Model 2), only the leverage ratio DTE is statistically significant, indicating higher leverage firms have stocks whose returns' volatility is higher following bad times. This is in line with the previous literature which argue leverage is one of the factors explaining the asymmetric volatility phenomenon (Dzieliński et al., 2018). However, for South Africa (Model 5), the relationship is the opposite. Finally, when considering professional attention, we see it is not related to volatility asymmetry in Brazil nor in South Africa, since the BSV coefficients are not statistically significant in Models 2 and 5.

As in Brazil, according to Model 3 from Table 5, stocks from higher leveraged Russian firms have higher volatility asymmetry, as well as firms with lower PTB, higher momentum and higher size, but, again, professional attention is not related to the γ. In India (Model 4), we see the opposite: while none of the control variables are statistically significant, we see the higher is professional attention, the higher is the volatility asymmetry, indicating professional attention exacerbates the tendency returns have to be more volatile during bad times than during good times. This is in line with Dzieliński et al. (2018), who found firms with higher attention from financial analysts in the United States experience higher asymmetrical volatility. This is the meerkat effect as Gherzi et al. (2014) describe.

Table 5: Regression results: Volatility asymmetry and professional and non-professional attention

	Dependent variable:				
	γ				
	All	Brazil	Russia	India	South Africa
	(1)	(2)	(3)	(4)	(5)
BSV	0.004	−0.015	0.005	0.780**	0.004
	(0.018)	(0.033)	(0.033)	(0.320)	(0.017)
Size	0.032	0.066	0.206***	0.005	0.027
	(0.037)	(0.055)	(0.055)	(0.437)	(0.050)
Momentum	−0.039	−0.126	0.509***	−0.108	−0.025
	(0.054)	(0.085)	(0.085)	(0.436)	(0.070)
PTB	0.010	−0.002	−0.284***	−0.145	0.019
	(0.017)	(0.024)	(0.024)	(0.114)	(0.024)
DTE	0.0001	0.001*	0.006***	−0.008	−0.001**
	(0.0004)	(0.0004)	(0.0004)	(0.006)	(0.001)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-clustered std. errors	Yes	Yes	Yes	Yes	Yes
Observations	1,853	721	135	71	926
R^2	0.011	0.029	0.148	0.256	0.024
Adjusted R^2	-0.130	-0.115	-0.190	-0.488	-0.101
F Statistic	1.019	1.032	1.039	1.338	1.099

Note: *p<0.1; **p<0.05; ***p<0.01

Next, Table 6 shows the same estimations from Table 5 but including the non-professional attention directed to each country stock market index among the explanatory variables. Since GSV is very sparse for the JALSH index (as seen in Figure 1), this analysis does not include South Africa. While BSV is only statistically significant for India, GSV is positive and statistically significant for the full sample as well as in Russia and India. In Brazil, only Momentum is statistically significant in this analysis. Therefore, the results from Table 6 show that when Google searches for the main domestic stock index are higher, volatility asymmetry for individual stocks is also higher. This indicates that higher non-profession attention is related to stocks' returns trend to be more volatile during bad times. This is a more pervasive pattern in the sample than when considering professional attention. Again, this result is related to the meerkat effect (Gherzi et al., 2014), where investors are more vigilant during bad times.

Table 6: Regression results: Volatility asymmetry and professional attention

	Dependent variable:			
	γ			
	All	Brazil	Russia	India
	(1)	(2)	(3)	(4)
BSV	0.005	−0.021	0.050	0.777**
	(0.032)	(0.034)	(0.034)	(0.338)
GSV (Index)	0.011**	0.004	0.043***	0.031**
	(0.005)	(0.006)	(0.006)	(0.013)
Size	0.074	0.073	0.177***	0.141
	(0.051)	(0.053)	(0.053)	(0.418)
Momentum	−0.088	−0.151*	0.535***	−0.054
	(0.081)	(0.086)	(0.086)	(0.403)
PTB	−0.005	−0.002	−0.228***	−0.118
	(0.023)	(0.025)	(0.025)	(0.098)
DTE	0.001	0.001	0.006***	−0.011**
	(0.0004)	(0.0004)	(0.0004)	(0.006)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm-clustered std. errors	Yes	Yes	Yes	Yes
Observations	868	662	135	71
R^2	0.026	0.031	0.173	0.337
Adjusted R^2	-0.168	-0.130	-0.167	-0.366
F Statistic	1.021	0.956	1.165	1.726
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Concluding Remarks

We verified how the attention of professional and retail investors affects the volatility asymmetry of the stock market of emerging economies, namely Brazil, Russia, India and South Africa. Based on previous studies that evidenced relationships between attention and volatility (Dimpfl & Jank, 2016; Tantaopas et al., 2016) and between attention and returns (Karlsson et al., 2009;

Sicherman et al., 2016), we hypothesize that retail attention induces volatility asymmetry in a way that it becomes higher in bad times.

We used daily data of stock and index returns for this analysis. The asymmetry was obtained by the specific parameter of an APARCH model, which is part of a family that is widely used to represent the market volatility. Attention was measured by the search volume performed at Google and Bloomberg, data providers commonly used by retail and professional investors, respectively. Variables such as those ones have increasingly become important given digital inclusion, the volume of information generated over the Internet and the propagation of online services.

The results confirmed our conjecture that the attention, particularly the non-professional one, increases the intensity of an stylized fact of financial markets: volatility is higher in bad times than in equivalent good times. While some investors may "hide their heads inside a hole" during bad times, noise trading performed by retail investors induces more volatility in bad times, increasing asymmetry. We found that moments with higher retail attention record volatility asymmetry on average four times higher than moments with lower attention. Our results are robust to different setups, to the inclusion of control variables and evidence that it is the retail attention that causes this impact on asymmetry.

Our findings offer some contributions to the literature and to practitioners. Firstly, we did not find an analysis of the effect of attention on daily asymmetry in the stock market. Neither did we find an study of the asymmetry induced by different types of investors, as well as in emerging markets. Previous studies report that retail investors are more prone to behavioral biases that lead to limited rationality. Measuring attention through internet activity, we complement the study made by Dzieliński et al. (2018) about the impact of analyst coverage on the US stock market.

Despite that, we did not find evidence of the classical leverage effect reported by Black (1976) and Christie (1982). This pattern is in line with the idea of Avramov et al. (2006) that the transitory and smooth behavior of daily changes in leverage limits the identification of the leverage effect. Studies that help to understand how cognitive resources influence the market behavior support decisions related to risk management, asset pricing and information releases.

Future studies may verify the effect of the attention on risk premiums, given its influence on levels and asymmetry of risk. Besides, several research lines can be developed to better understand the determinants and consequences of the ostrich effect in financial markets. A promising approach would be to analyze the joint effect of attention, trading volume, returns and volatility in emerging and developed markets, given their differences with respect to maturity, stability, concentration, share of non-professional investors, among other factors.

References

Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *The Review of Financial Studies*, *28*(1), 33–72 (cit. on pp. 3, 10).

Avramov, D., Chordia, T., & Goyal, A. (2006). The impact of trades on daily volatility. *The Review of Financial Studies*, *19*(4), 1241–1277 (cit. on pp. 2, 22).

Backus, D. K., Routledge, B. R., & Zin, S. E. (2004). Exotic preferences for macroeconomists. *NBER Macroeconomics Annual*, *19*, 319–390 (cit. on p. 10).

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional in. *The Review of Financial Studies*, *21*(2), 785–818 (cit. on p. 13).

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. *The Quarterly Journal of Economics*, *116*(1), 1–53 (cit. on p. 10).

Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *The Review of Financial Studies*, *13*(1), 1–42 (cit. on pp. 5, 6, 9).

Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research*, *33*(1), 1–27 (cit. on p. 13).

Black, F. (1976). Studies of stock price volatility changes. *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economical Statistics Section*, 177–181 (cit. on pp. 2, 5, 16, 22).

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327 (cit. on p. 15).

Breen, W., Glosten, L. R., & Jagannathan, R. (1989). Economic significance of predictable variations in stock index returns. *The Journal of Finance*, *44*(5), 1177–1189 (cit. on p. 2).

Campbell, J. Y., & Hentschel, L. (1991). *No news is good news: An asymmetric model of changing volatility in stock returns* (tech. rep.). National Bureau of Economic Research. (Cit. on pp. 2, 5, 15).

Cheung, Y.-W., & Ng, L. K. (1992). Stock price dynamics and firm size: An empirical investigation. *The Journal of Finance*, *47*(5), 1985–1997 (cit. on p. 9).

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, *10*(4), 407–432 (cit. on pp. 5, 7, 16, 22).

Cochrane, J. H. (2001). *Asset pricing*. Princeton University Press. (Cit. on p. 2).

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461–1499 (cit. on p. 3).

Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the pan: Continuous information and momentum. *The Review of Financial Studies*, *27*(7), 2171–2218 (cit. on p. 10).

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility? *European Financial Management*, *22*(2), 171–192 (cit. on pp. 3, 13, 21).

Ding, Z., Granger, C., & Engle, R. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, *1*, 83–106 (cit. on p. 15).

Dzieliński, M., Rieger, M. O., & Talpsepp, T. (2018). Asymmetric attention and volatility asymmetry. *Journal of Empirical Finance*, *45*, 59–67 (cit. on pp. 3, 15, 16, 20, 22).

Engelberg, J., & Parsons, C. A. (2016). Worrying about the stock market: Evidence from hospital admissions. *The Journal of Finance*, *71*(3), 1227–1250 (cit. on p. 3).

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimate of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, *50*, 987–1001 (cit. on p. 15).

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, *19*(1), 3 (cit. on pp. 2, 5).

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance*, *68*(3), 1267–1300 (cit. on p. 10).

Gasparini, D. C. d. S., et al. (2013). Verificação da performance de modelos aparch assimétricos aplicados a dados financeiros (cit. on p. 15).

Geweke, J. (1986). Comment on: Modelling the persistence of conditional variances. *Econometric Reviews*, *5*, 57–61 (cit. on p. 15).

Gherzi, S., Egan, D., Stewart, N., Haisley, E., & Ayton, P. (2014). The meerkat effect: Personality and market returns affect investors' portfolio monitoring behaviour. *Journal of Economic Behavior & Organization*, *107*, 512–526 (cit. on pp. 4, 20, 21).

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779–1801 (cit. on pp. 5, 15).

Griffin, J. M., Nardari, F., & Stulz, R. M. (2004). *Stock market trading and market conditions* (tech. rep.). National Bureau of Economic Research. (Cit. on p. 13).

Gul, F. (1991). A theory of disappointment aversion. *Econometrica: Journal of the Econometric Society*, 667–686 (cit. on p. 13).

Higgins, M. L., & Bera, A. K. (1992). A class of nonlinear arch models. *International Economic Review*, 137–158 (cit. on p. 15).

Karlsson, N., Loewenstein, G., & Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal of Risk and uncertainty*, *38*(2), 95–115 (cit. on pp. 3, 10, 13, 21).

Kaustia, M., & Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, *104*(2), 321–338 (cit. on p. 3).

Lehmann, B. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics*, (105), 1–28 (cit. on p. 2).

Loomes, G., & Sugden, R. (1986). Disappointment and dynamic consistency in choice under uncertainty. *The Review of Economic Studies*, *53*(2), 271–282 (cit. on p. 13).

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347–370 (cit. on p. 5).

Patton, A. J., & Timmermann, A. (2008). Generalized forecast errors, a change of measure, and forecast optimality. (Cit. on p. 10).

Pentula, S. (1986). Comments on “modelling the persistence of conditional variances.” *Econometric Reviews*, *5*, 71–74 (cit. on p. 15).

Pindyck, R. S. (1984). Risk, inflation, and the stock market. *American Economic Review*, *74*, 334–351 (cit. on pp. 2, 5).

Schneider, S. L. (2001). In search of realistic optimism: Meaning, knowledge, and warm fuzziness. *American Psychologist*, *56*(3), 250 (cit. on p. 12).

Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, *44*(5), 1115–1153 (cit. on pp. 2, 5).

Schwert, G. W. (1990). Stock volatility and the crash of’87. *The Review of Financial Studies*, *3*(1), 77–102 (cit. on p. 15).

Sicherman, N., Loewenstein, G., Seppi, D. J., & Utkus, S. P. (2016). Financial attention. *The Review of Financial Studies*, *29*(4), 863–897 (cit. on pp. 4, 21).

Sims, C. A. (1984). Martingale-like behavior of prices and interest rates. (Discussion Paper No. 205) (cit. on p. 2).

Talpsepp, T., & Rieger, M. O. (2010). Explaining asymmetric volatility around the world. *Journal of Empirical Finance*, *17*(5), 938–956 (cit. on pp. 3, 15).

Tantaopas, P., Padungsaksawasdi, C., & Treepongkaruna, S. (2016). Attention effect via internet search intensity in asia-pacific stock markets. *Pacific-Basin Finance Journal*, *38*, 107–124 (cit. on p. 21).

Taylor, S. (1986). *Modelling financial time series*. Wiley, New York. (Cit. on p. 15).

Turner, C. M., Startz, R., & Nelson, C. R. (1989). A markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics*, *25*(1), 3–22 (cit. on p. 5).

Tversky, A., & Kahneman, D. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, *47*(2), 263–291 (cit. on p. 3).

Van Nieuwerburgh, S., & Veldkamp, L. (2006). Learning asymmetries in real business cycles. *Journal of Monetary Economics*, *53*(4), 753–772 (cit. on p. 10).

Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, *18*(5), 931–955 (cit. on p. 15).

Zeelenberg, M., Van Dijk, W. W., Manstead, A. S., & vanr de Pligt, J. (2000). On bad decisions and disconfirmed expectancies: The psychology of regret and disappointment. *Cognition & Emotion*, *14*(4), 521–541 (cit. on p. 13).