# The Impact of Private and Public Information on the Trading Behavior in the Egyptian Stock Market[1]

**Dr. Ayman Hassan Metwally**

Arab Academy for Science
Technology & Maritime Transport

ametwally@aast.edu

**Dr. Omneya Darwish**

Arab Academy for Science
Technology & Maritime Transport

Odarwish@aast.edu

## ABSTRACT

*The purpose of this study is to examine The Impact of Private and Public Information on the Trading Behavior in the Egyptian Stock Market, as hypothesized by Daniel et al. (1998).*

*The data covering twelve years from the Egyptian Stock Market, namely the period from 2002 to 2012 on the aggregate market level, is divided into four sub-periods: two tranquil upward-trending periods (2002-2005 and 2005-2008) and two volatile and downward-trending periods (the financial crisis of 2008-2010 and the Egyptian Revolution period of (2010-2012).*

*The study results show that private information shocks have a significant effect on market trading volume, providing evidence of the strong influence of private information on market turnover. This framework not only establishes the presence of an overconfidence bias in the Egyptian Stock Market, but also indicates how the bias changes in response to volatility and dispersion.*

**KeyWords:** *Private information, public information, trading behavior, traditional finance, behavioral finance, Egyptian stock market, cognitive psychology.*

## I. INTRODUCTION

Over time, traditional financial theories have been unable to account for a number of anomalies seen in various security markets. In other words, standard finance theories aim to explain all observable abnormalities with a logical, beautiful, and mathematically sophisticated explanation that oversimplifies reality. Once the field of behavioral finance was assumed, some financial market conundrums that it could resolve what could not be resolved using these traditional finance theories are explained (Shleifer 2000).

People's behavior is not always rational, and psychological and empirical studies in finance have shown that systematic cognitive biases can lead to conclusions that differ from those derived from traditional financial theories.

According to the Efficient Market Hypothesis in traditional finance theories, investors who learn about news after it has already happened should not be able to profit from it. Furthermore, prices should not overreact or underreact to information, and the market should not show any trends or price reversals as a result. Rather, prices should respond to news swiftly and accurately. Despite this, these forecasts have been strongly challenged. The "single most embarrassing reality to the mainstream financial paradigm" is high trading volume (DeBondt and Thaler 1994). Behavioral finance theories have been utilized to help comprehend the financial market and present theories that differ from the premise of rational agents. This is because the fundamental paradigm in classic finance is unable to explain the excessive trading volume in financial markets.

Chen, J. J., & Zhang, Y. (2020) concluded that overconfidence is a common phenomenon in decision making and that it can lead to an overestimation of one's own performance. The authors also found that overconfidence can lead to an overestimation of one's own ability to make accurate predictions, resulting in suboptimal decision making. The authors concluded that it is important to recognize the potential risks of overconfidence and to take measures to reduce its effects.

The overconfidence bias of investors is one of the primary reasons for excessive trading, according to behavioral finance theories. "Perhaps the most robust finding in the psychology of judgement is that people are overconfident," write DeBondt and Thaler (1995). A cognitive bias is overconfidence. It results from heuristic simplification (i.e., self-deception). It happens when individuals have a

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tendency to overestimate their own abilities (Trivers 1991). People who act as though they are more capable than they actually are described in psychology and behavioral science literature as being overconfident (Lichtenstein et al., 1982; Yates, 1990 and Goodie and Foster, 2004). Investors who blame past failure on unluck and prior success on their skills are likely to be overconfident. An investor who is overconfident will try to use his imagined better abilities to get big returns. Overconfidence is therefore a trait of people rather than markets. (1998a, Odean)

Overconfidence bias will consequently affect the behavior of the broader Stock Market since market behavior is nothing more than an aggregate of the conduct of all market participants.

The overconfidence bias idea has been studied extensively in the literature on finance. According to Daniel et al. (1998), overconfidence is a result of a biased self-attribution with respect to previous investment outcomes. They contend that overconfidence results in overreacting to personal information and underreacting to public signals, which leads to mispricing on the market. The hypothesis that some investors have a propensity to inflate their own abilities and ignore the fact that they are in a bull market is later improved by the author in Gevias and Odean (2001). Statman conducts empirical study on the effects of overconfidence on trading volume in the US market in Statman et al. (2006). They utilize market return to gauge the degree of overconfidence since the level of overconfidence fluctuates with the market return. They discover a highly favorable correlation between lagged market returns and market-wide turnover and interpret it as proof of overconfidence. Additionally, Glaser and Weber's (2007) research supports Statman et al (2006).'s finding that investors with higher levels of confidence tend to invest more in the German stock market.

According to Morgan Stanely, one of the top rising financial markets is the Egyptian Stock Exchange. It is one of the emerging economies that is growing the fastest, with a growth rate of roughly 19%. Consequently, it justifies further thought and inquiry. Ansary (2013). Furthermore, recent studies have abundantly highlighted the Egyptian stock market's inefficiency and revealed that it is characterized by noisy and speculative trading. (Omran 2007 and Ansary 2012)

The goal of the study is to improve our understanding of the physiological

factors that affect how private and public information relates to market return and overall market turnover. More specifically, it will look into the extent to which market returns lead to overconfidence among inventors, which in turn influences the level of market turnover generally.

The study is based on time series analysis and uses secondary data from the Egyptian Stock Market for the last eleven years (2002–2012). The stated hypothesis and research questions are tested using a number of statistical techniques, including Granger Causality testing, Impulse Response Function, Vector auto regression, and optimal lag selection.

It offers a broad framework for understanding the relationship between the factors examined inside the Egyptian Stock Market. More crucially, the framework offered determines the strength, direction, and lead-lag relationship between all variables investigated.

## 2. RESEARCH FOCUS

In general, the Egyptian Stock Market, is considered one of the growing emerging markets, has always been investigated from the traditional finance perspective. Recent research shows that the Egyptian Stock Market exhibits market inefficiencies and noisy trading activity (Ansary & Khan, 2012). As a result, the main objective of this study is to analyze the trading patterns on the Egyptian Stock Market from the perspective of behavioral finance. It attempts to investigate how overconfident investors are impacted by both private and public information and how this impacts the general trading behavior on the Egyptian market.

## 3. RESEARCH AIM

the research aims to gain a knowledge of the overall Egyptian Stock Market Through the use of behavioral finance principles. It will primarily examine how overconfident investors behave on the Egyptian Stock Market in response to public and private information. The methodology is focused on looking at how market return and turnover interact with two other control variables, volatility and dispersion. Numerous research takes the stance that the high trading volume seen in the financial markets is caused by investors' overconfidence. Overconfident investors trade more than rational investors because they overestimate their own talents, claim DeBondt and Thaler (1995), Odean (1998a,

1998b, 1999), Gervais and Odean (2001), Barbaris and Thaler (2003), and Theorly and Vorkink (2006). (Gervais and Odean 2011).

The overconfidence theory has two main hypotheses that need to be tested:

first: private and public information affects the turnover of the Egyptian stock market second is that biased self-attribution causes the degree of overconfidence to vary depending on    various market outcomes and states.

## 4. LITERATURE REVIEW :FROM TRADITIONAL TO BEHAVIORAL FINANCE

### 4.1 Traditional Finance

Behavioral finance has been used to explain a variety of market phenomena such as the disposition effect and the equity premium puzzle. Additionally, it has been used to develop new investment strategies such as momentum investing and contrarian investing. These strategies have been found to be effective in generating higher returns than traditional strategies. However, many of these theories have been challenged due to their inability to explain the actual behavior of financial markets and their players. As a result, behavioral finance has emerged as an alternative to traditional finance theories. Behavioral finance is based on the assumption that investors are not always rational and often make decisions based on psychological factors such as emotions, cognitive biases, and heuristics.

overall, behavioral finance has become an important field of study in finance, providing a more realistic and comprehensive view of financial markets and its players. By understanding the psychological factors that influence financial decisions, investors and financial advisors can make more informed decisions that are better aligned with their goals. investors who are more behaviorally aware and who incorporate behavioral finance into their investment decisions may be able to improve their overall performance in the field of finance investors who had a better understanding of the psychological biases that can affect their financial decisions were more likely to make better decisions and to achieve higher returns. investors who were more behaviorally aware were more likely to take into account the long-term implications of their decisions and to be more disciplined in their investing Kumar (2018). decision-making is crucial, and there are other disciplines. Decision-making is common in fields including sociology, mathematics, economics, political science, and statistics (Kahneman & Tversky,

2013). By linking the utility value of their replacements, predicted utility theory divides decision-making into two categories: risky and uncertain vision (Kahneman & Tversky, 1979). The decision-makers are categorized as "risk averse," "risk taker," and "risk neutral" organizations in the future. As was already mentioned, the fundamental tenet of classical finance is that agents are rational and markets are efficient. Observing high trading volume is viewed as puzzling in such an ideal world, where investors are rational investors and markets are efficient. In a world with perfect rationality, Statman (2003) contends that it would be highly challenging to justify any trading activity. Milgrom and Stokey (1982) and Grossman (1976) observe that an Offers to trade serve as a warning to potential adversaries that the trader could possess sensitive information. Trading volume is equal to zero as a result of rational traders' refusal to trade in such circumstances. To escape the no-trading trap, Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990) introduce the function of liquidity traders, although this remedy is insufficient. Subrahmanyam (1991) goes on to demonstrate that sensible liquidity traders only trade baskets of assets and stay away from trading individual securities. However, as the pricing of baskets depends on the pricing of the underlying securities, baskets of securities cannot be traded without individual stocks first being traded. Statman (2003).

## 4.2 Trading Volume and Traditional Finance

As previously mentioned, the basic paradigm in traditional finance is based on the assumption that agents are rational and markets are efficient. In such an ideal world, where investors are rational investors and markets are efficient, observing high trading volume is considered a puzzle. rational investors tend to take advantage of market opportunities and increase their trading volume when stock prices are low and decrease it when prices are high. Statman (2003) argues that in a perfectly rational world, it is very difficult to explain why any trading activity takes place. Grossman (1976) and Milgrom and Stokey (1982) note that an offer to trade indicates to other counter parties that the trader might have private information. Rational traders refuse to trade under such conditions, and accordingly trading volume is equal to zero.

 liquidity trading is an important factor for rational investors when making decisions about their portfolio allocations. it is associated with higher returns and lower risk, and that it is especially beneficial for investors with short investment

horizons. liquidity trading can be used to reduce the impact of market fluctuations, providing a more stable portfolio. liquidity trading can be a valuable tool for rational investors to improve their portfolios Ben-David (2020).

Kyle (1985), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990) introduce the role of liquidity traders to get out of the no-trading trap, the trading trap meaning is that investors should be aware of the potential dangers of trading in the markets. They should take the time to understand the risks associated with trading and develop a plan to manage those risks. They should also be wary of any advice or strategies that promise quick and easy profits. Finally, investors should be sure to diversify their investments and use stop-loss orders to limit their losses. but this solution is incomplete. Later, Subrahmanyam (1991) shows that rational liquidity traders trade only baskets of securities, avoiding trades in individual securities. But baskets of securities cannot be traded unless individual securities are traded, since pricing of baskets requires pricing of the underlying securities. Statman (2003). Then, Harris and Raviv (1993) and Shalen (1993) attempt to overcome the no-trading equilibrium through traders who differ in their assessment of common information. However, it is still unclear why rational traders would differ in their interpretation of common information Statman (2003).

### 4.3 BEHAVIORAL FINANCE

Behavioral finance is a new paradigm that sheds light on the psychological aspects that influence how investors make financial decisions. The new field thus tries to understand financial occurrences that previous models were unable to assess. "The goal of behavioral finance is to clarify and deepen our understanding of investors' thought processes, including the emotional process involved and the extent to which they influence the decision-making process," state Riccardi and Simon (2000) in their definition of the field. Essentially, behavioral finance aims to provide a human perspective explanation of the what, why, and how of finance and investing.

The development of behavioral finance began in the 1980s after R. Thaler (1980) analyzed economic theories that examine how consumers choose their purchases. Economic theory, according to R. Thaler (R. Thaler, 1980), is a synthesis of normative and positive theories and is based on the "rational maximization model. Consumers make logical selections based on their interests using the

information available in the market to inform their purchasing decisions. To support BF in the mainstream, mainly in academia, a number of studies in the topic have been carried out. (Duxbury, 2015) claims that academics' attention has shifted from using econometric analysis to analyze time series data to behavioral theories that examine how human psychology affects the financial markets. The "National Bureau of Economic Research Conference" was subsequently founded in 1991 by Thaler and Shiller. putting behavioral finance in the foreground. The study of behavioral finance, which was developed during the psychological revolution in the 1990s, focuses on how human emotions affect financial decision-making (Hong, 2007; Miaszewicz, 2019). Faulkner, (2002) The emergence of behavioral finance and the development of psychological theories have contributed to a better understanding of the influences of behaviour on financial decision-making (Dhankar 2018; Mushinada, 2020). (Zahera, 2018). In the field of behavioural finance, human error is identified as the root source of the irregularities, (Jensen, 1978). De Bondt and Thaler (1985). behavioral finance has the potential to provide insights into investor decision making and financial markets that traditional finance theories cannot explain. This is due to the fact that behavioral finance takes into account the psychological and cognitive biases that can affect investor decisions, which traditional finance theories do not account for. Furthermore, behavioral finance can be used to inform investment strategies and to better understand financial markets. the importance of understanding investor preferences and behavior when making investment decisions. By taking into account the psychological and cognitive biases of investors, it is possible to gain an insight into how they may react to certain situations, thus allowing for more informed decision making. Additionally, the paper suggests that behavioral finance can be used to improve portfolio management strategies, as well as to better understand financial markets. It is important to understand investor preferences and behavior when making investment decision

By taking into account the psychological and cognitive biases of investors, it is possible to gain an insight into how they may react to certain situations, thus allowing for more informed decision making. Additionally, the paper suggests that behavioral finance can be used to improve portfolio management strategies, as well as to better understand financial markets. investors do not always make rational decisions due to cognitive biases, emotions, and other factors. Investors

often make decisions that are inconsistent with traditional financial theory, leading to suboptimal outcomes. investors' decisions are often affected by their personal preferences, such as their need for control or risk aversion. Additionally, investors tend to be overconfident and may take excessive risks or fail to diversify their portfolios. These findings suggest that investors should be aware of their own biases and strive to make decisions that are consistent with traditional financial theory (J. 2020).

According to Pembina's definition from 2007, "Cognitive psychology is the scientific study of cognition, or the mental processes thought to be responsible for regulating human behavior. Memory, attention, perception, knowledge representation, reasoning, creativity, and problem-solving are some of the areas of study in cognitive psychology. The cognitive psychology first appears in the late 1950s and early 1960s, but it doesn't really take off until 1958, when Donald Broadbent published his book "Perception and Communication." A cognitive psychology model of information processing was first presented by Broadbent. The model models mental processing using computer software (brain). Broadbent asserts that the concepts of input, representation, computation, and output are used to characterize human cognition. In the meantime, from the standpoint of preferences, investors may produce distortions when they assess risky bets because of emotional biases, like regret and loss aversion. The greatest hypothesis to explain the prevalence, reasons for, and consequences of human errors (preferences) that happen when making decisions in uncertain circumstances is the prospect theory put forth by Kahneman and Tversky in 1979.

## 4.4 COGNITIVE PSYCHOLOGY

Supporters of behavioral finance believe that cognitive psychology is the primary source of the emerging discipline. The two pillars of the behavioral finance discipline are cognitive psychology and arbitrage-related constraints. Thaler and Barbaris (2002).

cognitive psychology and behavioral finance have a significant impact on the financial decision-making process. Cognitive psychology and behavioral finance can help investors better understand the psychological and behavioral factors that influence their decisions, enabling them to make more informed decisions. Additionally, cognitive psychology and behavioral finance can help investors

identify and manage their biases and emotions, leading to more successful investments. Furthermore, cognitive psychology and behavioral finance can provide investors with a better understanding of the market environment, allowing them to take advantage of opportunities and avoid potential pitfalls. Finally, cognitive psychology and behavioral finance can help investors develop an investment strategy that is tailored to their individual needs and goals.

Cognitive psychology and behavioral finance are two interrelated fields of study that are gaining traction in the world of finance. Cognitive psychology focuses on how people think, make decisions, and perceive the world around them. Behavioral finance, on the other hand, looks at how people make decisions about investments, how they respond to market conditions, and how their biases and emotions influence their decision-making. Research in these two fields has shown that people are often irrational when it comes to making financial decisions, and that their biases and emotions can lead to poor investment outcomes. This has significant implications for financial advisors, investors, and policymakers, as it highlights the need for more effective ways to help people make better financial decisions. Overall, cognitive psychology and behavioral finance are two interrelated fields of study that are gaining traction in the world of finance. Research in these fields has shown that people are often irrational when it comes to making financial decisions, and that their biases and emotions can lead to poor investment outcomes. This has significant implications for financial advisors, investors, and policymakers, as it highlights the need for more effective ways to help people make better financial decisions Lai, K. (2020).

Unfortunately, Khaneman and Tverseky (1974) claimed that most people stray from this suggested systematic approach, become more subjective, use less ideal paths of reasoning, and choose the course of action that is consistent with their fundamental beliefs and preferences when metal processing is directly related to decision making under uncertainty. According to the authors, people are prone to "cognitive illusions" like thinking they can make it wealthy and famous or leave the market before a bubble bursts. As a result, when assessing their abilities, people exaggerate, and when making decisions, they downplay the influence of luck.

Cognitive psychology, according to Barabais and Thaler (2002), enables us to understand the systematic biases and errors that people make when developing

their ideas and preferences. People tend to use heuristics to make decisions easier, to be overconfident, to place too much weight on recent experience (representativeness), to separate decisions that should be combined, to present various issues incorrectly (framing), to take their time choosing chances, and more, according to the beliefs perspective, which examines how agents form their judgements and expectations (conservatism). While this is going on, investors may make errors in their assessments of risky bets due to emotional biases like regret and loss aversion.

## 4.5 PROSPECT THEORY

Prospect theory, which was developed by Amos Tverskey and Daniel Khaneman, is regarded as the conceptual cornerstone of behavioral finance (1979). Li et al. (2020) found that Prospect Theory have generally concluded that it is a useful and effective tool for understanding decision-making processes under uncertainty. It has been found to have a strong predictive power in many domains, including financial decision-making, risk assessment, and consumer choice. Additionally, the theory has been used to explain the behavior of investors, decision makers, and policy makers. In particular, the theory has been used to explain the behavior of investors during periods of market volatility and to inform policy decisions. Prospect Theory may also be useful in understanding the behavior of individuals in other contexts, such as health and environmental decision-making. investors tend to exhibit a preference for certain types of investments over others, such as those with higher expected returns or those with lower risk. Additionally, investors have been found to be more likely to invest in assets that have a higher potential for gains compared to those with a higher potential for losses. Prospect Theory has also been used to explain the behavior of investors in situations where they are faced with uncertainty or risk, as they tend to be more risk-averse in these situations. This behavior is often referred to as the 'risk-averse' effect. Finally, Prospect Theory has been used to explain how investors tend to be more likely to invest in assets that are familiar to them, as familiarity can provide a sense of comfort and security.

The theory is predicated on the idea that people's intuitive predictions and judgements under uncertainty do not adhere to the statistical principles or the law of probability. In other words, prospect theory serves as a stronger descriptive model of decision-making under uncertainty than expected utility

theory. The certainty effect and the isolation effect are both the foundations of the hypothesis. The latter relates with the inconsistent preferences people display when the same choice is presented in various contexts and ways, whereas the former leads to risk aversion in situations where certain benefits are guaranteed and risk seeking in situations where certain losses are guaranteed.

The idea is supported by both the certainty effect and the isolation effect. The former causes risk aversion when certain advantages are guaranteed and risk seeking when certain losses are guaranteed, whereas the latter is related to the inconsistent preferences people exhibit when the same choice is offered in different circumstances and ways.

## 5. behavioral biases

### 5.1 Overconfidence in Psychology

The 1960s was the first mention of the overconfidence effect in psychological literature. A few decades later, economists started to explore the effects of overconfidence and combine psychological studies into economic models, particularly in the areas of corporate finance and financial markets (see Skala, 2008; Malmendier and Tate, 2015; Daniel and Hirshleifer, 2015).

psychology on overconfidence generally finds that overconfidence can have both positive and negative effects depending on the situation. Positive effects include increased motivation and performance, while negative effects include difficulty adjusting to feedback and difficulty making accurate decisions. overconfidence in psychology suggests that overconfidence is a pervasive phenomenon in economic decision-making. It is a cognitive bias that leads people to overestimate their own abilities and underestimate the complexity of the task at hand. This bias can lead to poor decision-making and can have serious economic consequences K.D. (2016).

A lot of authors ceased using explicit measures of overconfidence in favor of a range of proxies for overconfidence and indirect measurements after influential research in this area indicated that overconfidence leads to excessive investment, trading, or innovation (Heaton, 2002). Hayward and Hambrick (1997), Adebambo and Yan (2016), Jouber (2013), Park and Chung (2017), Verberne (2010), Jouber (2013), Malmendier and Tate (2005), Park and Chung (2017), and Wong (2017). Some of them went so far as to substitute excessive investment or trading for overconfidence rather than assessing it (e.g. Chuang and Lee, 2006;

Hwang et al., 2014; Khajavi and Dehghani, 2016; Liu et al., 2016; Zia et al., 2017; Gupta and others ( 2018) In addition, concepts like optimism or the illusion of control that are similar to overconfidence started to be linked to it and occasionally confused with it (e.g. Lowe and Ziedonis, 2001; Hackbarth, 2008; Cassar, 2010; Han et al., (2015); Hilary et al (2016). Due to the varied operationalization of overconfidence, which produced some contradicting results, it was challenging to combine the data about the effect of overconfidence on financial decision-making. (Material analysis essay)

Investors who attribute past success to ability and past failure to luck are inclined to be overconfident. An overconfident investor will try to maximize returns by using what they believe to be their superior skills.

## 5.2 Overconfidence in Finance

Psychological research was originally included into economic models by economists in the 1970s, but the practice truly took off in the 1990s. Since that time, economists have been interested in the subject of overconfidence, especially as it relates to how people act on financial markets. Overestimating one's knowledge, accuracy, or capacity to comprehend sensitive information is commonly understood to be the definition of overconfidence. Alternately, a signal variance underestimation or asset value volatility is also considered. Some financial market riddles that had previously defied traditional economic theory might be effectively explained once overconfidence among investors was assumed. The disposition effect, or the tendency to sell winning stocks while hanging onto losing ones, excessive trading, and continuous undervaluation of securities are the main causes of these issues. An ongoing debate on the well-established notion of efficient markets and economic agent rationality was sparked by the possibility for overconfidence on the markets and its endurance over time. The ubiquity of overconfidence on financial markets has been frequently demonstrated, using techniques ranging from experimental and questionnaire studies to formal models and financial market data, despite considerable skepticism among economists regarding its existence and effect as such. overconfident investors tend to trade more often than necessary, take on more risk, and are less likely to diversify their portfolios. They are also more likely to overestimate their own knowledge and ability to predict future stock prices and market movements. This can lead to investors making decisions that

are not in their best interest, leading to losses in the long run. While overconfidence can be beneficial in some situations, it is important to recognize its potential risks and to be aware of the potential consequences of overconfidence in finance. overconfidence in finance has a significant effect on the behavior of investors and on economic outcomes. For example, a study published in the Journal of Financial Economics in 2020 found that overconfident investors tend to trade more often, leading to higher transaction costs and lower returns. Other research has found that overconfident investors are more likely to take on greater risk and to be over-exposed to certain asset classes. Furthermore, overconfident investors are more likely to overestimate their own abilities and make more mistakes in their decisions. These mistakes can lead to misallocation of resources, increased volatility, and reduced economic efficiency. Finally, overconfident investors are more likely to engage in market manipulation, which can lead to market inefficiencies and misallocation of resources. overconfidence and behavioral finance models have generally found that overconfidence leads to increased trading activity, higher trading costs, and lower returns on investments. Additionally, overconfidence has been found to lead to an increased likelihood of trading errors, such as the disposition effect, where investors tend to sell winning investments too quickly and hold onto losing investments for too long. Overconfidence has also been linked to an increase in the likelihood of taking excessive risks and making poor investment decisions. As such, it is important for investors to be aware of their own biases and to make informed decisions based on sound financial principles.

## 5.3 Overconfidence and Behavioral Finance Models

overconfidence can have a significant impact on financial decision-making. This has led to the development of several behavioral finance models to help investors better understand and manage their own overconfidence. These models suggest that investors should be aware of their own biases and use techniques such as diversification and portfolio rebalancing to reduce the potential for overconfidence-related errors. Additionally, investors should be aware of the potential for overconfidence to negatively impact their investment decisions and take steps to mitigate this risk. In the majority of the proposed behavioral finance models, overconfidence is frequently interpreted as investors overestimating the accuracy of their information (or, more specifically, overestimating private signals and underestimating the public ones) and/or investors underestimating

risk, causing them to, for example, hold riskier portfolios. In order to ascertain how overconfident investors, affect the financial markets, it is necessary to take into account the likelihood of such overconfidence. These effects materialize in market anomalies, including large trade volumes, lucrative trading, short- and long-term asset devaluations, and stock returns.

## 5.4 Overconfidence and Trading Volume

According to Odean (1998), traders exhibit the better-than-average effect, judging their information to be superior to that of their colleagues. overconfidence can lead to higher trading volume, particularly in the short-term. This is because overconfident investors tend to overestimate their ability to predict future stock prices, leading them to trade more frequently. In addition, that overconfident investors are more likely to engage in speculative trading, which can also lead to higher trading volume. overconfidence can lead to increased trading costs due to the frequent trading, which can reduce returns for investors R. W. (2014).

t is also believed that insiders and market makers unwittingly overestimate the reliability of their knowledge and rely on it excessively. Participants in the market who are so overconfident boost trade volume. In his model of an auction market with experienced traders, Benos (1998) demonstrated the similar effects, whereby again the participation of risk-neutral investors overestimating the veracity of their information leads in a rise in trading volume. Excessive trading and a spike in trade volume are the outcomes of overconfidence. The idea that overconfidence plays a crucial role in understanding why people engage in excessive trading was first put out by De Bondt and Thaler in 1995. "The fundamental behavioral factor needed to understand the trading puzzle," they claimed, is overconfidence." Overconfident investors trade more than rational investors, which lowers their expected utility as a result of overconfidence (Odean, 1998)

## 5.5 Overconfidence and Learning Bias

On the contrary side, Gravis and Odean (2001) offer a model that explains how traders discover their skill as well as how learning bias can lead to overconfident traders. They contend that a trader is more likely to exhibit overconfidence when he or she is novice and having success in the beginning stages of their investment careers, but an experienced trader can engage in self-evaluation. The Gervais and

Odean model also assert, as in Odean (1998b), that expected trading volume and volatility rise in proportion to the extent of a trader's learning bias. Financial literacy, according to Yang et al. (2021; Garg & Singh, 2018), is the understanding of financial ideas, products, and skills necessary to make wise financial decisions. Financial literacy, as defined by Raut et al. (2020), is the capacity to comprehend financial issues as well as knowledge and awareness of financial tools and their applications in both professional and personal settings. People with high financial literacy are predicted to be able to make wise financial decisions so that the outcomes will likewise be wise (Gerrans & Heaney, (2019); Goyal & Kumar, (2021) because understanding financial literacy is a significant behavioral antecedent. Shah and Ahmad (2022). High financial literacy allows an investor to make wise financial decisions and comprehend how those actions affect him, others, and the environment Baker et al (2019); Lusardi, (2019). This is due to the fact that those who have a high degree of financial literacy would typically be more cautious when allocating and using their investment funds (Nguyen & Rozsa, (2019); Warmath & Zimmerman (2019); Abad-Segura & González-Zamar, (2019); Mitchell, (2020). In the past, Karakurum-Ozdemir et al. (2019); Kadoya & Khan, (2020); Strömbäck et al; (2017) have performed research. have discovered a favorable correlation between financial literacy and financial behavior, including investment decisions. These findings suggest that investors behave better in terms of money management the more financially literate they are. They will behave better financially as a result, and they will feel more secure financially in their own minds. Overconfidence and Trading Return DHS Model Daniel et al. (1998) in their model also demonstrate that overconfident informed investors are loss-making, on average, but indicate that profits of overconfident traders can in some cases exceed profits of rational investors, and indeed Daniel et al. (2001) make such an assumption trough a simple model that explicitly distinguishes between tangible and intangible information. They show that stock prices overreact to intangible information rather than tangible information and conclude that their findings are consistent with the psychology literature suggesting that individuals react differently to information that is difficult to interpret.

## 5.6 Overconfidence and Trading Return DHS Model

investors should be aware of their own behavioral biases and be mindful of the potential consequences of overconfidence in their trading decisions.

Overconfidence can lead to excessive trading, which can have a negative effect on overall trading returns. Investors should be aware of the potential pitfalls of overconfidence and strive to maintain a balanced approach to trading and investing. Additionally, investors should consider diversifying their portfolios to reduce the risk of overconfidence leading to poor trading decisions., and be aware of their own emotions and biases when making trading decisions, as these can have a significant impact on trading returns Sengmueller et al (2020).Daniel et al. (1998) similarly demonstrate that overconfident informed investors lose money on average, but they also make the case that overconfident traders might occasionally outperform overconfident investors in terms of profits. This premise is supported by Daniel et al. (2001), who provide a simple model that explicitly distinguishes between tangible and ethereal information. By showing that stock prices overreact to ethereal information rather than physical information, they come to the conclusion that their findings are congruent with psychology literature that maintains that people react differently to information that is difficult to interpret.

## 5.7 OVERCONFIDENCE AND PUBLIC AND PRIVATE INFORMATION

Daniel et al. (1998) provides a complex model of investor overconfidence and skewed self-attribution in which security market under- and overreactions happen in response to, respectively, public and private signals. Such overconfidence effects imply higher stock return volatility and long-term negative autocorrelation. The study by Daniel et al. (1998) also accounts for overconfidence that changes over time. Similar to Gervais and Odean, confidence in the model varies when the overconfidence effect and a self-attribution bias are present. Investor confidence increases after receiving confirmation of earlier private signals. However, investor confidence changes very little, if at all, if previously unconfirmed private information turns out to be accurate. This causes a short-term upward trend in security prices (an overreaction), which is ultimately reversed as new information becomes available to the public and causes the stock price to adjust back towards its fundamentals.

overconfidence can lead to both positive and negative outcomes depending on the context. Studies have found that overconfidence in public information can lead to better decision making, as people are more likely to take risks and make bolder decisions. On the other hand, overconfidence in private information can

lead to poor decision making, as people are more likely to overestimate their own abilities Investors are often subject to overconfidence bias, which can lead them to overestimate the accuracy of their predictions and the value of their investments. This can be exacerbated by the availability of public and private information, which can be used to make overly optimistic predictions. Studies have shown that investors tend to overestimate the accuracy of their predictions and underestimate the risk associated with their investments, leading to poor decision-making and suboptimal investment outcomes (Chen et al. (2020); Grinblatt et al. (2019). This suggests that investors should be aware of the potential biases associated with overconfidence and the potential risks associated with relying on public and private information. Overall, the evidence suggests that overconfidence can be beneficial in some contexts, such as when making decisions based on public information, but can be detrimental in other contexts, such as when making decisions based on private information. Therefore, it is important to recognize the potential benefits and drawbacks of overconfidence when making decisions.

The relationship between overconfidence and volatility surrounding public and private signals and the evaluation of stocks has also been modelled. Daniel et al. provide an asset pricing model with overconfidence that results in an equilibrium mispricing of securities (2001). Arbitrage allows some rational market participants to profit from pricing errors, but risk aversion keeps them from being totally eradicated. The model looks into how risk and incorrect investor assumptions impact anticipated future returns on assets. Unlike the previous inter-temporal model, in order to jointly show the impact of risk aversion, various hazardous assets, and arbitrageurs, Daniel et al. (2001) only analyse static overconfidence in a single time. We employ dispersion, which is the mean return for each stock, in order to capture this unique risk for each individual security. We then multiply the corresponding market-capitalization weights to produce disp series, which represents the cross-sectional volatility of specific firms within EGX on a monthly basis. To account for probable trading activity related to portfolio rebalancing, we first computed squared deviation from Statman (2006) and incorporated return dispersion as a control variable. This was done in the manner of Campbell and Lettau (1999). Large spreads between individual stock returns, for instance, may encourage investor trading, so indicating the degree of private knowledge.

## 5.8 Overconfidence in Developing Financial Market

The overconfidence in developing financial markets can lead to excessive risk taking, which can lead to significant losses for investors. The lack of reliable information and the complexity of the financial markets can also contribute to overconfidence. This can lead to investors taking risks that they may not understand fully or may not be able to afford. Furthermore, the lack of transparency in some markets can lead to investors taking on more risk than they are aware of. Finally, the lack of regulation in some markets can lead to investors taking on more risk than they can handle. investors should be aware that overconfidence in developing financial markets can lead to poor investment decisions and may result in significant financial losses. Investors should also be aware of the potential for large swings in market prices, as well as the potential for fraud or other risks. Additionally, investors should be mindful of the lack of transparency in developing markets, which can increase the risk of mispricing or manipulation. Finally, investors should seek professional advice before making any investment decisions in developing markets.

The overconfidence bias in the Tunisian and Chinese financial markets is studied by Ziane (2013). Overconfidence bias is known to exist in both markets, albeit Tunisia has less proof than China. Additionally, trade activity in the two markets under examination over a few months is influenced by previous market results. Volatility and volume have a strong, current positive relationship that is documented.

Additionally, the research demonstrate that stock returns may be predicted based on lag volume, which is another breach of market efficiency (Karpoff, 1987; Gallant et al., 1992; Zhao and Wang, 2003; Wang and Huang 2012). The overconfidence of investors in the Pakistani stock market is the subject of two empirical investigations. Fayaz and Riaz's (2012) study aim to determine whether overconfident investors engage in more aggressive trading. They make the assumption that because turnover is positively correlated with historical returns, overconfidence is caused by poor performance in the past. Additionally, they propose that excessively confident investors' trading increases return volatility. Market information from the Karachi Stock Exchange (KSE) for the years November 1999 to October 2010 is used in the research.

After adjusting for concurrent and lag return dispersion and return volatility, the

study finds a strong positive response of turnover to market return shock. This answer persisted for a considerable amount of time. Results thus support the existence of excessive investor trust at KSE. The study discovers a large, simultaneous positive association between turnover and returns volatility, which is in line with earlier research. Investors respond to cross-sectional swings in share prices by rebalancing their portfolios every two months in order to reduce unsystematic risk. The stringent market efficiency hypothesis, which has previously been asserted in developing financial markets like China and Tunisia, is violated by the predictability of returns based on prior turnover in the VAR and its accompanying impulse response function analysis. Tariq and Ulla give the second study on the Pakistan stock market (2013). The study's findings showed that yesterday's turnover was influenced by previous day's returns, suggesting that Pakistani investors are overconfident as a result of monitoring security returns. This could result in irrational choices being made, which would result in losses. Despite the rapid turnover, the impulse response function suggests that returns are reverting to zero. Investors will lose money as a result, and the market will correct.

## 6. THE EGYPTIAN STOCK MARKETS

The Alexandria Stock Exchange was founded in 1888, while the Cairo Stock Exchange was founded in 1903. The Egyptian stock market is one of the oldest in the world, and it consists of two exchanges that have recently been linked so that investors can access stocks listed on both of them. Prior to the nationalization of industry and the adoption of central planning policies in the early 1950s, In the 1940s, when industry was nationalized and central planning programmed were put into place, it had the fifth-highest trading volume worldwide. The market remained largely dormant during the 1980s as a result of the drastic reduction in market activity brought on by these regulations. The market started to rebound in the 1990s after 40 years of stagnation, and ever since then, it has been considered as the Middle East and North Africa's top capital market that best serves its stakeholders (Mecagni & Sourial, 1999). The Egyptian Market was named the second-best developing stock market in Africa in 2009. (The Egyptian stock exchange, 2010). Furthermore, it took first place in the 2008 New York Stock Market award for best stock exchange in Africa. The Egyptian Stock Market's is still facing a number of challenges, including a lack of liquidity, low

investor confidence, and a limited number of tradable securities. Despite these issues, the market is expected to remain resilient due to strong fundamentals, such as a young and growing population, a diversified economy, and a large and growing domestic savings rate. There is noticed increase in potential for foreign investment in the coming years, as well as the market needs for improving corporate governance, transparency, and market infrastructure. El-Gohayr (2016).

## 7. MARKET PLAYERS WITHIN THE EGYPTIAN STOCK MARKET

the variety of investors who participate in the Egyptian stock market. Sakr et al. provide evidence of the prevalence of retail investors in the Egyptian market (2014). Their analysis shows that retail investment increased to 66% in 2008. The market's high percentage of retail investors reveals several important facts about it, showing that it is more prone to psychological distortions than other markets. Ansary and Ateua (2012) claim that between 2004 and 2009, retail investors' share of the total value transacted increased steadily. This demonstrates how a sizable amount of market transactions are controlled by retail investors, who consequently have a significant impact on the market's behavior as a whole.

## 8. THE EGYPTIAN STOCK MARKET TRADING BEHAVIOR

Habib looked in his study at the empirical relationships between stock return and trading volume in the Egyptian stock market. The study uses data from The Egyptian Stock Exchange for 26 securities between 1998 and 2005 to show numerous regularities about the role of trading volume in predicting the volatility of stock return and return itself. The major finding is that lagged stock trading has minimal bearing on predicting the volatility of future return. The predictability of returns is the subject of the paper's second finding. Third, a bidirectional causal relationship between volume and volatility is revealed by the Granger causality tests. Particularly, Changes in return volatility always follow changes in trading volume, and vice versa. But there is no proof of a causal relationship between stock return and volume, according to the study. Egyptian stock market is characterized by low liquidity, high volatility, and low efficiency. Additionally, the market is found to be driven by a few large investors and subject to significant information asymmetry. The market is also found to be sensitive to global economic and political events, and is subject to manipulation. market has limited potential for long-term investment and requires further

development in order to become more attractive to investors. the impact of macroeconomic events. Studies have found that the Egyptian stock market is characterized by high volatility and low liquidity, and that liquidity is further reduced during periods of macroeconomic uncertainty. The market is also highly concentrated, with a few large investors dominating trading activity. Additionally, the market has been found to be inefficient, with investors exhibiting a tendency to overreact to news and underreact to long-term fundamentals. Finally, the market has been found to be relatively resilient to shocks, with trading activity quickly returning to normal levels following major macroeconomic events El-Sobky (2019). Anasary and Attuea (2012) examined the relationship between trading volume and stock return in a different study. The study looks at the pattern of information arrival at the Egyptian Stock Exchange. The sample covered the years 2001 to 2010 and comprised 26 securities from the 30 companies that were listed on the EGX. The study makes a number of surprising discoveries, including a relationship between trading volume and return that is favorable (using the logarithms of turnover ratio and transaction number as measures of trading volume), a weak but highly significant contemporaneous relationship between trading volume and return (using both measures), and evidence of noise traders in the market. The study's findings and those of Omran and Girard (2007). Additionally, a negative lagged relationship between trading volume (using both measures) and return was discovered using lag times of two and five days. This resulted in the finding that rising (falling) trading volume in the preceding two and five days was accompanied by rising (falling) return, and vice versa. This result shows how the Egyptian security market is different from other emerging and developed markets, and it goes against the findings of past studies. Additionally, they claim that persistence and clustering are characteristics of return in the Egyptian security market, providing proof that the market is informationally inefficient. Most recently, a study by Abdeldayem and Mahmoud (2013) investigates the impact of trading motives on the dynamic relationship between stock returns and trading volume in Egypt by using the daily trading information for all 167 listed equities traded on the Egyptian Exchange (EGX) for a six-year period, from January 2006 to December 2011. According to the study, speculative trade predominates in developing economies and is linked to positive serial autocorrelation in stock returns. More specifically, the study discovers that the Egyptian Exchange (EGX) has a positive

serial autocorrelation that is common; 83% of our sample has positive serial autocorrelations, and 60% of the sample has strong positive autocorrelations. This result is in line with the literature since emerging countries tend to have more market anomalies and because the Egyptian stock market.

## 9. DATA

This study data covers the period form the January 2002 up to December 2012. The data set consists of two main data samples:

A) Daily based Data.

- Daily stocks opening prices
- Daily records for EGX30 index return points
- Daily market trading value
- Daily market trading volume
- Daily stocks closing data

B) Monthly based Date

- Monthly value capitalization
- Monthly volume of traded shares
- Monthly market of traded shares
- Monthly number of markets listed shares

The study focuses on monthly observations under the perspective that changes in investor overconfidence occur over monthly or annual horizons (Odean, 1998; Gervais and Odean, 2001; Statman, Thorley and Vorkink, 2006).

Data is divided divided four sub periods; two tranquil periods and two volatile periods. The sub periods are:

Table 1

| Tranquil periods | Volatile periods |
|---|---|
| 2002 – 2004 | 2008 – 2010 |
| 2005 – 2007 | 2011- 2012 |

These sub periods are used to compare the obtained results in different market states.

## Dependent Variable

Market turnover, mturnt, is the month t Market turnover expressed in percentage points. According to Lo and Wang (2000), turnover can be calculated by dividing monthly traded shares by the number of outstanding shares.

## Independent Variable

*Monthly Market return, mrett, is the month t return According to Sheikh et al. (2012), the returns of the EGX 30 are used as proxies for the overall Egyptian stock market return in this study. The index return is calculated as the difference between the natural log of the index's ending value on a daily and monthly basis.*

$$R_t = L_n(P_t) \quad L_n(P_{t-1}) = L_n(P_t/P_{t-1})$$

Hence, the Rt is market return for period t, Pt is current period closing value of index and Pt-1 is previous period closing value of the index.

To test for the private and public information two control variables are added:

Two Control Variables: As by Staman (2006), the inclusion of two exogenous variables is to control for other explanations of the trading volume/ value behavior,

- Market Volatility: Market volatility (misg), as defined by Statman (2006), is the monthly volatility of market returns for the value weight composite of all EGX common shares, measured in percentage points. The volatility, like the mean absolute deviation (MAD) metric in Bessembinder, Chan, and Seguin's trading volume study, is based on Karpoff's (1987) survey of studies on the contemporaneous volume volatility relationship (1996). Monthly realized volatility estimates, according to French, Schwert, and Stambaugh, are based on daily market returns within the month and account for realized autocorrelation (1987). This is how volatility is calculated.:

$$misg_t = \sum_{i=1}^{N} r_i^2 + 2\sum_{i=1}^{N-1} r_i r_{i+1} \qquad (2)$$

- Market Dispersion: The addition of the second control variable, dispersion, was inspired by Campbell and Lettau's (1999) working paper, which evaluates volatility not only at the market level but also takes firm-specific influence

into account. To represent this unique risk for each investment, we use dispersion, which is the cross-sectional volatility of individual enterprises within EGX on a monthly basis. We first compute the squared deviation from the mean return for each stock in accordance with Campbell and Lettau (1999), and then multiply the relevant market-capitalization weights to obtain the disp series. portfolio rebalancing

Statman (2006) used return dispersion as a control variable to account for anticipated trading activity related to for example, large differences in individual stock returns may encourage investor trading, represents the level of private information.

$$disp_t = \sqrt{\sum_{i=1}^{N} w_i (r_i - \bar{r})^2} \qquad (3)$$

## 10. RESEARCH HYPOTHESIS

H1:  *Overconfident investors overreact to private information and underreact to public information.*

H2:  *investors become more overconfident, overestimate private information, and trade more aggressively in subsequent periods.*

## 11. TESTING DATA

### 11.1 Normality Testing

A data collection should have a normal distribution or be well modelled by one. As the normality test results for the dimensions under consideration are shown in the table below, all of the dimensions are found to be normal with P-values > 0.05, meaning that the normality hypothesis is accepted.

## *Normality Testing*

### Table: 2

|  | Kolmogorov-Smirnov[a] | | |
|  | Statistic | Df | Sig. |
|---|---|---|---|
| Value | .182 | 12 | .200[*] |
| Volume | .237 | 12 | .061 |
| Return | .151 | 12 | .200[*] |

## 11.2 Unit Root Test

Through the Augmented Dickey Fuller (ADF) tests, which are used to check for unit roots in the time series, a unit root test has been implemented to estimate the VAR model. The alternative, that the index under research has no unit roots (Stationary), is the null hypothesis, which is that the index under examination contains unit roots (non-Stationary).

The ADF's findings demonstrate that the unit root-containing null hypothesis of all the under-consideration series is dramatically rejected at the 1% level. The stationary nature of those variables guarantees the validity of the empirical analyses presented below. More significantly, when using the (limited) VAR model, we do not need to consider the potential cointegration issue related to stock return and trading volume.

### *Unit Root Test for the variables under study*

### Table: 3

| Variables | P-value | Decision | |
|---|---|---|---|
| Turnover in Volume | 0.000 | Stationary | Level |
| Turnover in Value | 0.000 | Stationary | Level |
| Return | 0.000 | Stationary | First Difference |

**11.3 Testing the effect of private and public information on Investors' Overconfidence**

*H1: "Overconfident investors react inappropriately to public information and excessively to private information.*

$$
\begin{bmatrix} mturn_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{1,t} \\ \alpha_{2,t} \end{bmatrix} + \sum_{i=1}^{2} A_i \begin{bmatrix} mturn_{t-i} \\ mret_{t-i} \end{bmatrix} + \sum_{j=0}^{1} B_j \begin{bmatrix} msig_{t-j} \\ disp_{t-j} \end{bmatrix}.
$$

This hypothesis has been tested twice. The impact of the past market return and the other two controlling variables on the volume-represented market turnover is investigated for the first time. The impact of the value-represented market turnover is examined a second time. Including control variables (Volatility and Dispersion) in the VAR model
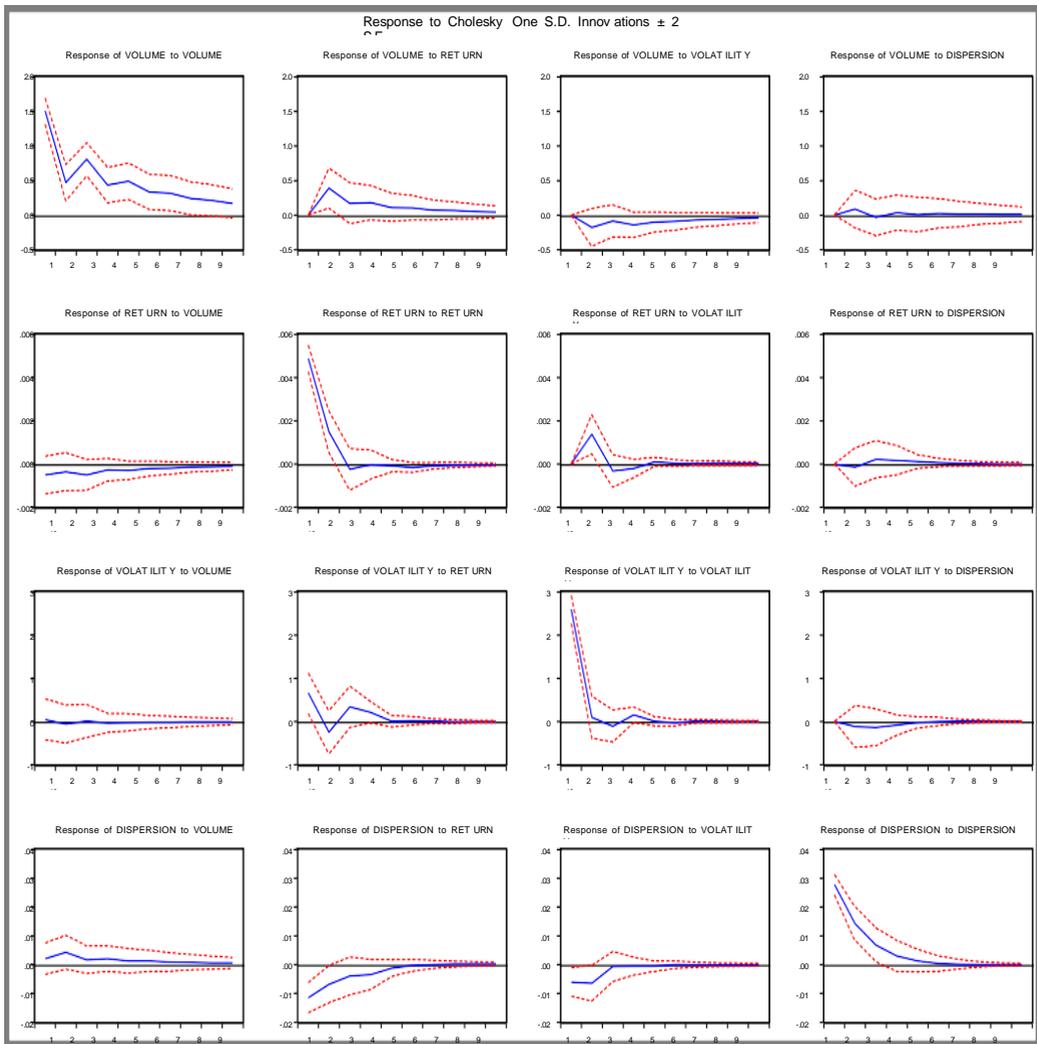
    a- Turnover in Volume

*1- Estimated VAR*

The estimation of the market VAR system, which includes the endogenous variables detrended logged market turnover in volume, mturn, and market return, mret, is shown in Table (4.17). Market volatility (misg) and market dispersion (disp) are the control variables. The dependent variables are arranged in columns, and the lag terms and control variables are arranged in rows.

*2- Impulse Response function*

The graph below shows that volatility has a slight positive response to volume until lag 4, after which it becomes stable or has no response at all. Also, until lag 6, Dispersion has a relatively higher positive response to volume, after which it begins to decrease. As a result, the dispersion response is generally stronger and longer.

**Figure 4.3  Impulse Response Function for Turnover in volume for**

## 3- *Granger Causality*

It is possible to assert that volume granger turnover causes return as a P-value, as shown below. Furthermore, as a P-value, return is asserted to be a granger cause or predicted volume turnover. In terms of granger causality, it was discovered that volatility can cause volume turnover at a 0.1 significance level but cannot granger cause the opposite. Finally, at a 0.1 significance level, dispersion can granger cause volume turnover and the latter variable can granger cause dispersion. Granger Causality for Volume in H1:

**Table:4**

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| RETURN does not Granger Cause VOLUME | 121 | 3.94594 | 0.0025 |
| VOLUME does not Granger Cause RETURN | | 2.87007 | 0.0179 |
| VOLATILITY does not Granger Cause VOLUME | 121 | 0.25160 | 0.0938 |
| VOLUME does not Granger Cause VOLATILITY | | 1.16287 | 0.3321 |
| DISPERSION does not Granger Cause VOLUME | 121 | 0.79265 | 0.0557 |
| VOLUME does not Granger Cause DISPERSION | | 0.80618 | 0.0547 |
| VOLATILITY does not Granger Cause RETURN | 121 | 2.20803 | 0.0585 |
| RETURN does not Granger Cause VOLATILITY | | 2.22253 | 0.0570 |
| DISPERSION does not Granger Cause RETURN | 121 | 0.39389 | 0.8521 |
| RETURN does not Granger Cause DISPERSION | | 0.34823 | 0.8824 |
| DISPERSION does not Granger Cause VOLATILITY | 121 | 0.47182 | 0.7966 |
| VOLATILITY does not Granger Cause DISPERSION | | 0.96092 | 0.4451 |

Our estimate result suggests that volatility has a significant impact when taking into account the relationship between volatility and volume turnover. On the other hand, the private information coefficient dispersion is 0.050108 with a p value of 0.03439.

The current volatility parameter, with a coefficient of 3.416581 and a p value of 0.05400, is also significant.

The variable coefficient suggests that both the cross-sectional volatility of individual companies (disp) and the intertemporal market return fluctuations (misg) have a significant impact on market turnover, with the dispersion having a bigger effect. That may be caused by market information events.
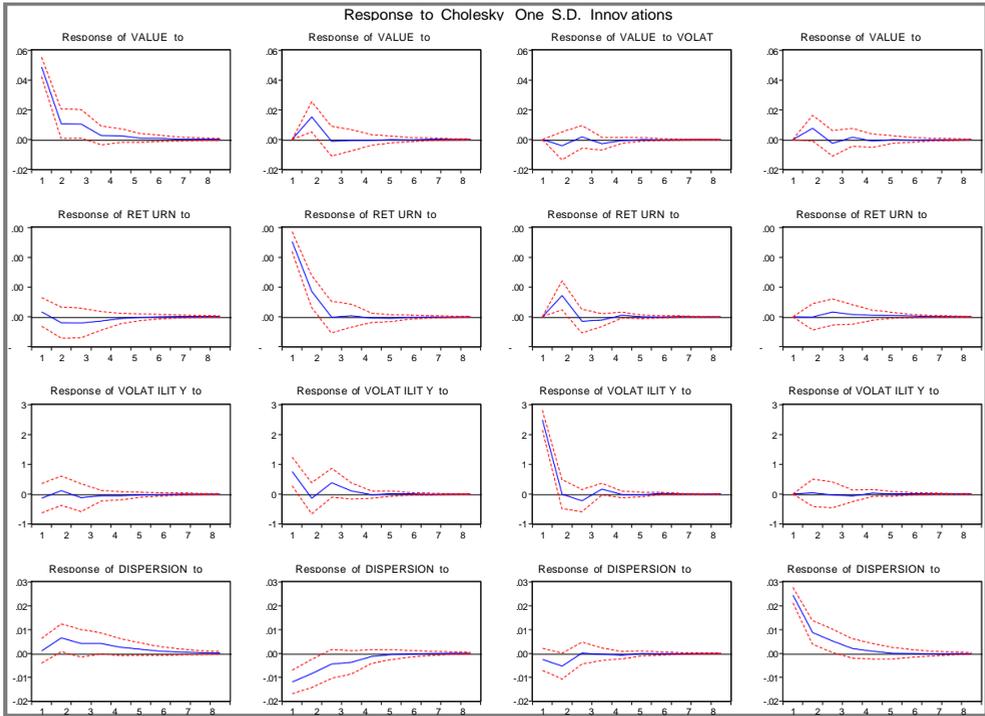
b- **Turnover in Value**

*1- Estimated VAR*

Estimation of the market VAR system, which includes the endogenous variables detrended recorded market turnover in value (mturn) and market return (mret), is shown in Table (4.19). Market volatility (misg) and market dispersion (disp) are the control variables. The dependent variables are arranged in columns, and

the lag terms and control variables are arranged in rows. Estimated VAR for Value in H1

## 2 -*Impulse Response function*

The figure below shows that volatility has a slight positive response to value until lag 4, after which it becomes stable or has no response at all. Furthermore, until lag 7, Dispersion exhibits a relatively higher positive response to value, after which it exhibits no response at all.



Impulse Response Function for Turnover in value for H1

Granger Causality

As shown in table (4.20), turnover in value cannot be claimed to granger cause return as P-value > 0.05, whereas return is claimed to granger cause or forecast turnover in value as P-value 0.05. Concerning the granger causality between volatility and value turnover, it was discovered that volatility cannot granger cause value turnover at the 0.1 significance level. Furthermore, value turnover cannot cause volatility. Finally, at the 0.1 significance level, dispersion can granger cause turnover in value, and turnover in value can granger cause dispersion at the 0.05 significance level.

Granger Causality for Value in H1

**Table: 5**

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| RETURN does not Granger Cause VALUE | 109 | 3.62020 | 0.0157 |
| VALUE does not Granger Cause RETURN | | 1.61169 | 0.1913 |
| VOLATILITY does not Granger Cause VALUE | 109 | 0.77546 | 0.5103 |
| VALUE does not Granger Cause VOLATILITY | | 0.33477 | 0.8002 |
| DISPERSION does not Granger Cause VALUE | 109 | 0.64574 | 0.0587 |
| VALUE does not Granger Cause DISPERSION | | 1.31848 | 0.0272 |
| VOLATILITY does not Granger Cause RETURN | 125 | 2.99267 | 0.0337 |
| RETURN does not Granger Cause VOLATILITY | | 0.88757 | 0.4498 |
| DISPERSION does not Granger Cause RETURN | 125 | 0.67844 | 0.5669 |
| RETURN does not Granger Cause DISPERSION | | 0.41639 | 0.7416 |
| DISPERSION does not Granger Cause VOLATILITY | 125 | 0.68978 | 0.5600 |
| VOLATILITY does not Granger Cause DISPERSION | | 1.14504 | 0.3339 |

## 10.4 Testing the effect of private information on investors' overconfidence

H2 "As investors become more overconfident, they overestimate private information and trade more aggressively in subsequent periods."

It could be argued that turnover is changing, as is investor confidence in changing levels of private information. As a result, we will test risk returns with various trading strategies. The effect was tested for both volume and value turnover, as shown below.

a- Turnover in Volume

Estimated Equation

An equation with a dummy variable was estimated to reflect different risk returns with different sub periods. The table below shows that there is a significant positive effect at the 0.01 significance level (P-value = 0.0000). This

means that there has been a significant change in volume turnover with a different risk return.

Estimated Equation for Volume in H2

### Table: 6

|  | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C(1) | 3.019002 | 0.383370 | 7.874910 | 0.0000 |
| C(2) | 8.064801 | 4.814134 | 1.675234 | 0.0963 |
| C(3) | -14.50594 | - 4.309928 | 3.365703 | 0.0010 |
| R-squared | 0.087242 | Mean dependent var | | 3.087266 |
| Adjusted R-squared | 0.072980 | S.D. dependent var | | 1.998769 |
| S.E. of regression | 1.924453 | Akaike info criterion | | 4.169795 |
| Sum squared resid | 474.0504 | Schwarz criterion | | 4.235639 |
| Log likelihood | -270.1216 | Hannan-Quinn criter. | | 4.196550 |
| F-statistic | 6.117127 | Durbin-Watson stat | | 0.983139 |
| Prob(F-statistic) | 0.002903 | | | |

b- Turnover in Value

Estimated Equation

An equation was estimated for the effect of risk return on value turnover, which included a dummy variable to represent different risk returns. The table below shows that there is a significant positive effect at the 0.01 significance level (P-value = 0.0003). This indicates that there is a significant change in value turnover with different risk return

Estimated Equation for Value in H2

## Table: 7

|  | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C (1) | 0.067706 | 0.010900 | 6.211679 | 0.0000 |
| C (2) | 0.112079 | 0.133423 | 0.840026 | 0.4026 |
| C (3) | -0.340610 | 0.114879 | -2.964953 | 0.0037 |
| R-squared | 0.071215 | Mean dependent var |  | 0.064413 |
| Adjusted R-squared | 0.055062 | S.D. dependent var |  | 0.052011 |
| S.E. of regression | 0.050559 | Akaike info criterion |  | -3.106254 |
| Sum squared resid | 0.293965 | Schwarz criterion |  | -3.035813 |
| Log likelihood | 186.2690 | Hannan-Quinn criter. |  | -3.077653 |
| F-statistic | 4.408840 | Durbin-Watson stat |  | 1.689119 |
| Prob(F-statistic) | 0.014293 |  |  |  |

### Normality Testing

A data set should be normal or well-modeled by a normal distribution. As the table below shows the normality test of the dimensions under study, where it was found that all dimensions under study are found to be normal as P-value > 0.05, which means that the hypothesis of normality is accepted.

### Normality Testing

#### Table: 8

|  | Kolmogorov-Smirnov[a] | | |
|---|---|---|---|
|  | Statistic | Df | Sig. |
| **Value** | .182 | 12 | .200[*] |
| **Volume** | .237 | 12 | .061 |
| **Return** | .151 | 12 | .200[*] |

### Unit Root Test

Through the Augmented Dickey Fuller (ADF) tests, which are used to test for unit roots in time series, a unit root test was used to estimate the VAR model. The null hypothesis is that the index under study contains a unit root (non-

Stationary), as opposed to the alternative that the index contains no unit root (Stationary). The ADF results show that the null hypothesis that the series under consideration are not stationary (i.e., have a unit root) is significantly rejected in all cases at the 1% level. The stationarity of those variables ensures that our empirical analyses below will not produce erroneous results. even more importantly, when performing the (restricted) VAR model, we do not need to consider the potential cointegration problem associated with stock return and trading volume.

### Unit Root Test for the variables under study

### Table 9

| Variables | P-value | Decision | |
|---|---|---|---|
| Turnover in Volume | 0.000 | Stationary | Level |
| Turnover in Value | 0.000 | Stationary | Level |
| Return | 0.000 | Stationary | First Difference |

## 12. RESULTS

The following conclusions are offered following the execution of several statistical tests:

1. Current turnover in volume is more affected by past market return than it is by value over a longer period of time. This result is consistent with Daniel et al overconfidence a self-attribution theory (1997). It ensures market overreaction to shocks resulting from private knowledge and encouraging market return signals.

2. By including volatility and dispersion in our calculated VAR model, the following results were also obtained:

- Private information has a large impact on market turnover, which demonstrates that private information shock has a big impact on trading volume. The Egyptian Stock Market exhibits overconfidence bias, according to the overconfidence theories.

- Volume turnover is only somewhat significantly impacted by current volatility. This relationship demonstrates that market risk has no bearing on the volume of trading in the Egyptian stock market, which is expected due to irrational investor behavior.

- Current volatility is unaffected by current trading volume, which again runs counter to conventional finance. Trading volume and volatility have a strong positive contemporaneous relationship, according to the Mixture of Distribution hypothesis (MDH) (Clark 1973).and Mestal and Gurgel (2005).

- Additionally, historical volatility has a favorable, considerable effect on current turnover in value. This doesn't the impact of public information and market risk on the turnover represented in value.

- Current dispersion is impacted by current turnover. Particularly, the impact of volume turnover is stronger. This clear correlation between turnover in volume and dispersion highlights how overconfident investors exaggerate their knowledge of their personal past and present situations and trade more.

- Turnover is compared to volatility and dispersion, and it is discovered that dispersion from the past has a bigger positive significant impact than volatility on the current trade turnover as represented in both volume and value.

## Proposed Overconfidence Frameworks
### *Volume based Overconfidence Framework*
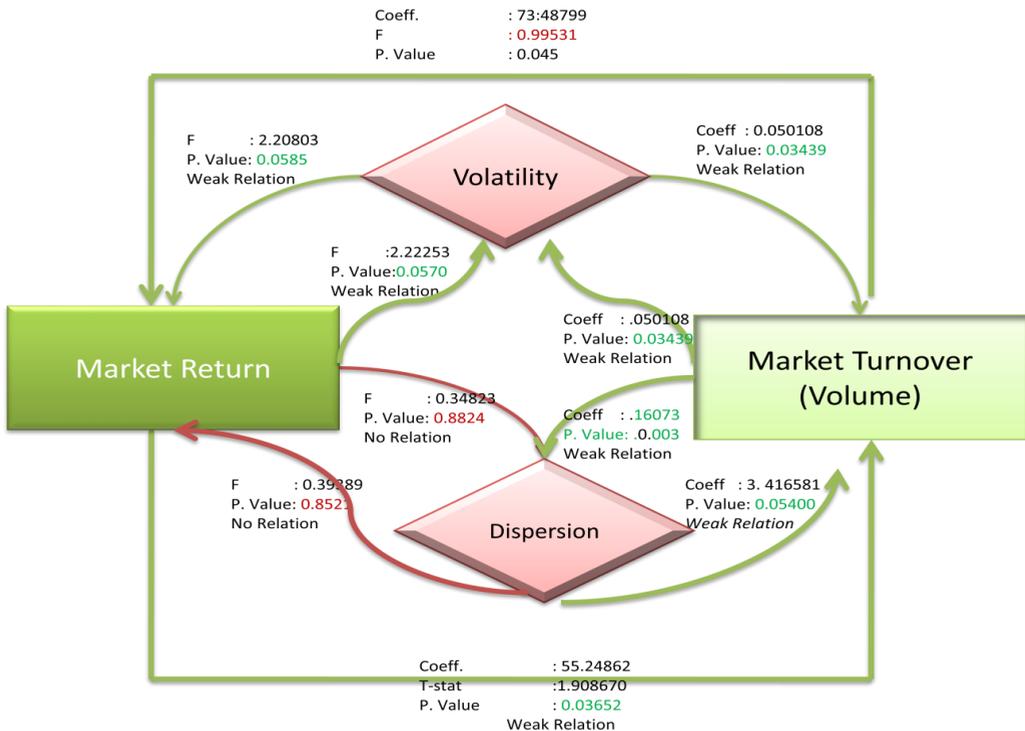
*Value based Overconfidence Framework*
**Value Based Overconfidence Framework**

3. It is possible to conclude that investors attribute previous market returns to their trading and valuation abilities.
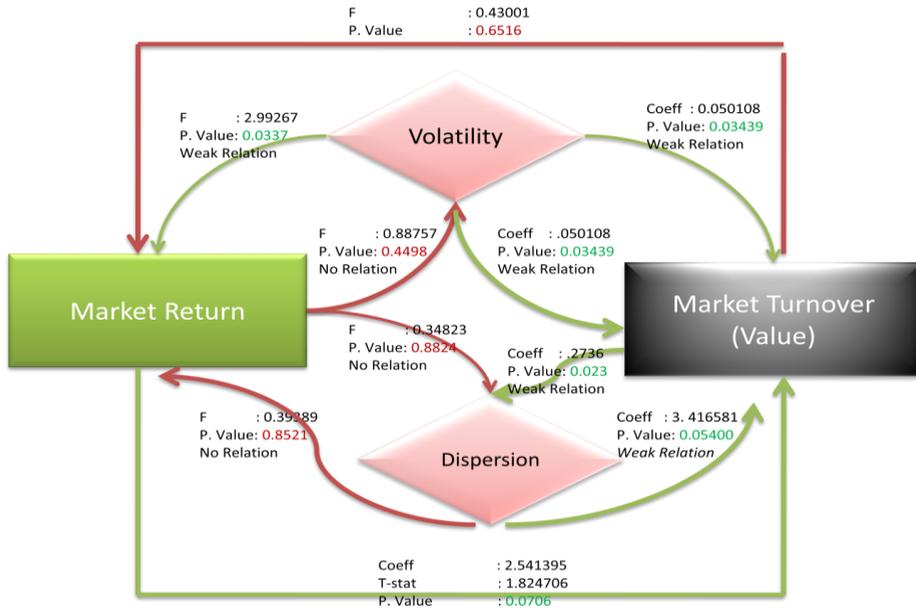


4. Egyptian investors exaggerate the precision and accuracy of their data. As a result, they trade more aggressively in the aftermath of higher market returns in order to maximize their trading utility.

5. When the market falls, traders reduce their trading activity in subsequent period.

6. When the overall stock market is trending upward, increased trading activity in the Egyptian stock market is triggered by investors' overconfidence.

7. Market gains have a significant positive impact on turnover in both value and volume in subsequent periods.

## 13. DISCUSSION

The results of the current study support the theoretical and empirical literature of the findings Kumar (2018) and Ansary (2012). Most researchers concur that private information has great significant positive impact on trading behavior, Moreover, these results are expected in the context of an emerging market, such as the Egyptian stock market, where transparency might be viewed as lacking and insider trading is common market practice.

## 14. CONCLUSION

a) The psychological state of the Egyptian Stock Market has an effect on its performance.

b) The Egyptian market turnover represented in volume is more significant than those calculated in value.

c) The Egyptian investors within the market are proven to be overconfident, as private information has a significant effect on the trading volume and value

d) The Egyptian investor's tendency to overvalue their private information and undervalue public information results in a greater impact of dispersion on market turnover than volatility.

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# تأثير المعلومات الخاصة والعامة على سلوك التداول في البورصة المصرية

د. أيمن حسن متولي          د. أمنية درويش

## ملخص البحث باللغة العربية

الغرض من هذه الدراسة هو دراسة تأثير المعلومات الخاصة والعامة على سلوك التداول في سوق الأوراق المالية المصرية ، كما افترض دانيال واخرون 1998.

البيانات التي تغطي اثني عشر عاما من سوق الأسهم المصرية ، وهي الفترة من 2002 إلى 2012 على مستوى السوق الكلي ، مقسمة إلى أربع فترات فرعية : فترتان هادئتان تتجهان إلى الأعلى (2002– 2005 و 2005–2008) وفترتان متقلبتان وتتجهان إلى الأسفل الأزمة المالية 2008–2010 وفترة الثورة المصرية 2010–2012.

تظهر نتائج الدراسة أن صدمات المعلومات الخاصة لها تأثير كبير على حجم التداول في السوق ، مما يوفر دليلا على التأثير القوي للمعلومات الخاصة على دوران السوق. لا يحدد هذا الإطار وجود تحيز الثقة المفرطة في سوق الأسهم المصرية فحسب ، بل يشير أيضا إلى كيفية تغير التحيز الاستجابة للتقلبات والتغيرات.

**الكلمات الدالة** : المعلومات الخاصة ، المعلومات العامة ، السلوك التجاري ، التمويل التقليدي ، التمويل السلوكي ، سوق الأوراق المالية المصرية ، علم النفس المعرفي.