A Behavioural Approach to Corporate Finance:

A Study of the Egyptian and UK Markets

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Abstract

This thesis empirically investigates the effect of managerial overconfidence bias on investment decisions, stock price crash risk and default risk. Overconfidence is manifested in an exaggerated sense of being attentive only to one's own information, believing that they are better than the average person, and an inflated belief in their ability to control events. Following recent theoretical work, I propose three models. My first model proposes that overconfident managers overinvest when they have abundant internal funds or riskless debt but restrict investment when forced to issue equity or take on risky debt to raise funds. In the second model, I expect managerial overconfidence increases bad news hoarding, leading to increased stock price crash risk. The third model predicts that overconfident managers engage in exaggerated risk-taking activities, increasing the risk of default. Empirical testing is applied on all listed firms in the Egyptian and the UK market. The overconfidence measures are insignificant for Egypt across all three models. For the UK, the following results are found. In the first model, investment of overconfident managers is significantly more responsive to cashflow, particularly in firms that are financially constrained. In the second model, I find that managerial overconfidence does lead to an increase in stock price crash risk. In the third model, I find that, contrary to the hypothesis, there is a significant negative relationship between managerial overconfidence and default risk. The results are then linked to existing empirical evidence and several conclusions are drawn, particularly in relation to manager overconfidence in developing countries.

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Abbreviations

APD Abnormal Probability of Default
AR Autoregressive
CEO Chief Executive Officer
CF Cashflow
CFO Chief Financial Officer
DCF Discounted cashflow
DD Distance to Default
DUVOL Dual Volatility
EDF Expected Default Frequency
EGP Egyptian Pound
EMH Efficient Market Hypothesis
FE Fixed Effects
GBP Great British Pound
GLS Generalized Least Squares
GMM Generalized Method of Moments
IRR Internal Rate of Return
IV Instrumental variable
LSDV Least Squares Dummy Variable
MDA Multiple Discriminate Analyses
MM Merton Model
MMT Market Timing Theory
NPR Net Purchase Ratio
NPV Net Present Value
NSKEW Negative Skewness
OC Overconfidence
OLS Ordinary Least Squares
OPT Optimism
PD Probability of Default
POT Pecking Order Theory
RE Random Effects
SPCR Stock Price Crash Risk
TT Tradeoff Theory
USD US Dollar
VIF Variance Inflation Factor

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Chapter 1
Introduction

1.1 Rational Economics versus Behavioural Finance

Traditional research in finance and economics often conceptualizes a world populated by calculating, rational, unemotional optimizers. Researchers often make several assumptions about human nature that behavioural and psychological research suggests are often wrong. The standard economic model includes three unrealistic assumptions: agents have unbounded rationality, unbounded willpower, and unbounded selfishness (Conlisk, 1996).

As far back as 1790, Adam Smith emphasised the importance of considering the psychology of an economic agent including concepts of self-interest and bias. He asserts that even a "perfectly virtuous" man with full knowledge of what is right and just, may be misled by his passions to violate all the rules that he approves of. However, it wasn't until recently that researchers have started to focus on the behavioural biases that may drive how firms "actually" behave rather than how they are "expected" to behave (unbounded rationality).

It becomes therefore important to consider the behavioural side of financial markets. The subject matter can be broken down into two main categories: behavioural biases that affect investors and behavioural biases that affect managers. Heaton (2002) maintains that research in behavioural finance remains relatively lacking and, while research into investor behaviour has recently picked up pace, research into behavioural corporate finance is still in its early stages of development (Baker and Wurgler, 2011). This thesis is an attempt to contribute to research in the latter direction.

1.2 Research Background

In an effort to integrate behavioural finance with the traditional theories of finance, this thesis will focus mainly on the overconfidence bias. Malmendier and Tate (2015) assert that the overconfidence bias is the most prominent bias that could affect managerial decisions. They argue that this is because top management are often portrayed as “larger than life” by the media. As such, these managers will often have excess overconfidence in the way they operate their firms, and in their decision-making. Overconfident managers tend to over-estimate returns while simultaneously underestimate risk (Heaton, 2002). This makes them more likely to take on greater risk. While overconfident managers are more likely to invest in more innovative projects, they may ignore negative signals that they receive regarding their investment decisions. This causes them to overinvest, often investing in negative NPV projects whenever there is excess internal cashflow (retained earnings) (Malmendier and Tate, 2005).

While most research in corporate behavioural finance studies how behavioural biases impact managerial decision making, a small percentage of this research delves into what this means in terms of firm value or risk. In this thesis, I aim to narrow that gap. I start off by supporting the hypothesis that managerial overconfidence impacts decision making (specifically the impact of managerial overconfidence on investment sensitivity to cashflow), then I move on to explore how overconfidence may affect firm risk, I define and measure risk in two different ways Stock Price Crash Risk (henceforth SPCR) and default risk. I particularly focus on how behavioural biases may be affected during periods of abnormal economic as well as political events. For this purpose, I investigate two specific case studies: the Egyptian market around the period 2005 to 2018, which witnessed a big political unrest around 2011 and I compare this with the UK market, which apart from the global economic financial crisis of 2007- 2008, (the consequences appeared mainly in 2008-2009 in my study) and the Brexit referendum passed in 2016 (which was proceeded by much uncertainty and confusion) remained relatively stable.

1.3 Research Aims and Objectives

This thesis aims to extend the existing body of research on the psychological aspects of corporate finance during periods of abnormal events. The research can be divided into two main components.

1. A theoretical component through which models are formulated followed by a statement of hypotheses. I start by reviewing the traditional theory of “rational” finance in Chapter 2 and justify the need to include the behavioural component. In Section 3.3 of Chapter 3, I present a comprehensive review of several behavioural biases likely to affect managers. However, this thesis focuses specifically on overconfidence bias, as it is recognized by researchers as one of the prominent biases that may play an important role in managers financing and investment decisions (Fairchild, 2005).
2. A two-part empirical component, aiming first to test and support the understanding of how overconfidence affects firms’ investment decision and its sensitivity to cashflow. Then I go a step further in understanding and testing how these biases affect firm risk. Testing is performed on the Egyptian and the UK market simultaneously. The Egyptian market is an interesting case, considering the recent Egyptian political unrest, as I believe that behavioural biases are more likely to be

relevant during periods of instability. In addition, the study will also extend the empirical literature for the Egyptian market, as very little testing has been performed on the cognitive biases with respect to managers in the Egyptian market. Finally, the UK market is used as a comparative market. While Egypt is still an emerging market the UK is developed. However, while Egypt has endured periods of severe political turmoil, the UK has also experienced a period of economic instability following the Brexit referendum. Nevertheless, the UK is comparatively more stable politically. The contrast between Egypt and the UK markets should help us account for the moderating effect that market development (in terms of size, regulation, history, information, depth and liquidity) has on the impact of overconfidence on corporate finance.

1.4 Briefing on Theoretical Background, Hypotheses, and Empirical Tests

Managerial bias and firm bias are considered interchangeable, this is because the vital financial and investment decisions of a firm are made by the top management (Malmendier and Tate, 2005; 2008). Therefore, any biased firm decisions stem from the bias of its management. To measure managerial overconfidence, two main methods are used in this thesis. The first approach measures overconfidence through the exaggerated financing and investment activities of the firm, there are two alternative measures developed by Schrand and Zechman (2012) and Campbell (2014). The second measure utilises insider stock purchase information, this measure is proposed primarily by Malmendier and Tate (2005) and developed by Campbell *et al.* (2011). The latter measurement is applicable only for the UK, as the data required for it is not available for the Egyptian market. While there are several other measures of managerial overconfidence proposed in literature, data limitation of the

Egyptian market, constrains the methods of measurement. This limitation is discussed in detail in Section 4.6 of Chapter 4. The principal hypothesis is that managerial biases affect firm decisions, which may in turn influence the performance of the firm. The principal hypothesis is tested through the following three empirical tests:

1.4.1 Study 1: Does managerial overconfidence affect investment decisions? (Justified empirical test is performed in Chapter 5)

Previous research as Baker *et al*. (2004), Malmendier and Tate (2005), Ben-David *et al*. (2007), among others, showed that investment decisions of an overconfident manager depend largely on the source of funding. An overconfident manager seems to follow a pecking order method where he or she will overinvest when there is sufficient internal cashflow (retained earnings). Overinvesting means managers will choose negative NPV projects, but due to excessive optimism they believe them to be positive. Conditional on the ability to access the external market, an overconfident manager will prefer to issue debt. Once internal cashflow (retained earnings) and debt sources are depleted, an overconfident manager refuses to issue equity, turning down positive NPV projects, because he believes that the firm equity is undervalued by the public. In Chapter 5 the model developed by Malmendier and Tate (2005) is used to empirically test the Egyptian and the UK market to find out whether overconfident managers are likely to invest if there is an abundance of internal cashflow. The results from this model show that managerial overconfidence is insignificant to investment sensitivity to cashflow in the Egyptian market, however, are significant and positive for the UK market as predicted by the hypothesis. Further, the Kaplan-Zingales (1997) is used to test if an overconfident manager chooses not to invest if the firm is financially constrained, i.e. has no internal cashflow and has depleted its sources of riskless debt. The KZ index is a relative measure of a firm's reliance on external financing. Firm's with higher KZ index scores may be more likely to experience financial difficulties when financial conditions tighten as they may have difficulty financing their ongoing operations. The KZ model is applied only to the UK market where significant results of overconfidence were achieved. The results show as predicted that the effect of managerial overconfidence on investment sensitivity to cashflow is especially significant in firms which are most financially constrained or have the highest KZ score. Finally, a conditional model for the Egyptian market is developed, to test for the effect of managerial overconfidence and investment sensitivity to cashflow during the years of political turmoil. The model includes a dummy variable 1 for years with political instability and 0 otherwise. The results of the model again indicate that there is no significant relationship between managerial overconfidence and investment sensitivity to cashflow. I conclude that this is due to the extreme level of political instability, where even overconfident managers with abundance in cashflow did not feel it was a safe environment to increase the level of their investments.

1.4.2 Study 2: Does managerial overconfidence lead to increased stock price crash risk? (This empirical test is performed in Chapter 6)

Several studies cite bad news hoarding as a key factor in the formation of stock price crash risk (Chang *et al*., 2017). Managers possess more private information about firm operations, asset values, and firm prospects than outsider investors. There may be several reasons why managers will choose to hide this information and not share it with the public immediately. However, there is only a certain amount of bad news that a manager is willing or able to withhold, before it is leaked to the public at once engendering crash risk. Overconfident managers are theorized to have increased bad news hoarding, leading to an increase in crash risk (Kim *et al.*, 2016). This is because an overconfident manager, even when operating negative NPV projects, has an optimistic outlook and believes that eventually the project will turn around and start to bring in positive returns. The bad news continues to stockpile until the overconfident manager cannot contain it any longer and will have to leak it to the public. In Chapter 6, the model developed by Chen *et al.* (2001) and Kim *et al.* (2016) is used to test whether managerial overconfidence leads to an increase in stock price crash risk in the Egyptian and the UK markets. The model employs three separate measures of Stock Price Crash Risk (SPCR). As with the results in the previous model, the effect of managerial overconfidence on SPCR was insignificant for the Egyptian market but was positive and significant for the UK market as hypothesized. I argue that the results for the Egyptian market may be due to the extreme level of political risk, where managerial overconfidence had little or no impact. Alternatively, I argue that, the Egyptian market being inefficient, may mean that investors do not react to excessive risk taking activities of overconfident managers.

1.4.3 Study 3: Does managerial overconfidence lead to increased default risk? (This empirical test is performed in Chapter 7)

There is empirical evidence that overconfidence influences managerial decisions, which alters managerial actions and impacts firm value and risk. In Chapter 7, I propose a method of measuring the influence of managerial overconfidence on risk. Focusing primarily on the risk of default as measured by the *Merton Model* discussed in detail in Chapter 2. Default risk is defined as the uncertainty regarding a firm's ability to pay back its debts and obligations (Moody, 2002). The illusion of control and the above average effect consequential of overconfidence, means that overconfident managers have a tendency to overestimate return while simultaneously underestimating risk, they will ignore negative signals and remain optimistic that events will get better and will continue to hoard bad news. Thus, instead of learning from past mistakes, overconfidence causes decision makers to fool themselves into believing that their decisions were right all along. To admit that the decision made is risky will threaten the agent's positive self-image and create an uncomfortable self-dissonance. He will thus manipulate his beliefs, telling himself that the decisions made are not that risky, hindering the agent from adjusting his behaviour appropriately. Chapter 3 discusses several biased corporate decisions associated with overconfident managers documented in previous literature, that could lead to increased firm risk. I thus hypothesize that overconfidence in managers even in states of risk, as the state of political risk in Egypt, will continue to underestimate bankruptcy costs, make more risky decisions, and when presented with negative signals they will ignore them, leading to an increase in the probability of default. In Chapter 7, I use the Merton Model (MM) to test the effect of managerial overconfidence against both the probability of default, and the abnormal probability of default (adjusted for industry average). The results of the third model are insignificant for the Egyptian market, however, contrary to my hypothesis the empirical results of the UK market indicate a negative significant relationship between managerial overconfidence and probability of default. This implies that the risk-taking activities of overconfident managers may be beneficial for a firm. By creating more value for the firm, an overconfident manager may help move his/her firm away from default.

1.5 Thesis Contribution

The thesis compares the effects of managerial overconfidence on the Egyptian and UK markets. The Egyptian market is a particular market of interest as it recently suffered several episodes of political instability and is a relatively developing market, lacking information efficiency. Therefore, I expected to see exaggerated effects of managerial overconfidence. This is in comparison to the UK market which is a more developed market and except for the Brexit referendum remains relatively stable throughout the study period. The results from this comparison hints that the impact of managerial overconfidence differs in relation to the degree of external (political risk). The conclusion mapped out in Figure 5.3, is that the impact of overconfidence on managerial decision making is concave to the degree of political risk. At zero or extreme levels of risk, the decisions made by overconfident and rational managers converge. However, I propose that there is an optimal level of risk, where managerial overconfidence will be most pronounced.

Further, while there are several documented effects of managerial overconfidence on various financial decisions, there is an ongoing debate as to whether managerial overconfidence is beneficial or detrimental to the firm. The empirical results of the third model, which is a novel model in this thesis, shows that there is a negative relationship between managerial overconfidence and default risk. This implies that an overconfident manager is better able to create value for his firm and thus move the firm away from default. This might be particularly beneficial for firms when making hiring and firing decisions of firms. Certain firms, especially underinvested ones, might find it more beneficial to employ an overconfident manager who will follow optimal risky investment opportunities with a flatter compensation schedule. Furthermore, overconfidence commits a manager to exert more effort to gather information that improves the success rate and value of the firm’s investments (Gervais, Heaton and Odeon, 2011).

1.6 Structure of the Thesis

This chapter briefly reviewed the background of corporate behavioural finance and the importance of integrating psychological biases with traditional theories of finance to explain firm behaviour. It also provided a look ahead into the principal hypothesis, theoretical background and the separate empirical tests performed. The rest of the thesis is organised as follows.

Chapter 2: Literature Review I. Traditional theory used to explain firm investment decisions and firm risk is presented. A summary of the previous literature findings, and the empirical research performed is given. I conclude the presentation of the chapter with a discussion of the pitfalls and/or inadequacies of traditional theory and the need to integrate a behavioural component.

Chapter 3: Literature Review II. The failure of the models discussed in Chapter 2 to comprehensively explain firm behaviour justifies the need to incorporate behavioural finance into the analysis. A review of previous behavioural research will form a background of the theoretical framework on which I base my hypothesis for each model.

Chapter 4: Research Methodology. The intended research strategy is concisely stated. The main methodology: panel data analysis is discussed, along with a brief description of the methods of data collection and the intended period of study. I also justify the choice of the Egyptian market as the main market of choice for empirical testing. Through the course of the chapter, data limitations regarding the Egyptian market is discussed. Due to these limitations, the models had to be slightly altered from those used in previous research.

Chapter 5: Investment Decisions Findings and Analysis (Study I). This chapter reports the findings of the first model. The findings generally support the results found in the literature. Comparisons between the Egyptian market and the UK market are also presented.

Chapter 6: Stock Price Crash Risk Findings and Analysis (Study II). This chapter tests the effect of managerial overconfidence on stock price crash risk. While there are some dissimilarities, the results are generally in support of the hypothesis and the literature.

Chapter 7: Default Risk Findings and Analysis (Study III). This chapter will focus on the effect of overconfidence on both the probability of default and the abnormal probability of default for the Egyptian and the UK markets. The results of this chapter turned out different from the standard hypothesis, a discussion of the most probable reason for divergence is provided.

Chapter 8: Conclusions and Recommendations. The final chapter will summarize the whole thesis and findings; restate the aims and objectives of this thesis, as well as re-iterate the main motivations for performing this research. Finally, the chapter will outline the main conclusions and offer suggestions for further research.

Chapter 2

Literature Review I: Traditional Theories of Corporate Finance

2.1 Introduction

The pattern of corporate financial decisions is important for the financial success of firms (Singh and Luthra, 2013). Corporate financial decisions, directly or indirectly, affect various facets of corporate management, which will ultimately determine the wealth of investors. The financial strategy of a corporation is usually set by the management committee or above, at the Board level, and involves capital structure policy, dividend policy and investment policy.

The aim of this thesis is to investigate how behavioural biases may have an impact on financial decisions, and how this will ultimately affect the level of corporate risk as measured by stock price crash risk and default risk. It is important to note that this thesis proposes integrating behavioural finance into the traditional theories of finance. Thus, before delving into the behavioural field this chapter will focus on the traditional theories of corporate finance.

This chapter aims to provide a comprehensive insight regarding the prominent theories and factors used as basis for traditional corporate finance models. The criticisms of traditional models are also discussed to justify the addition of new factors (behavioural factors) to enhance these models. This chapter consists of three main sections. In Section 2.2, I discuss key theories of investment decisions and how these decisions are affected by the sources of funds, in Section 2.3, the traditional theories of stock price crash risk are discussed and its determinants, in Section 2.4, Default risk is defined and the different measures used in previous literature are discussed.

2.2 Investment Decisions

Capital expenditure (investment) is an important decision made by financial managers (Durnev *et al.,* 2005). Capital expenditure is the process of determining which investment projects will lead to the maximization of shareholder value. Discounted cashflow (DCF) methods; the Internal Rate of Return (IRR), the Net Present Value (NPV) and the payback method are widely used to evaluate investment decisions in firms. Capital expenditure evaluation methods take into account the cost of a particular project, the cash inflows expected from the project, the residual value of the asset at the end of its useful life, and the riskiness of those cashflows. Under the NPV method, management first determines the cost of capital at which the cash outflows should be discounted, and then calculates the present value of expected cash outflows and compares it to the present value of cash inflows. The IRR method, on the other hand, determines the rate at which the NPV will equal to zero, the higher the IRR the more desirable the project. Otherwise, the project is also considered acceptable if the IRR is greater than the cost of capital. The payback method calculates how long it takes a firm to recover the capital allocated into an investment. It can either use the cash inflow as is, or discounted.

A second important decision that attains to corporate investment is a firm’s capital structure. Theories of corporate investment and capital structure are closely linked. Modigliani and Miller (1958) demonstrate that under certain conditions financial structure for real investment decisions are irrelevant, i.e. the value of the firm is dependent on its profitability rather than its capital structure. Thus, in a frictionless capital market, a firm’s financial structure should not affect its market value. They argue that the proportion of debt and equity should not be a concern for management because in a perfect market any combination of debt and equity will be equivalent to any alternative combination. Their theory is further supported by Stizlitz (1969) who incorporated risky debt in his model and proved that firm value is not affected by capital structure. He holds that, in the absence of bankruptcy cost payments, it does not make any difference whether debt is risk-free or risky. Firm value, he emphasizes, is obtained by discounting expected cashflows from the firm investments. It should not therefore be impacted by whether these cashflows are financed by risky debt or risky equity.

However, this theory is based on several restrictive assumptions, namely

1. Firms operate in frictionless, competitive markets where there are no transaction costs;

2. Firms are price takers;

3. There are no taxes and no bankruptcy costs (i.e. a firm cashflow will not depend on its financial policy) and all agents have the same information level;

4. Individuals and firms have the same costs of financial transactions.

If these assumptions hold true a firm's investment decision, motivated by the maximization of shareholder's value, should be independent of financial factors such as liquidity, leverage, or dividend payments. However, this is not true in the real world. If these simplifying assumptions are not made, then the choice of capital structure becomes an important factor in determining the investment decisions made by a firm.

More recent literature, however, suggests that capital markets are in fact imperfect. There are several reasons why firms may not invest at optimal levels that maximize shareholder value, leading to over or underinvestment problems. Information asymmetries and costly contract enforceability generate agency costs that result in outside investors demanding a premium on the debt or stock issued by the firm. The resulting decrease in liquidity could cause a firm to reduce its scale of investment (Fazzari *et al.*, 1987), and cause internal and external funding by the firm to be inequivalent substitutes (Hornstein and Zhao, 2011).

Investment thus depends on financial factors (such as liquidity, leverage and dividend pay-outs) and the availability of internal finance, ease of access to debt or new equity finance, or the efficiency of particular credit markets (Myers, 2001). Capital market imperfections will constrain capital expenditure and the mobilization of capital for investment and create a wedge between the costs of internal and external financing. In such situations, firms will prefer to finance investments with internal funds as external funds become more costly due to transaction costs, agency problems, and asymmetric information.

2.2.1 How investment decisions are affected by capital structure

Capital structure refers to how a firm uses debt and/or equity to finance its operations and growth. A managerial capital structure decision affects the value of a firm (Chowdhury and Chowdhury, 2010) by affecting the market value of shares, which in turn affects shareholders' wealth. Any change in capital structure consequently influences the cost of capital and value of the firm. When firms decide to use debt financing, they are reallocating some expected future cashflows away from equity claimants in exchange for cash up front.

In contrast to the Modigliani and Miller (1958) theory, Ross (1977) notes that the irrelevance proposition assumes that the market knows the expected cashflow of a firm and its market value to determine firm value. He argues that the market firm value at the “perceived” stream of future cashflows may depend on the effect of capital structure signaling. With the choice of financial leverage, managers may send unambiguous signals to the outsiders about a firm financial standing. For example, by choosing higher financial leverage, managers may signal that they are optimistic about the future of the firm, which will, in turn increase the perceived value of the firm. Changes in firm capital structure may change the market perceived risk classification of the firm, even though the firm's actual risk classification may remain unchanged.

Since then, several theories were suggested to explain the variation in capital structures across firms, and the link between the choice of capital structure and investment decision. This section discusses three main theories: the Trade-off Theory (TT), the Pecking Order Theory (POT), and the Market Timing Theory (MTT).

(i) The Trade-off Theory

The Trade-off Theory posits that the optimal capital structure is determined by the trade-off between the benefit and cost of debt. There are many ways to view these costs and benefits. According to the "tax-bankruptcy trade-off," firms balance the tax benefits of debt against the costs of bankruptcy. The primary version of this hypothesis was proposed by Kraus and Litzenberger (1973).

TT states that debt is considered beneficial because of the debt-tax shields that help to minimize the firm's expected tax bills and maximize its after-tax cashflows. The optimal level of leverage is thus achieved by balancing the tax benefits of interest payments against the costs of issuing debt. Several researchers tried to identify the relevant costs associated with debt financing that firms trade off against this corporate tax benefit, and the two most popular of such costs include bankruptcy costs and agency costs. Other considerations that may also affect these costs include, market interaction and corporate control (Antwi *et al*., 2012). The Trade-off Theory predicts a positive relationship between earnings and leverage ratios because, as mentioned earlier, interest paid on debt reduces the firm's taxable income in contrast to dividends. However, most empirical research has found this relationship to be consistently negative (Myers, 1989). This means that the static trade-off is inadequate as a real-world description of capital structure.

In an extension of trade-off theory, researchers considered the *agency cost theory*. The Agency Cost Theory states that the separation of ownership and control in firms creates conflicts of interest between the firm's managers and its shareholders (Jensen and Meckling, 1976).

The Agency Cost Theory reasons that managers will often indulge in investment activities that enhance their own personal benefits rather than maximizing the value of the firm. Stein (2001) explains this in light of several scenarios; managers may be empire builders, desiring to work in larger firms not necessarily profitable ones. Another possible scenario is referred to as "short-termism" where managers will indulge in activities that will improve their performance measures in the short-term, regardless of the long-term consequences. Furthermore, Stein (2001) provides that managers have reputation and career concerns that will cause them to act in a way that improves their reputation and ultimately their perceived value in the labour market. It thus stands to reason that firm managers will be less likely to give up control of the firm and will resist liquidation even when it is in the best interest of shareholders.

Accordingly, firms should use more leverage in their capital structure and mitigate agency costs by regulating the choice of investment, the amount of risk undertaken, and the conditions under which the firm can resort to liquidation. This should constrain or encourage managers to act in the interests of shareholders, and consequently have a positive effect on firm profitability and performance (Jensen, 1999). However, while increased leverage may reduce the agency conflicts between shareholders and managers, it will also bring with it a commitment for future cash outflows resulting in higher expected costs of financial distress, bankruptcy and/or liquidation. As bankruptcy and distress become more likely, an increase in leverage can result in higher agency costs and thus reduce firm profitability and performance.

Altman (1968) measures financial distress through a decline in a firm's sales relative to others in its industry and/or a discrepancy between the firm's actual and forecast earning. Continued financial distress may lead to bankruptcy. Jensen and Meckling (1976), while acknowledging that the exact legal definition of bankruptcy is difficult to specify precisely, provide differentiating definitions for bankruptcy and liquidation. They define bankruptcy as the inability of a firm to meet a current payment on a debt obligation, or when one or more of the other indenture provisions providing for bankruptcy are violated by the firm. In the event of bankruptcy stockholders will have lost all claims on the firm and the remaining loss (difference between the face value of the fixed claims and the market value of the firm) is borne by debtholders. They define liquidation as occurring only when the market value of the future cashflows generated by the firm is less than the opportunity cost of the assets, i.e., the sum of all the values that could be realized if the assets were sold piecemeal.

Financial risk is the result of the use of excess financial leverage that may affect the value of the firm and could lead to bankruptcy. The relationship between bankruptcy and financial leverage is not always specifically linear. If the level of leverage is low, and a firm increases its reliance on debt financing, this may not necessarily exert a significant effect on the likelihood of bankruptcy. However, an accelerated rate of increase of leverage beyond a certain threshold may cause an increase in bankruptcy costs, which could have a negative effect on the value of the firm and the cost of capital.

Jensen and Meckling (1976) explain that if both parties are utility maximisers, it is likely that the agent (i.e. the manager) will not always act in the best interest of the principal (i.e. the shareholders). They further establish that for the principal to limit this divergence he will have to incur some costs.[1] Jensen and Meckling thus propose shared ownership, compensation schemes and other such devices to align the interests of managers with that of shareholders.

There are different forms of costs associated with bankruptcy. There are direct (out of pocket) costs that include legal, administrative and advisory fees paid by the firm. There are also indirect costs, which arise because financial distress affects the company's ability to conduct its business, which may be reduced sales or increased production costs.

(ii) The Pecking Order Theory

The Trade-Off Theory uses target adjustment models to measure the speed at which companies adjust toward their capital structure. On the other hand, the Pecking Order Theory studies the relationship between changes in leverage and companies' financing deficits (Frank and Goyal, 2003). The Pecking Order Theory prioritizes the allocation of funds among the three main sources: internal cashflow (retained earnings), debt and equity. Myers and Majluf (1984) explain the Pecking Order Model in light of a presence of asymmetric information between managers and less-informed outsiders. They show that the asymmetry leads a firm to prefer internal financing to external financing. They argue that if managers act in the best interest of shareholders, they will refuse to issue shares, to the extent that they may choose to

[1] Costs include monitoring costs designed to monitor and limit the aberrant activities of the agent. Bonding costs designed to guarantee that the agent will not take certain actions which would harm the principal or ensure that the principal will be compensated if this does happen. Residual losses this is the dollar equivalent of the reduction in welfare experienced by the principal as a result of the divergence between principal and agent.

pass up on good investment opportunities. Further, they argue that when internal finance is exhausted and there is a deficit in funds a firm prefer safer debt to riskier equity. Firms will raise funds through issuing equity only after the capacity to issue debt has been exhausted. Thus, they provide that there exists a preferential financial hierarchy starting with internal funds, followed by external debt, and ending with external equity.

They discuss that there is a serious adverse selection problem with equity as outside investors will view it as strictly riskier than debt. Thus, rational investors will devalue a firm's securities when it announces a security issue by demanding a higher risk premium on equity. Conditional on issuing equity, this drop in the valuation of equity makes it look undervalued. Myers and Majluf assume that managers act in the best interest of existing shareholders and will refuse to issue undervalued shares under the assumption of rationality.

This problem could be avoided by the use of retained earnings as a source of funding, where available. If retained earnings are inadequate, the firm will resort to using debt; while debt is still risky, it has a minor adverse selection problem. Shyam-Sunder (1991) explains that a rational manager who believes that the shares of their companies are undervalued will choose to issue debt rather than equity. A manager willing to issue equity will find no one to buy those shares as those will then be considered a "bad buy". Shyam-Sunder believes that equity issues will only occur when the cost of issuing debt is too high, that is, if the company already has a high portion of debt and can foresee costs of financial distress. The firm will only use equity if they have depleted all other sources of funds. This theory of leverage does not adhere to the concept of an optimal leverage ratio as assumed by the TT.

Myers (2001) criticizes pecking order models because it assumes that managers act in the interest of shareholders by trying to maximize the value of existing shares. It does not show why, in the absence of explicit treatment of management incentives, they should care if newly issued stocks are undervalued or overvalued. Furthermore, even though the Pecking Order Theory does show how information differences can affect financing, it cannot explain the persistence of this unmitigated asymmetry.

(iii) The Market Timing Theory

The Market Timing Theory states that when managers need to raise funds, they will look at the current market conditions for debt and equity and will choose the more favourable option (Baker and Wurgler, 2002). If the current conditions are unusually favourable, funds may still be raised even if the firm has no current need for those funds, thereby suggesting that stock returns and debt market conditions will play an important role in the capital market decisions. Thus, it holds that capital structure evolves as the cumulative outcomes of past attempts to time the market.

Baker and Wurgler (2002) show that under the equity market timing there are two versions of the theory that lead to similar capital structure dynamics. The first version involves rational managers and investors as well as adverse selection costs that vary across firms or across time. In this case information is usually first released to reduce asymmetry before equity announcements happen. In this version, variations in adverse selection is measured through temporary fluctuations in the market to book ratio. They observe that if the costs of deviating from an optimal capital structure is small compared to the resulting variation in issuing costs, then past variation in the market to book ratio can have long lasting effects. In the second version of the theory, they assume that investors and/or managers are irrational, and there are time varying mispricing, or perceptions of mispricing. They explain that managers will issue equity when they believe its cost is exceptionally low and repurchase equity when they believe its cost is exceptionally high. They justify by stating that market to book ratios are well known to be inversely related to future equity returns, and that extreme values of market to book have been connected to extreme investor expectations. Thus, if managers are trying to exploit extreme expectation, net equity issues will be positively related to market to book ratio, which is proved through their empirical model. If managers believe that there is no optimal capital structure, they will not need to reverse decisions when the firm appears to be correctly valued and the cost of equity appears to be normal, this will lead to temporary fluctuations in market to book ratios having permanent effect on leverage.

This section reviewed the most prominent theories of capital structure. This is particularly important because investment decisions are impacted by the source of funding available. The next section will discuss an important theory of corporate investment: the q-theory, which serves as a platform for the analysis of investment behaviour both theoretically and empirically (Blundell *et al.*, 1992).

2.2.2 The Q-Theory of Investment

A dominant investment theory that is often used in the literature to measure the future investment opportunities of a firm is the "Q-theory" suggested by Tobin (Hayashi, 1982).

The Q-theory approach was pioneered by Tobin (1969) where he used a straightforward arbitrage argument: the firm will invest if Tobin's Q exceeds one, where Q is:

$$Q = \frac{capital\ stock\ value}{replacement\ value} \tag{2.1}$$

The cost is defined as the replacement cost of physical assets, or equivalently, the replacement cost of the share of capital. The logic behind this is that if Q is greater than one, then the profits generated from the investment will exceed the cost of the firm's assets thus additional investment in the firm would make sense. However, if Q is less than one, the firm would be better off selling its assets instead of trying to put them to productive use.

A related concept in this respect is the marginal Q. Lucas and Prescott (1971) require the unit cost of investment goods be compared to an expected marginal return, the ratio of which is termed the marginal Q. In what follows, this ratio and its relation to Q is clarified. The cost of investment is defined as disruption costs that occur during the installation of any new or replacement capital plus the cost of learning as the structure of production may change. Disruption costs include delivery lags, time to install and cost of irreversibility that may occur due to lack of secondary markets for capital goods (Cooper and Haltiwanger, 2006). The marginal adjustment and purchase costs of investment should equal the shadow value of capital. The shadow value of capital here is the firm manager's expectation of the marginal contribution of new capital goods to future profit.

To summarize,

$$\begin{aligned} Marginal\ Q &= \frac{expected\ marginal\ return/unit}{cost\ of investment/unit} \\ &= \frac{shadow\ value\ of\ capital}{marginal\ adjustment\ and\ purchase\ costs} \end{aligned} \tag{2.2}$$

Hayashi (1982) simplifies this by showing that, if a financial market is efficient, then its valuation of the capital stock equals the manager's valuation of the said stocks. Thus, with constant returns to scale and perfect competition, marginal Q should be equal to average Q.

The Tobin's Q ratio was later developed into a proxy for future firm investment opportunities by taking the ratio of a firm's total market value to its book value (a rough proxy for Tobin's

Q) (Fama and French, 2002). Not only does the firm's total market value measure the value of future investments but also the value of the assets in place. By including the market value of the firm, the Q ratio implicitly uses the correct risk-adjusted discount rate, imputes equilibrium returns, and minimizes distortions due to tax laws and accounting conventions. This definition has become an acceptable measure of firm performance or firm value in the literature. The Q-theory remains popular because of its intuitive appeal, simplicity and sound theoretical underpinnings.

2.3 Stock Price Crash Risk

Chen *et al.* (2001) state that cumulative stock market returns are asymmetrically distributed, and that this asymmetry is for the most part negative rather than positive. They argue that large movements in the market are usually melt downs rather than melt ups. For a long time, traditional financial theory relied heavily on the assumption that equity returns follow a normal distribution, however, there is sufficient evidence that this does not hold true in reality (Harris and Küçüközmen, 2001). Empirical evidence as far back as Fama (1965) show that daily stock returns display significant departures from normality, with a skewed or "fat tail" distribution. This is referred to as tail risk, i.e. the risk that an asset price will move more than three standard deviations away from the mean. While tail risk refers both to the left and right tails, financial analysts and researchers are concerned with the left tail signifying extreme downside risk or losses (Harris *et al*., 2019). This thesis is concerned with the risk of extreme loss in equity value of individual stocks.

Stock Price Crash Risk (SPCR) is defined by Chen *et al.,* (2001) and Kim *et al*. (2011) as the negative skewness in the distribution of individual stock returns. Hong and Stein (2003, pg. 487) define a stock crash as an "unusually large movement in stock prices that occurs without a correspondingly large public news event" and this movement is negative. Stock price crash risk is normally captured through the higher moment of extreme negative stock return as variance, skewness and kurtosis (discussed in more detail in Chapter 6). In what follows I will review literature on the underlying economic mechanism that these asymmetries reflect.

The determinants of SPCR vary. One strand of literature focuses on investors and their behaviour. Cao *et al.* (2002) argue that after recent price run-ups, stock returns are negatively skewed, causing a large drop in stock prices. They reason that this could be due to "information blockage". They explain that as favourable information is released, informed investors will immediately act on this information and engage in active trading. However, the sidelined (less informed) investors will not act immediately. As the latter investors start to trade, they push prices up. However, this distribution of returns is now a function of past information with no additional news. This movement will then have to correct itself causing the price to fall. Similarly, Hong and Stein (2003) argue that differences of opinions among investors may drive prices down, the opinion of bearish investors may signal private information, which would cause other investors to sell. This fall in stock prices is further exasperated by short sales (Hutton *et al.*, 2008).

Another traditional theory on the determinant of stock price crash risk is based on leverage effects. While this theory is based on a drop in price, raising operating and financial leverage which increases the volatility of subsequent returns, Habib *et al.* (2018) argue these leverage effects are not found to have sufficient quantitative importance to explain the data. They argue that, if one were interested in explaining returns asymmetry at a relatively high frequency as in daily data, it would be very difficult to link the volatility of a certain day to an increase in leverage from the same day.

On the other hand, Habib *et al.* (2018) argue that another determinant of SPCR may stem from industry related factors. They reason that the fundamental nature of the stocks and the environment they operate in may engender them to higher probabilities of crash risk. For example, the collapse in the price of oil in 2014 happened to the whole industry irrespective of any individual firm. Alternatively, stock price crashes may be the result of a stochastic bubbles, as the dotcom crisis of 2000, whereby a massive growth in the market was the result of excessive market valuation and stock overvaluation, once this bubble burst, stock prices start to move towards true fundamental value which causes the market to crash. Harris *et al.* (2019) argue the importance of considering a component in the tail risk of individual assets being a result of systematic or market wide factors.

2.3.1 SPCR and managerial bad news hoarding

One of the more prominent theories regarding the determinants of SPCR, is that managers tend to withhold bad information, and release it all at once causing the stock to crash (Kim *et al.*, 2011). The factors involved in managerial hoarding of negative information are many.

Jin and Myers (2006) explain managerial bad news hoarding in light of the agency theory. In the presence of asymmetric information between managers and external stakeholders, managers are better able to hide bad news for an extended period, to protect themselves from any negative repercussions. However, once the bad news accumulates, it becomes more difficult for managers to continue to hide it and eventually leak all that information out at once causing a crash.

Certain factors such as financial reporting opacity (Francis *et al.*, 2014) accounting conservatism (Kim and Zhang, 2016), and tax avoidance (Kim et al., 2011) can exaggerate managerial bad news hoarding. The agency theory literature suggests that the reasons managers choose to hoard bad news may arise due to personal managerial incentives, such as career concerns, desire to appear successful in front of peers, or equity based incentives that entice managers to continue with negative NPV projects to protect their incentive packages. Alternatively, managers may manipulate earnings and conceal negative firm-specific information to avoid paying taxes. These manipulation techniques are designed to hide bad news and mislead investors.

Other research, such as Callen and Fang (2015), argues that religion can effectively curb bad news hoarding. They perform their test on different counties in the US with varying degrees of religiosity, and find that firms headquartered in counties with higher levels of religiosity exhibit significantly lower levels of future SPCR. Further, Cao *et al.* (2016) argue that social norms have a strong influence on human behaviour. Firms that operate in environments where there is strong social trust are less likely to experience SPCR. They believe that whether the managers themselves are honest or not, if they operate in a high social trust environment, they are under pressure to alter their behaviour positively. Thus, rather than hoarding bad information, managers will release any bad information as it occurs reducing the chances of SPCR.

The next section will discuss the probability of default risk faced by a firm, which is typically affected by the decisions of financial managers. The question to be addressed is how decisions made by managers increase or reduce default risk. The key observation here is that a firm’s choice of financing should be determined largely by the nature of the cashflows on its assets (Malmendier and Tate, 2005). To achieve the goal then, a firm should match its financing choices to asset characteristics. As will be discussed in the next section, how a firm chooses to finance its assets may increase the probability of default.

2.4 Default Risk

A firm is said to default when it fails to meet its debt or other financial obligations. Default probability is the probability that a firm will fail to service its obligations (Moody's KMV, 2003). Default risk induces the lender to demand a higher spread from the borrower over the risk-free rate of interest. The higher the probability of default, the greater the required spread. Thus, required rate of return is an increasing function of probability of default (Vassalou and Xing, 2004).

As default is a result of loss of credit, different approaches are used to define and measure credit loss. Among them are the default-model paradigm, where a credit loss arises only if a borrower defaults within the planning horizon, and the mark-to-market paradigm, where credit deterioration short of default is also incorporated in the definition (Basle, 1999).

Prominent methods for calculating default risk include external rating services provided by organizations such as Moody's, Standard & Poor's and Fitch, as well as financial statement analysis models such as the Altman Z-score and Moody's RiskCalc. Other techniques such as the VaR (Value at Risk) model measure the probability of default by measuring expected losses over a given period of time at a given tolerance level. In this section, the relative merits of the different techniques used to measure default risk are discussed.

2.4.1 External rating services

Rating agencies such as Moody's, Standard & Poor's and Fitch, among others, provide a forward-looking opinion about the creditworthiness of an obligor and their probability of default. In the financial context, an obligor is a bond issuer, debtor, insurer or other party who has an obligation to repay back all principal payment plus interest on debt. When setting their ratings, they consider factors such as environmental conditions, competitive position, management quality, and the financial strength of the business. They also take into account the currency in which the obligation is denominated. Ratings provide the rating agency's opinion of the obligor's capacity and willingness to meet its financial commitments as they fall due. They may also assess terms such as collateral security and subordination, which could affect ultimate payment in the event of default.

Table 2.1 Rating schemes of the different credit rating agencies

S&P	Moody's	Fitch	
AAA	Aaa	AAA	Highest quality, lowest credit risk
AA+	Aa1	AA+	
AA	Aa2	AA	
AA-	Aa3	AA-	
A+	A1	A+	
A-	A3	A-	
BBB+	Baa1	BBB+	
BBB	Baa2	BBB	Credit quality diminishes as ratings diminish.
BBB-	Baa3	BBB-	
BB+	Ba1	BB+	
BB-	Ba3	BB-	
B+	B1	B+	
B-	B3	B-	
CCC+	Caa1	CCC+	
CCC-	Caa3	CCC-	
CC	Ca	CC	
C	C	C	
D		D	Issuer is in default

Table 2.1 provides a mapping of the different ratings provided by the most prominent rating agencies. The ratings shown move from the strongest capacity to meet financial commitments, through to the highly vulnerable in meeting financial commitments, down to firms in default. They provide a relative ranking of one entity (firm) to another such that the lower the rating, the greater the probability of default. Rating agencies expressly state that

their ratings only provide relative opinions about the creditworthiness of the issuer and cannot be used as a guarantee of credit quality (Standard and Poor's, 2011). They rate the creditworthiness of the issuer's position as a whole, and not on a particular debt issue, using the likelihood of default as the single most important driver of the rating. One of the advantages of credit ratings is that they are formulated through a comprehensive analysis of an entity's business as well as economic environment risk. Further, ratings are available for use by banks and researchers, allowing them to save the time of producing their own credit risk model. However, one downside to credit ratings is that they do not fluctuate with market conditions.[2]

2.4.2 Financial statement analysis models

Financial statement analysis models are used to calculate the probability of default based on the analysis of various financial items and ratios for the individual borrower. In his seminal work on credit risk analysis Altman (1968) uses multiple discriminant analyses (MDA) to study whether financial ratios could be used to determine whether a firm falls into a potentially bankrupt or non-bankrupt category. From an original list of twenty-two ratios studied in the literature he finds that profitability, liquidity, and solvency prevail as the most significant predictions of bankruptcy. He developed a Z-score that calculates the risk of default based on balance sheet risk indices and historical probabilities of default. His Z-score reads:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.01X_5 \tag{2.3}$$

[2] Allen and Powell (2011) find that even though the impaired assets of Banks in Australia increased fivefold over the global financial crisis period, there was a negligible change in the underlying ratings of firm credit risk over the same period.

Where

X_1 = Current Assets/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings Before Interest and Taxes/Total Assets

X_4 = Market Value of Equity/Book Value of Total Liabilities

X_5 = Sales/Total Assets

X_1 is a measure of liquid assets in relation to firm size, i.e. it measures liquidity. Generally, a firm experiencing consistent operating losses will suffer falling current assets in relation to total assets. It was found that net working capital/total assets was more effective when compared to liquidity and quick ratio.

X_2 is a measure of the firm's leverage. Firms with high X_2 ratios finance their assets through the retention of profits and do not utilize as much debt. The retained earnings account reports the total amount of reinvested earnings of a firm.

X_3 is a measure of the true productivity of the firm assets, before any tax or leverage factors. A firm's ultimate continuation as a going concern is based on the earnings power of its assets. Insolvency, in a bankruptcy sense, occurs when the total liabilities exceed the fair valuation of the firm assets, with the value of the firm assets determined by the earnings power of the assets.

X_4 is a measure of how much the firm assets may decline in value before the liabilities exceed the assets and the firm becomes insolvent.

X_5 is a measure of the sales generating ability of the firm assets.

The coefficients in the Z-score are values that were found by Altman as he studied 66 publicly held US manufacturing firms with comparable industry size over the period 1946-1965, half of which had declared bankruptcy and half of which survived. The results of the study also show that X_1 through X_4 are significant at the 1% level, indicating an extremely significant distinction in these variables between the two groups. Variable X_5, however, was insignificant between the bankrupt and survivor firms.

Altman finds that all variables have positive weights. Thus, a higher value of the Z-score indicates a higher probability of survival and a lower value indicates a higher probability of bankruptcy. He divides the Z-score into three zones of discrimination:

$Z > 2.99$ is considered "safe zone"

$1.81 < Z < 2.99$ is considered "grey zone" and

$Z < 1.81$ is considered "distress zone".

Altman (2000) later revised his model for non-manufacturing firms, and in emerging markets for wider applicability. He removed X_5, reasoning that the effect of asset turnover was unlikely to be important in the non-manufacturing industry and arrived at a new Z-score with different zones of discrimination.

Altman *et al.* (2017) study the performance of the Z-score model for primarily non-financial firms from 31 European and 3 non-European countries. Since the accounting legislation and practice, creditor rights, investor protection, judicial efficiency, corporate governance, bankruptcy protection, insolvency management, and risk taking differ in different markets, it is natural to test the international applicability of the bankruptcy prediction model across different types of markets. The non-European countries include the US, as this is the country where the Altman model first originated and has the largest market capitalization in the world. They also choose China and Colombia, which represent two culturally and institutionally different emerging markets. Their results conclude that the Z-score model performs very well in an international context. They determine that while the original Z-score performs well in an international context it may be beneficial to include a set of additional background variables that are specific to each country. They believe that adding country specific estimators will help boost the classification accuracy of the model to a much higher level.

Another financial statement model which predicts the probability of default for private, middle market companies, is developed by Moody's KMV (2002), and modified in 2004. The earlier model includes only financial statement variables, while the later model adds further financial statement variables as well as industry adjustments, blending market-based information with firm specific financial statement information. The list of financial statement ratios includes profitability, leverage, debt coverage, growth variables, liquidity, activity ratios, and size, with the exact list employed differing from one country to another. The data used is from the Credit Research Database, which is a database gathered from portfolios of banks and corporate lenders from North America.

The model assists institutions and investors in determining the risk of default, missed payments, and other credit events. It defines default in terms of the following insolvency-related events: receiverships, winding-up petitions, moratoriums, and liquidations.

Although the above-mentioned models are the most prominent amongst financial statement analysis models, researchers have introduced other variants. The popularity of these financial statement models stems from their simplicity and ease of use. In most cases, a researcher simply calculates the ratios and plugs the financial statement figures into the model. However, because the variables used in the Altman model and other balance sheet models are designed for use in specific industries, the applicability of the model to other industries is questioned. The variables used in the Altman model are indiscriminate in the case of financial companies, as they depend more on off-balance-sheet items. Thus, they are not recommended for use within the financial industry.

Vassalou and Xing (2004) voice concerns regarding the use of accounts-based (or spreadsheet) models in estimating default risk. They point out that accounting models use information derived from the financial statements, and as such, they are inherently backward looking because those statements report the firm’s past performance rather than its future prospects. They contrast accounts-based models to the Merton (1974) model, which uses the market value of a firm equity in calculating its default risk, and further estimates the market value rather than the book value of debt. Vassalou and Xing justify that since market prices reflect investor’s expectations about a firm’s future performance, the Merton model is forward-looking, and better suited for calculating the likelihood of default. Further, Vassalou and Xing argue that accounting models imply that firms with similar financial ratios should have similar likelihoods of default, this is in contrast to the Merton model where firms may have similar levels of equity and debt, but have different likelihoods of default, if the volatilities of their assets are different. Thus, Vassalou and Xing support the Merton model, which implies that the volatility of firm assets provides crucial information about its probability of default.

2.4.3 Structural models

Structural models as the Merton Model measure changes in default probabilities based on the distance to default, which is a combination of asset values, debt, and the standard deviation of asset values. Moody's KMV (2003) specify three main measures that would determine the default probability of a firm:

(i) Market value of assets: Measured by the present value of the future free cashflows produced by the assets. It represents the firm's future prospects and incorporates relevant information about the firm's industry and the environment economy.

(ii) Asset risk: The assets value is an uncertain estimate and thus should be understood in the context of the firm's business or asset risk. It measures the firm's business and industry risk.

(iii) Leverage: Measures the extent of the firm's contractual liabilities. It is measured as the book value of the firm's liabilities relative to the market value of its assets.

When the asset value of a firm lies somewhere between short-term liabilities and total liabilities, it is called a point of default. Pareek (2010) highlights the importance of noting that in the KMV a firm does not have to default the moment its asset value falls below the face value of debt. That is, a firm may not default even if the value of assets has fallen to less than the total debt. It is the current cash needs, driven by short-term debt that can cause default. A firm may have enough cash to keep paying all liabilities as they come due even if the total liabilities are greater than the total assets.

Moody's (2003) model essentially follows three steps to determine the default probability of a firm:

(i) estimate the asset value and volatility (these are estimated from the market value and volatility of equity) and the book value of debt;

(ii) calculate the distance to default: calculated using step (i); and

(iii) calculate the default probability: determined directly from step (ii) and the default rate for given levels of the distance to default.

Asset risk is measured as asset volatility, i.e. the standard deviation of the annual percentage change in the asset value. The greater the volatility of the assets the closer the entity moves to default. Asset volatility is magnified by a firm's leverage. Industries with high asset volatility tend to take on less leverage than industries with low asset volatility, thus asset volatility is related to the size and nature of the firm's business.

The market value of assets, business risk, and leverage can be combined into a single measure of default risk. This measure is referred to as the Distance to Default (DD), which compares market net worth to the size of a one standard deviation move in the asset value. More explicitly,

$$\mathrm{DD} = \frac{(\text{Market Value of Assets}) - (\text{Default Point})}{(\text{Market Value of Assets})(\text{Asset Volatility})} \tag{2.4}$$

If the probability distribution of the assets is known, or equivalently, if the default rate for a given level of distance to default is known, the default probability can then be computed from the distance to default. In this case the default probability would simply be the likelihood that the final asset value was below the default point.

$$PD = N(-\mathrm{DD}) \tag{2.5}$$

However, since this is not the case in practice, and assumptions of normal or lognormal distributions cannot be used, Moody's KMV first measures the distance to default (DD), which represents the number of standard deviations from default, and then it uses empirical data to determine the corresponding default probability.

To compute the default probability of a publicly traded firm, there are three key pieces of information required: financial ratios, market prices of the firm's debt and equity, and subjective appraisals of the firm's prospects of risk. Market prices represent the combined willingness of many investors to buy and sell, and thus prices embody the synthesized views and forecasts of many investors, allowing the model to be inherently forward looking. Moody's KMV (2003) state that the most effective default measurement derives from models that utilize both market prices and financial statements. Market prices are thus used in the determination of default risk because prices add considerable predictive power to the estimates of default risk.

Equity has limited liability and is the residual claim on assets after meeting all obligations of the firm (Easterbrook and Fischel, 1985). Limited liability means that equity holders have the right but not the obligation to pay off debt holders and takeover the remaining assets of the firm. The option nature of equity can then be exploited to relate the market value of equity and book value of debt to determine the implied market value of assets. As the Merton Model is the measure of default used in this thesis, the estimation techniques are detailed in Chapter 7.

In contrast to other models, structural models have a major strength as they incorporate market data as a key component in the model, making it more responsive to changing market conditions (Allen and Powell, 2011).

2.5. Conclusion

This chapter starts out by discussing traditional theories of the main models in this research. First, the traditional theories of financial decision making are reviewed, followed by an examination of the traditional theories on the causes of stock price crash risk, finally, concluding with traditional theories of causes of firm probability of default. There are two main reasons to review the traditional theories. First, this will help in integrating traditional models with behavioural models for empirical testing. Further, despite the many theories used to explain financial decisions of managers, or the causes of increased firm risk, researchers still know relatively little about how firms actually behave (Jahanzeb *et al.*, 2014). There remains a gap between theories of how firms should behave, and empirical evidence that shows a distortion from expectations. The next chapter will consider a set of behavioural factors that may affect the financial decisions of managers.

Chapter 3

Literature Review II: Behavioural Theories of Corporate Finance

3.1 Introduction

The discussion of Chapter 2 suggests that most traditional theories of corporate finance have one thing in common: they assume that skills, expertise and personalities of managers themselves do not matter. The theories focus largely on firm and industry factors, while ignoring the personalities and biases of the agents who run those firms. However, research on the cross-sectional determinants of capital structure, for instance, shows that a large amount of variation of actual debt/equity levels remains unexplained after controlling for firm and industry level characteristics proposed in the theoretical models. It becomes important to consider whether manager personalities, as opposed to market factors, can account for these unexplained variations.

Traditional finance theory assumes that individuals are rational and ignores individual decision maker personality. However, behaviourists tend to stress the importance of bounded rationality due to cognitive limitations, leading us to the science of Behavioural Finance. Behavioural finance is a paradigm where financial markets are studied using models that are less narrow and restrictive than those based on the Von Neumann-Morgenstern (1947) expected utility theory and arbitrage assumptions. The Von Neumann-Morgenstern utility theory shows that under certain axioms of rational behaviour, a decision-maker faced with risky (probabilistic) outcomes of different choices will behave as if he is maximizing the expected value of some function defined over the potential outcomes at some specified point in the future. Thus, a rational decision maker chooses between risky or uncertain prospects by comparing their expected utility values (a sum of utility values of outcomes weighted by their respective probabilities). However, this elementary and straightforward decision rule does not explain adequately the empirically observed decision-making process.

Traditional financial theory focuses on the effects of agency problems and information asymmetry on investment and financing decisions. Research into behavioural corporate finance, however, is still relatively young. Researchers in the study of behavioural corporate finance increasingly recognize that the psychological biases that affect investors may also be widespread amongst corporate managers. Behavioural finance uses models in which agents are considered not to be fully rational, either because of preference or because of mistaken beliefs (Ritter, 2003).

This thesis studies the effect of behavioural biases on the decisions of managers and its effect on firm risk. In this respect it deals with behavioural corporate finance, one of the branches of behavioural finance. Financial managers acting on behalf of shareholders and investors are also economic agents, this topic thus falls under the branch of behavioural economics as well. This thesis is thus a hybrid of two recently growing topics of interest, and so the assumptions and criticisms of both topics will be tackled in the forthcoming sections.

This chapter will look at a range of manager and investor biases considered in the literature, focusing on the most common managerial biases relevant for this study, justifying the need to depart from traditional theories of decision making in favour of a more comprehensive theory that incorporates behavioural factors.

3.2 Departure from Traditional Theories of Finance

Economics traditionally conceptualizes a world populated by calculating, unemotional maximisers labelled "Homo Economicus". Cartwright (2018) describes Homo Economicus as individuals who are rational, calculating and selfish, with unlimited computational capacity and never making systematic mistakes.

One of the earliest critics of unbounded rationality is Simon (1995) describing bounded rationality as a more realistic conception of human nature. Simon argues that under the standard model of rational choice, a decision maker is assumed to have almost complete, clear and voluminous knowledge of his environment. The individual is also assumed to have computational abilities that allow him to simultaneously evaluate and choose among alternative courses of action the course with the highest attainable point on his preference scale. However, Simon emphasizes that under these assumptions, whenever researchers try to examine the behaviour of individual actors in more details, problems start to arise. Instead, Simon brings forward the idea of bounded rationality. He states that the ability of the human mind to formulate and solve complex problems is very small compared with the size of the problems required for objectively rational behaviour in the real world.

Simon (1995) finds that, in the natural environment, people tend to make quick decisions under pressure, and from a small amount of information. To make these quick decisions, individuals use mental shortcuts referred to as rules of thumb or heuristics. Decision makers will almost always halt their decision process when a satisfactory solution is found, and long before all alternatives have been examined. The goal of behavioural finance is to investigate behaviourally grounded departures from these assumptions that seem economically relevant (Rabin, 2002).

Mullainathan and Thaler (2000) argue that people, even when they know what is best, sometimes fail to choose it for self-control reasons, as presented by people smoking or drinking. While people know that smoking and drinking present a health hazard, they are unable to control these unhealthy habits. Mullainathan and Thaler also maintain that people are boundedly selfish.

Upon reviewing the differences in literature between bounded rationality and behavioural economics Mallard (2016) finds that although both disciplines are concerned with studying the decision-making process at a lower level, their specific focuses are different. Mallard finds that works of bounded rationality focus on the wider economic consequences of decision-making. Bounded rationality focuses on situations in which the decision maker is unable to act according to the standard model of rational choice, due to his limited cognitive abilities and the complexity of the decisions he faces. In contrast, research of behavioural economics tends to focus on the precise cognitive processes and influences involved in decision making, including the nature of people preferences and the way in which their decision making can be manipulated. Thus, while the works of bounded rationality are largely abstract analysis of theoretical models of decision-making, the works of behavioural economics focus on experimentation and an observation of how subjects respond to different kinds of information. Mallard (2016) stresses the importance of both works being combined to form a unifying framework, which could be used across different situations.

3.2.1 Modifying unrealistic assumptions

In this sub-section we will look at some of the unrealistic assumptions made in the field of corporate finance. Financial markets have been based on conventional assumptions of rationality of profit maximization and informational efficiency (efficient market hypothesis) and use of complex econometric models.

Traditional corporate finance theory also assumes that both managers and investors act rationally, assuming efficient financial markets. According to the Agency Theory, investors assume that managers are intentionally self-serving and thus should be provided with incentives to bring the interests of managers in line with the shareholders' interests as explained in Chapter 2. However, researchers need to focus more on unintentional value reducing decisions that occur due to psychological reasons, to allow such mistakes to be avoided through the implementation of management training and education.

Managers must make several financial and non-financial decisions. The psychological biases of managers do not necessarily result in decisions that are consistent with the expected preference of investors. The behavioural analysis considers the human element that goes into any decision, including the human perception and evaluation of outside situation and events, and more importantly, the emotions associated with any financial decision. This relatively new field of modern finance emphasizes that the motivations, emotions, and feelings are indispensable to any human decision, including financial ones (Mitroi and Oproiu, 2014).

Bertrand and Schoar (2003) argue that the neoclassical view of corporate decisions assumes that top managers are homogeneous and selfless. They argue that this is a "narrow view" where managers are regarded as perfect substitutes for one another, and top managers are not related to what is going on within a firm. Executives do differ in their preferences, risk aversion or skill levels. However, under the neoclassical assumption, this will not translate into actual corporate policies if a person cannot easily affect these policies. Under the neoclassical assumption firms within the same industry, facing identical market conditions, and that share similar technologies and processes, should make similar choices, regardless of the management team.

Bertrand and Schoar (2003) study managerial fixed effects on corporate policies. Managerial fixed effects include variables such as age, gender, education, and cultural background. The specific corporate variables they study are related to investment policy (capital expenditures, investment to Q sensitivity, investment to cashflow sensitivity and acquisition policy), financial policy (financial leverage, interest coverage, cash holdings, and dividend pay-outs), organizational strategy (R&D expenditures, advertising expenditures, diversification policy and cost cutting policy) and performance.

They find that there are significant managerial fixed effects in performance that are statistically related to some of the fixed effects in corporate practices. Particularly, they find that managerial fixed effects are especially important in acquisitions or diversification decisions, dividend policy, interest coverage and cost-cutting policy. They are able to link differences in behaviour across managers to two main managerial characteristics, namely age and degree level, showing that older generations of managers are financially more conservative, while managers who are MBA holders follow more aggressive strategies. Where managers engaging in a higher amount of external acquisitions and diversification also display lower levels of capital expenditures and R&D. Furthermore, managers who have high investment to Q fixed effects rank lower in their investment to cashflow sensitivity, implying that managers may differ when making their investment decisions.

Their results indicate that top executives vary considerably in what they refer to as "management styles", suggesting a need for a more novel approach in the study of corporate financial research. They stress the need to study why managers behave so differently in similar economic conditions, and whether these differences can be related to preferences, absolute or relative skill, or opinion.

Models that allow managers to differ in their preferences, risk aversion, skill levels or opinions will allow for differences in corporate practices. Thus far, there are two main interpretations as to how these managerial differences translate into corporate choices. The first interpretation allows managers to impose their own idiosyncratic style on a company if the corporate control is poor or limited. Thus, as internal and external control weakens, there is an expected increase in managerial impact. The second interpretation implies that a firm purposefully chooses managers because of some specific attributes. Thus, managers do not actually impose their idiosyncratic style on the firm.

3.3 Documented Behavioural Biases

There are several recorded biases in literature that are found to affect a person's decisions (Kahneman and Tversky, 1979; Weinstein, 1980; Odean, 1998; Thaler and Sunstein, 2008; Moosa and Ramiah, 2017).[3] The most popular biases in behavioural finance include, but are not limited to:

- Confirmation bias, which refers to a person's tendency to pay close attention to information that supports his hypotheses or beliefs while ignoring information that does not.
- Anchoring bias, which theorizes that people anchor their decisions on pre-existing information or first data points received.

[3]Most of the biases presented, are discussed hypothetically in relation to crisis periods or public events, but little empirical studies have been performed, partly due to the difficulty of measuring the above biases in a corporate setting.

- Loss aversion bias, which is a person’s inclination to try to avoid losses on the grounds that grief from a loss is greater than happiness from an equivalent gain. This explains why people sell their gains fast but hold on to their losses for a longer period in hopes that the situation may reverse.
- Availability bias, which refers to people’s likelihood to base their decision on information that is widely available, thus over weighing information that is more readily available and under weighing information that is not.
- Representativeness bias, which refers to people using heuristics or mental short cuts to arrive at a decision. While this method may be faster, it may also come at the cost of making the correct decision.
- Hindsight bias, which is a person’s belief that they were able to predict an event when it occurred. Hindsight bias can lead to an increase in overconfidence and reduce a person’s ability to consider the impact and implications of an event subjectively.
- Panic, which can best be described as a sudden and uncontrollable feeling of fear that leads to rushed and unthought of behaviour. Panic can lead to both bubbles and crashes. Bubbles are created when there is an uncontrolled amount of buying leading to an exaggerated price, while crashes occur when there is collective selling that can lead to a crisis.
- Herd behaviour, which refers to people mimicking the actions of others believing that they have superior information than themselves. Herding is typically associated with periods of financial crisis, as investors follow the majority view and act accordingly, causing both bubble and crash.

- Overconfidence and optimism bias, this bias makes people think they are invulnerable. They create errors in judgment since they are unrealistic: people believe that, compared to the population, negative events are less likely to happen to them and positive events are more likely to happen to them.

The most popular bias tested in a corporate setting is the overconfidence/optimism bias (Malmendier and Taylor, 2015), largely due to its intuitive appeal. The next section will focus mainly on the overconfidence/ optimism bias, as it the main bias of interest in this thesis.

3.3.1 Overconfidence and optimism

Most researchers do not distinguish between overconfidence and optimism and often use the terms interchangeably. In the psychology literature, overconfidence has several manifestations[4]: miscalibration, the above-average effect, and the illusion of control. Miscalibration is defined as excessive confidence about having precise information (Gervais and Odean, 2001, Shefrin, 2005). Miscalibrated decisions means that people tend to overestimate the precision of their own forecasts or underestimate the variance of risky processes. The above-average effect is defined as the tendency of individuals to believe that they are better than their peers within a particular group (Weinstein, 1980). Finally, the illusion of control is defined as the tendency of individuals to overestimate their ability to control events over which they have limited influence (Langer, 1975). These unrealistic biases can affect the decision of financial managers as they are deeply embedded in applied work pertaining to risk perception and risk behaviour (Harris and Hahn, 2011).

[4] The distinguishing feature between the agency theory and overconfidence bias is that under the agency theory managers know what they are doing but do it anyway to reap private benefits, overconfidence however is a subconscious bias that skews a manager’s perception of return and risk.

Overconfidence is closely related to narcissism.[5] Daniel *et al.* (1998), Benos (1998) and Odean (1998) argue that overconfidence may be interpreted as agents overestimating the precision of their information, thereby giving greater importance to private information versus public information. Skala (2008, p.38) adds, "people tend to have an unrealistically positive view of themselves. Most people, when comparing themselves to a group (of co-students, co-workers, random participants), believe themselves to be superior to an average representative of that group in various fields".

Overconfidence will lead an agent to believe that they can make an efficient decision with minimal time and energy. This may also lead to a systematic overestimation of probabilities associated with current events, and a systematic underestimation of the probabilities associated with rare and severe events. This bias causes the decision maker to be overconfident in their ability to predict a phenomenon and overestimate his/her ability to provide an accurate forecast. Overconfidence cannot be explained by the classical norms as it represents irrational behaviour, and most economic agents are found to be overconfident, causing the rationality of their decision to be either limited or non-existent (Jarboui and Boujelbene, 2012).

Optimism deals with humans tending to have an overly optimistic view of reality, or the refusal to believe that objective probability distributions apply to them, and this is often referred to as "unrealistic optimism". Under unrealistic optimism, agents tend to perceive their own future as more positive than the average person. Specifically, people rate negative (positive) future events as less (more) likely to happen to themselves compared to the average

[5] Schrand and Zechman (2012) explain narcissism as an extreme form of overconfidence. They argue that narcissism is distinguished with an extreme "self-love" or need for attention that would cause them to put their egomaniacal needs and beliefs before the needs and interests of the firm and its shareholders.

person, thus limiting the rationality of their decisions, and impeding the placement of necessary preventative steps as they underestimate the chance of negative events (Harris and Hahn, 2011). This may have a perverse effect on economic decisions, feeding unrealistic expectations or causing an inability for a person to realize the risk of loss (Jarboui and Boujelbene, 2012). This should call for further development in the role of behaviour in decision-making.

Optimism is sometimes distinguished from overconfidence in that optimism is usually modeled as an overestimation of the mean ability or outcome, while overconfidence is usually modeled as an underestimation in variance (Baker and Wurgler, 2011). In contrast to optimism, overconfidence bias reduces the level of perceived risk or increases the risk-taking capacity of the individual. Baker and Wurgler further stress the importance of focusing on these particular biases in a managerial setting, as such biases are strong and robust, and are often fairly easy to integrate into existing models.

3.4 Overconfidence Bias and Cultural Dimensions

This thesis makes a comparison of the impact of managerial overconfidence in the Egyptian and UK market. The chosen markets are not only different in stages of development and informational efficiency but will also differ in cultural aspects (more on market efficiency and political instability in Chapter 3). Moore et al. (2018) maintain that there exists differences in overconfidence across populations and cultures, and that these differences may be as a result of the costs and benefits created by the specific physical and social environments in which the individuals live and interact. This section will discuss how managerial overconfidence may be affected by cultural dimensions.

Li and Tang (2013) maintain that executive characteristics are subject to social stimuli, and thus overconfidence and other hubris may differ regarding social context. The culture in which managers work may influence how they behave by providing stimuli to shape their thoughts and behaviours.

Hofstede (1983) defines culture along six dimensions 1) individualism vs. collectivism 2) power distance 3) uncertainty avoidance 4) long-term orientation 5) masculinity versus femininity 6) indulgence. The most frequently studied cultural dimension in relation to overconfidence is individualism vs collectivism. Several authors have found that social stimuli play a more important role in a culture that emphasizes individualism vs. collectivism. Individualism and collectivism describe ways in which individuals think and behave in relation to one another and in relation to their society. Differences between these two groups stem from attitudes toward motivation, wants, needs and social status (Antoncyzk and Salzmann, 2014). Individualism is associated with an "I-consciousness", where individual goals and rights are stressed. In an individualistic society, people work in autonomy, they set personal goals and objects, and are motivated by personal rewards and benefits. In contrast collectivism is associated with a group context. Individuals in a collectivist culture are motivated by group goals thus the happiness of the group is considered more important than the happiness of the self. Individualistic cultures exhibit more optimism/overconfidence than collectivist cultures. As persons in an individualist culture are self-dependent, this tends to enhance a positive self-view and inflate perceptions of competence. Persons in a collectivist culture on the other hand are more self-critical and exhibit more self-discipline. Empirical research by Ferris et al. (2013) shows that this holds true even in the field of corporate finance, where CEOs situated in an individualistic society display more overconfidence than those in a collectivist.

Cultural differences and their impact on psychology may also be different due to the educational system, the masculinity of the group or the age. Similar to the notion of individualism vs. collectivism, cultures where the educational system focuses on analytical thinking and analysis are likely to have more overconfident individuals than educational systems where viewpoints are challenged much less (Margolin, 2013). Further the level of education in a population may affect the amount of overconfidence. A person who is more educated and more competent becomes more confident in their abilities and their level of perceived accuracy. The empirical results that education increases overconfidence and its effect on financial decisions is supported in empirical research as Malmendier and Tate (2005) and Ben-David et al. (2006). Gender could also be an important factor of difference from one culture to another. In a culture where masculinity is prevalent, overconfidence is expected to be more pronounced as men are stereotypically considered to show more overconfidence than women. In a study, Barber and Odean (2001), base their measure of overconfidence on the trading volume of an individual. They analyse the trading activity of male and female investors and find that male investors trade 45% more than women. They emphasize that overconfidence in males is particularly more exaggerated in areas of finance. Another determinant of cultural differences may be explained by age. Bertrand and Schoar (2003) show that older managers are more conservative, while younger managers are more confident and take on increased levels of risk. Thus, in a culture dominated by an older population of managers we would expect to find decreased overconfidence and risk-taking activities than a younger population of managers.

3.5 Overconfidence Bias and Corporate Decisions

Previous research in the area of corporate finance found that managerial overconfidence and optimism affects a broad set of corporate decisions as financial and accounting policies, capital budgeting, capital structure, and mergers and acquisitions. This section will review some of the documented effects of managerial overconfidence on corporate decisions, forming a foundation for upcoming hypotheses.

Theoretical models developed by Hackbarth (2008) distinguish between optimism and overconfidence in that they define optimistic managers as overestimating the mean of their firms' cashflows (referred to as growth perception bias) while overconfident managers underestimate the volatility of their firms' future cashflows (referred to as risk perception bias). He notes that managers with growth perception bias believe that their firm is more profitable than it actually is, and therefore less prone to suffer financial distress. They overestimate the profitability of the firm and prefer debt to equity, as they perceive their firm equity as severely undervalued. Managers with risk perception bias believe that the volatility of the firm cashflow is lower than it actually is and therefore underestimate the expected cost of bankruptcy causing them to take on more debt. The author finds that biased managers select dynamically higher debt levels leading to costly distortions of capital structures.

Baker *et al.* (2004) review the theories, empirical challenges, and evidence pertaining to managerial biases and financing decisions. Regarding investment decisions, they find that "entrepreneurial start-ups are generally made under a halo of overconfidence and optimism" (Baker and Wurgler, 2011, pg. 390). Entrepreneurs think that their start-up is more likely to succeed than comparable enterprises, while also underestimating the task of starting up a business. The actual performance of start-ups is a lot worse. Only half of all start-ups survive the first 3 years. Further, they find that optimism also appears to influence investment in more mature firms. Optimism biases, they find, are strong in project cost forecasts, whereas the actual costs are typically more than twice as much as the initial estimates, causing managers to overinvest. They establish that optimistic CEOs complete more mergers.

Barros and Silveira (2007) assert that managerial biases should be ranked among "the potential determinants of capital structure". They find that a wide range of literature is dedicated to the empirical investigations of determinants of capital structure, resulting in discarding or confirming the relevance of different theoretical approaches and guiding the development of new theories. However, none of these works considers any argument based on the effect of cognitive biases of managers, although the literature of behavioural theory strongly suggests that the degree of optimism and overconfidence of managers can significantly influence the debt/equity choice.

Barros and Silveira (2007) maintain that there is one theoretical result related to capital structure decisions that is compatible with all available models and emerges as the central prediction in the body of theoretical work. This result establishes that managers who are cognitively biased towards optimism and/or overconfidence will choose to issue more debt than their rational peers. In accordance with Hackbarth's (2008) model, this occurs because biased managers believe that the firm is less likely to experience financial distress than it actually is. The manager will thus underestimate the expected cost of bankruptcy and will take on more debt to exploit its tax benefits (or other benefits discussed under the Trade-off Theory).

Hribar and Yang (2010) use popular press characterizations of the CEO as their measure of overconfidence. They use the same classification of Malmendier and Tate (2008), classifying a CEO as overconfident if he/she is more frequently described as "confident" and "optimistic" relative to descriptors such as "frugal, conservative, cautious, practical, reliable or steady". Hribar and Yang maintain that overconfidence manifests itself either as excessive optimism about future firm performance or an underestimate of the variance underlying future performance. They provide evidence that overconfident managers issue upwardly biased forecasts, and this has two implications. First, overconfident CEOs are more likely to miss their own forecasts after controlling for other predictors of ex-post forecast accuracy such as accounting flexibility, litigation costs, forecast horizon and growth prospects. Second, overconfident managers are associated with the use of aggressive accounting policies subsequent to the forecast.

Similarly, Ahmed and Duellman (2012) argue that managerial overconfidence will affect both short term and long-term accounting policies of a firm that may lead to decisions that could destroy firm value. They hypothesize that overconfident managers will overestimate future returns from their firm projects and hence will be more likely to delay recognition of losses and less likely to use conservative accounting policies. They expect overconfident managers to use overly optimistic estimates in determining asset values (as inventory, receivables or fixed assets) which again will lead to lower levels of accounting conservatism. They also expect that overconfident managers will undervalue their liabilities. As an overconfident manager will tend to overestimate the probability of the collection of accounts receivables, he/she will consequently understate the allowance for bad debts thereby overstating net receivables. They study S&P 1500 firms from 1993 to 2009 and find evidence of a significant negative relationship between both conditional and unconditional accounting conservatism. Furthermore, they find that changes in managerial overconfidence are negatively related to changes in accounting conservatism following a CEO change.

Cronqvist and Yonker (2012) attempt to explain corporate capital structure based on CEOs personal behaviour and debt tolerance through past personal leverage choices. Their study focuses primarily on the "Behavioural Consistency Theory" which states that individuals behave consistently across situations. This led the researchers to believe that the debt tolerance of CEOs should be consistent in the firms they lead as well as in their personal life. This allows CEO personal behaviour to, in part, predict the corporate financial behaviour of the firms they manage. They choose the financing of the CEOs' primary homes, as it relates to the domain of debt decisions. They view that the purchase of a home is an important decision, and the mortgage debt tends to be the most important source of debt, even if not a measure of total personal indebtedness.

Cronqvist and Yonker (2012) regress corporate leverage on personal home leverage and find a statistically positive relationship. The more conservative a CEO personal leverage is, the more conservative his firm capital structure is. They provided two mechanisms that can explain a positive relation between personal and corporate leverage. One mechanism is the CEO-firm matching mechanism, whereby firms systematically replace a CEO with one with a similar personal debt preference. An alternative mechanism is that CEOs imprint their personal preferences on the capital structure of the firms they manage, whether optimal or not, this is particularly true for firms with weaker corporate governance. Either way, there is an ideal matching where CEOs who are willing to bear more financial risk match better with firms for which more financial leverage is optimal.

Malmendier *et al.* (2012) study and differentiate the effect of overconfidence on the decisions of two most prominent managerial positions: CEO and CFO. They use overconfidence and optimism interchangeably as they define overconfidence as people who are likely to be "optimistic" about the outcomes they can control. They expect that overconfident managers will overestimate the outcomes of the decisions under their control. They combine several data sources on option holding to construct a panel of 1,156 firms from the S&P 1500 index from 1996 to 2010 and use it to test the impact of CEO and CFO overconfidence on both financing and non-financing decisions such as investments, acquisitions, and innovations.

They find that overconfident CEOs and CFOs are significantly more likely to issue debt when accessing external capital market than their non-overconfident peers. However, they find that only overconfident CFOs use significantly more debt financing when the financial deficit of the firm is high. Likewise, overconfident CFOs are significantly less likely to issue equity when using external capital and use less equity financing to cover their financial deficits. Both decisions do not hold true for overconfident CEOs. Furthermore, they find that overconfident CEOs significantly increase investment cashflow sensitivity and cashflow and R&D expenditure. Overconfident CEOs in firms with abundant cash or low book leverage were also found to spend significantly more on acquisitions, which does not hold true for overconfident CFOs. Further, they find that the most debt conservative overconfident CEOs are also equity-conservative, i.e. they are least likely to issue equity. Moreover, they do not substitute equity for debt, confirming their preference to avoid public markets. Malmendier and Tate (2008) further find that since overconfident CEOs over-estimate their ability to generate returns, they overpay for target companies and undertake value-destroying mergers. This effect is found to be particularly strongest if a firm has access to internal financing.

Graham *et al.* (2013) use a new form of psychometric personality tests to provide new insight into the CEOs characteristics and the processes behind the corporate decisions. Their survey-based approach is used to gauge risk-aversion and measure other behavioural phenomena and relate them to firm-level policies such as leverage policy, debt maturity, and acquisition activity. They administer these surveys to CEOs and CFOs of private and public firms, in the US and outside, to identify whether there will be a significant difference in attitudes. Their results show that the personality traits of executives, as optimism and risk aversion, are significantly related to corporate financial policies. For example, they find that CEOs who are more risk tolerant initiate more mergers and acquisitions, and CEOs who are optimistic use more short-term debt than their less optimistic counterparts. They also find evidence that male CEOs are more likely to have higher debt ratios, specifically short-term debt ratios, than their female correspondents. Furthermore, CEO's with past experience in financing/accounting use significantly more total debt. They also relate firm traits to CEO traits, finding that firms with high historical or future growth rates are more likely to be run by risk tolerant CEOs. These CEOs are likely to be younger, and more likely to be taller than average, suggesting a higher level of overconfidence.

Although the findings of Graham *et al.* (2013) prove a significant relationship between CEO characteristics and company characteristics, they cannot determine the direction of causality. For example, they find that risk tolerant CEOs are more likely to be found in growth firms. They are not able to determine whether managers self-select into growth companies, or whether companies hire managers with the "right personality", that is, a firm becomes a growth firm as a result of hiring a risk tolerant manager.

In this section, a portion of documented effects of managerial overconfidence on corporate decisions was discussed, this will be used with additional literature to form the hypotheses in the next three subsections.

3.5.1 Overconfidence, source of funds and investment

Chen and Lin (2013) find that a firm with a highly optimistic CEO will invest more than firms whose CEOs have lower levels of optimism. Further, they find that an under-invested firm with an optimistic CEO improves the firm's investment efficiency by reducing the amount of underinvestment, thereby increasing the value of the firm. However, they were unable to find evidence for the alternate scenario, i.e. for an over-invested firm, CEOs with a lower level of managerial optimism do not appear to effectively improve the firm's investment efficiency and increase firm value by reducing the value of overinvestment. Finally, they find that overconfident CEOs in financially constrained firms are still willing to increase their capital expenditure, leading to an increase in firm value.

Campbell *et al.* (2011) use a theoretical model to show that a moderate level of optimism causes a CEO to invest at the first best level (investment level that maximizes firm value). While optimism levels below (above) the interior value-maximizing level of optimism lead the CEO to underinvest (overinvest), thus proving that firm value is concave in CEO optimism. Concluding that if the board wants to maximize firm-value they should observe CEO optimism prior to hiring or correct their mistakes later through firing decisions. They further empirically prove that both low-optimism CEOs and high-optimism CEOs do not maximize firm value and are thus subject to higher forced turnover.

Thus, while some research finds that overconfident managers will tend to overinvest (whether this investment is beneficial to firm value or not) a large body of literature links this over or under investment levels of overconfident managers to a firm's current capital structure and to the source of funding available.

Heaton (2002) adopts a behavioural approach in simple corporate finance models and examines its implications in the free cashflow debate. He contends that managerial optimism leads managers to believe that an efficient capital market undervalues their firm securities, leading optimistic managers to prefer internal funds. On the other hand, optimistic managers dependent on external finance may sometimes also decline projects with positive net present value, as they believe that the cost of external finance is simply too high. Optimistic managers will want to undertake more projects. However, this investment is highly dependent on the source of funding where more optimistic managers are the less likely to invest if they are forced to finance these projects externally. This underinvestment will be more costly to shareholders.

Thus, free cashflow can be valuable. It can prevent social losses from under-investment, where biased managers would have otherwise normally declined a positive net present value project because of an incorrect perception of high external financing cost. Conversely, managerial optimism causes systematically upward biased cashflow forecasts and causes managers to overvalue a firm investment opportunity. In this case, free cashflow may be harmful as it alleviates the need to obtain external financing and makes it easier to take negative net present value projects mistakenly perceived to be positive net present value projects. Managerial optimism theory thus links the benefits and costs of free cashflow to two variables, the level of managerial optimism and the investment opportunities available to the firm. Heaton concludes that whether savings in preventing bad investment outweighs the social cost of underinvestment will likely vary by firm. He argues that if all managers are optimistic and markets are efficient, then shareholders may prefer large amounts of free cashflow to be retained by firms with good investment opportunities.

Overconfidence, thus, can be defined as the overestimation of the quality and precision of information available to the individual, and the underestimation of the volatility of the processes involving uncertainty. The model offered by Heaton (2002), described above, is in line with the Pecking Order Theory, where optimistic managers believe that the projects available to their firms will have higher expected returns than will be true. They thus believe that the securities issued by the firm, whether bonds or stocks are systematically undervalued by outside investors. As stocks are the securities most subject to the perceived undervaluation, consequently, the firm will prefer to fund its investment projects with internally generated resources followed by issuing debt security, leaving the issuance of stocks only as a last resort. Thus, this type of model predicts that the pecking order type of behaviour will be more pronounced with more optimistic managers.

Malmendier and Tate (2005) findings also uphold the Pecking Order Theory, where they relate measures of overconfidence and formative past experiences to corporate financial policies. They measure overconfidence using data on CEO option holding. They consider CEOs who hold non-tradable in the money executive stock options until expiration rather than exercise them after the vesting period. This delay in exercise does not yield abnormal returns over a simple strategy of exercising and diversifying. They thus interpret this delay as the CEO overestimating the mean of their firms' future cashflows. They supplement their data with personal information about the CEOs' educational background and employment history.

Malmendier and Tate (2005) first use a theoretical model[6] to show that overconfident CEOs are likely to increase their investment levels with the availability of internal cashflow (retained earnings). Conditional on accessing external funding they will prefer to raise more debt. Such CEOs are significantly less likely to issue equity, as they believe (incorrectly) that the public underestimates the present value of their investment returns, thus if they issue shares, they will be diluting the claims of current shareholders. This proves that overconfident managers view external financing as unjustifiably costly and prefer to use cash or riskless debt. In their empirical model, they regress investment level against cashflow, managerial overconfidence, and an interaction term of cashflow with managerial overconfidence. Their results show that the interaction term is statistically significant and positive. They conclude that overconfident CEOs have a heightened sensitivity of corporate investment to cashflow, and this is particularly true among equity dependent firms.

Following the above discussion, it can be deduced that investment levels of overconfident managers are largely dependent on the source of funding available. Overconfident managers will overestimate the returns to their investment projects, which would normally lead them to overinvest. However, they view external funds, particularly share issues, as costly as shares are undervalued by the public. Thus, overconfident CEOs will overinvest if they have sufficient internal funds or access to riskless financing, i.e. untapped sources of debt. An overconfident CEO, however, does not necessarily overinvest, and may even underinvest if internal or riskless financing is insufficient for the desired investment. This is because overconfidence also implies a misperception of the cost of external financing. Thus, the

[6] The theoretical model developed by Heaton (2002), Baker and Wurgler (2013) and Malmendier and Tate (2005) is provided in appendix A3A.

degree of investment will depend on the availability of financing and its perceived value. Based on this argument the following hypothesis is formulated:

H_1: managerial overconfidence increases investment decision sensitivity to cashflow.

3.5.2 Overconfidence and stock price crash risk

The previous section discussed the effect of overconfidence bias on firm investment level. This section will consider the effect of overconfidence on Stock Price Crash Risk. Section 2.3 discussed bad news hoarding as one of the most prominent determinant of SPCR. While the aforementioned section discussed several reasons for bad news hoarding including managers trying to avoid taxes or to reap private benefits, this section argues that managerial overconfidence may be one of the reasons managers choose to hoard bad news.

In the only paper that studies the relationship between SPCR and managerial overconfidence, Kim *et al.* (2016) argue that there should be a positive relationship between SPCR and managerial overconfidence. They stress that their argument is different to the rational agency problem, where managers are empire builders and choose to hoard bad news for private benefits. Instead, they build their argument on two main facets, the better than average effect and the interpretation bias. The better than average effect means that overconfident managers overestimate their capabilities, they are very optimistic regarding the returns on their projects, and they underestimate the risk involved. Interpretation bias means that overconfident managers perceive negative feedback as uninformative or inaccurate and are likely to ignore negative signals regarding their investments and stick only to the positive signals. In fact, this interpretation bias is likely to increase post decision, as a manager subconsciously tries to defend the investment choice made. Thus, even when the returns on current investment projects seems modest, they will ignore any negative signals.

They will hold from informing the public about this news and will persevere with their negative NPV projects all the while overestimating their ability to change the current situation into a more favourable one. When faced with the inevitable loss of their project, they leak this information at once creating a SPCR. Unlike the moral hazard problem, overconfident managers' interests are perfectly aligned with outside investors, they are not trying to reap private benefits but believe that they are acting in the best interest of shareholders.

Kim et al. (2016) study the constituent companies of the S&P 1500 between 1993 and 2010 and find a strong positive relationship between CEO overconfidence and stock price crash risk. Further, they find that this relationship changes with CEO turnover and changes in overconfidence, and that the impact of CEO overconfidence on crash risk is less pronounced for firms with stronger and more conservative accounting. Finally, they find that differences of opinions between investors are likely to exacerbate the effect of overconfident CEOs. They explain this as overconfident CEOs being less likely to listen to signals from investors if they are not providing a united front.

Based on the above argument this thesis seeks to complement the work of Kim *et al.* (2016) and propose the following hypothesis:

H_2: there is a positive relationship between the level of managerial overconfidence and SPCR.

3.5.3 Overconfidence and default risk

Milidonis and Stathopoulos (2014) argue that risk-averse CEOs, faced with increased career concerns, will proactively reduce risk, even in the presence of strong-risk taking incentives. They further hypothesize that this should be particularly true for firms that are highly levered and firms with high default probability. They test their hypothesis using all firms covered in the Standard & Poor ExecuComp database for the period 1992-2005. They group their firms into firms with high probability vs. low probability of default (against the industry average) and use it to study the effect of managerial risk aversion against the distance to default. Their results show a negative and highly significant relationship between managerial risk aversion and firm risk in firms with high probability of default. Where a one standard deviation increase in vega (their measure of risk aversion) is associated with a reduction in total firm risk by 1.5%. They find no relationship between vega and firms with low probability of default. They conclude that CEOs operating in firms with high probability of default can reduce firm-specific risk, even when the firms' shareholders increase the CEOs' risk-taking incentives.

I argue that the opposite should hold true for overconfident managers. Overconfident managers with an inflated sense of narcissism, will underestimate bankruptcy costs, ignore negative signals and take financial decisions that increase corporate risk. This should hold true even for firms with increased external or systematic risk, as with the state of political instability in Egypt[7]. In fact Adam *et al.* (2015) using a sample of 92 gold mining firms in North America included in the Gold and Silver Hedge Outlook (a quarterly survey of derivatives activities) conducted from 1989 to 1999, find that managerial overconfidence leads managers to increase their level of speculative activities using derivatives following a speculative gain, but do not similarly reduce their speculative activities following speculative losses.

[7] The exact dates and events that occurred in Egypt are discussed in more detail in Chapter 4.

Ben-David *et al.* (2010) use surveys that require CFOs to predict one year of ten stock returns, as well as the tenth and ninetieth percentiles of the distribution of market returns of the S&P500, to test for overconfidence. They label a CFO as overconfident if his prediction of the confidence interval for the probability distribution of stock returns is too narrow. They find that CFOs are on average severely miscalibrated, with only 40% of stock market realizations falling within the 80% confidence intervals provided by company executives. Further, they find that confidence intervals are wider in periods of high market-wide uncertainty, but over these periods, CFOs are even more miscalibrated. They argue that miscalibration depends on personal traits (skills) in addition to company characteristics. They find evidence that CFO over-precision appears to be related to corporate decision-making, investing more, and engaging in more acquisitions. They also find modest evidence that firms with miscalibrated executives have on average higher debt leverage, rely more on long-term debt, and pay fewer dividends. Miscalibrated executives repurchase more shares after a decline in share price but issue fewer shares following price run-ups. Finally, the authors find that executive compensation in firms with overconfident CFOs is performance-based.

The empirical results of Skala (2010), show that the influence of increased risk taking, driven by overconfidence, may be positive in the short-term, but is likely to be negative in the long-term. Overconfidence may result in bank managers taking greater risk because they overestimate their future performance and believe they will be able to cope with future risk better than peers. They may also wrongly assume that they are capable of controlling external events and are inclined to see the future as unrealistically bright. Expected losses take more time to materialize, thus the adverse consequences of their decisions will likely appear in future performance. This is because overconfidence is likely to generate profits in the short-term but is likely to adversely affect the future performance of firms.

Other authors, such as Baker *et al.* (2004), Malmendier and Tate (2005, 2008), Campbell *et al.* (2011) Kim *et al.* (2016) find that managerial optimism and overconfidence lead a manager to overestimate the returns on their investment projects. A manager who hand-picks an investment is more likely to believe that he can control its outcome and is also more likely to underestimate the likelihood of failure (Malmendier and Tate, 2005). Overconfidence will lead a manager to invest free cashflows more rapidly, initiate more mergers, invest in more novel projects, stick with an unprofitable investment policy for too long (Gervais, 2009) and use less conservative accounting. This is because overconfident/optimistic managers will tend to overestimate project cashflows. If there are no corporate governance mechanisms to control managerial bias, such managers will overvalue their own projects, overinvest, invest earlier than their rational counterparts, and may even invest in projects with negative NPV (Oran, 2013). In fact, Goel and Thakor (2008) theorize that governance boards favour an overconfident manager as managers choose riskier projects making them are likely to be promoted than rational managers. They argue that merit-based promotions make an overconfident manager more likely to be appointed as CEO as said manager has the highest perceived ability. They further stress that a moderate degree of overconfidence may actually be beneficial to shareholders, however, it is exaggerated overconfidence that will lead managers to make value destroying investments.

The above findings lead us to confer that as overconfident managers take on increasingly risky decisions, there should exist a relationship between managerial overconfidence and total firm risk as measured by the risk of default. Following the logic of Milidonis and

Stathopoulos (2014), I hypothesize that overconfident managers will not work towards proactively reducing firm risk, rather they take on decisions all the while underestimating the risk of bankruptcy. An overconfident manager believes that he/she is working in the best interest of shareholders, and thus is not trying to reap private benefits based on career concerns, they are simply skewed in their view of projected returns and risk. This means that overconfident managers are more likely to increase total firm risk regardless of the managerial incentives. I thus hypothesize that the relationship between managerial overconfidence and default risk is likely to be positive, and thus propose the following hypothesis:

H_3: There is a positive relationship between managerial overconfidence and probability of default.

It may be necessary to point out that while H_1 and H_2 are taken from existing models and applied to the Egyptian and UK markets for meaningful comparisons. To my knowledge, H_3 is a novel hypothesis that has not been studied before.

3.6 Conclusion

Traditional theories and determinants of financial decisions related to capital structure and firm investment level, stock price crash risk, and the degree of default risk were discussed in the previous chapter. As these theories were built on strict assumptions that may not hold true in reality and were found not to fully explain the variation in models, other determinants had to be considered. This chapter focused on the departure from the traditional determinants of financial decisions, incorporating behavioural determinants into the managerial decision-making process. It focused on the two most prevalent documented biases, overconfidence, and optimism, and reviewed findings in the literature regarding how these biases affect managerial financial decisions and firm risk. The main conclusions found are that overconfident CEOs are more likely to: miss their own forecasts; overestimate return while underestimating risk, use aggressive accounting; and hoard bad news. Overconfident managers also tend to overinvest, invest cashflows more rapidly and initiate more mergers and acquisitions. Finally, conditional on the level of access to the external markets, overconfident managers tend to use more debt financing as they view their firms shares as undervalued by the public.

Chapter 4

Research Methodology

4.1 Introduction

This chapter outlines the main methodological concepts that will be used to test the behavioural model. Specifically focusing on the overconfidence/optimism bias. Barros and Silveira (2007) state that while optimism and overconfidence may be treated separately for analytical purposes, psychological and behavioural research reveals that these biases are closely related and thus do not need separate proxies to distinguish between them. As such this study will not differentiate between the two metrics.

The rest of the chapter is organised as follows. The next section provides justification for choosing the Egyptian market as the primary market for model validation. However, the UK market is also included in this study for comparative purposes. Section 4.3 provides a conceptual model of the study and re-states the hypotheses developed in Chapter 3. The main method of model estimation, namely panel regression, is summarized in Section 4.4. Section 4.5 provide details about the data used in the study. Finally, Section 4.6 discusses the proxies used to measure overconfidence.

4.2 Behavioural Finance in Catastrophic Events

This study is based particularly on firms within the Egyptian market as a case study. In this section I justify the choice of the Egyptian market as the primary market of interest in my thesis.

Long before behavioural economics and finance were formed, Keynes (1936) highlighted the role of psychology in economics. He maintains that sentiment reflected in unrealistic optimism or pessimism leads to booms and busts. He noticed that securities often diverge from their intrinsic values, and explored the implications of such divergence for employment, income, and money.

Barberis (2011) argues that the greatest contributing factor to financial crises is excessive risk taking due to biased beliefs. A financial crisis is normally discussed in terms of the real estate "bubble" where, due to irrational thinking, real estate prices are pushed to unsustainably high levels. Barberis (2011) defines a bubble as an episode in which irrational thinking or friction causes an asset price to rise to a level higher than it would otherwise be. He further explains that this price level is such that a rational observer, armed with the necessary information, would forecast a low long-term return on the asset. Barberis (2011) argues that even though traders on mortgage desks are vaguely aware that their business model may entail serious risks, they manipulate their beliefs by deluding themselves that their business models were not risky but worth pursuing. This self-manipulation could be explained in terms of the several biases discussed in Section 3.3, among which is the overconfidence bias. Yu (2014) supports this view and explains the financial crisis of 2008 in the wake of CEOs overconfidence and earnings manipulation. Recent studies have taken a behavioural approach to analyse the global crisis of 2008, which can be conceptualized as a series of catastrophic events. Such studies aim to acquire a better understanding of what must be changed in the society's economic thinking whether in principle or approach in order to avoid similar scenarios in the future.

While most studies focus on the effects of overconfidence leading up to the financial crisis period, the empirical literature on whether those biases continued during the crisis period is limited. Eisenbach and Schmalz (2018) argue that decision makers bias is heightened during times of volatility. They maintain specifically that people with access to the best information about risk level and those who make decisions are systematically the most biased. They use a theoretical economic model to show that agents will especially be biased during times when risks are high. Their model describes overconfidence resulting from the choice to ignore risk signals. They theorise that this heightened risk taken by decision makers at times of volatility is due to the fact that an agent’s beliefs are driven by personal prejudice rather than by the reality of the situation. They refer to this as an intra-personal manipulation game, where agents try to convince their later selves that risk levels are lower than they are. Furthermore, self-incentives will result in the agents choosing to forget any additional information about risk.

Perhaps this increase in overconfidence during periods of increased volatility can be explained by the illusion of control. As explained in Section 3.3, the illusion of control refers to people tending to believe that they are in control or at least can influence an event that is uncontrollable. The illusion of control will lead people to ignore external clues received when things are less under their control than they believe (Moosa and Ramiah, 2017).

4.2.1 Behavioural finance in emerging markets

The efficient market hypothesis (EMH) has been, for a long time, central to finance. The term efficiency is used to describe a market where all relevant information is reflected in the price of financial assets (Shiller, 2003). Malkiel (2013) interprets the EMH as a consequence of the random walk theory. He explains that, as, by definition, news is unpredictable; price changes must also be unpredictable and random. Therefore, prices will fully reflect all known information, and even uninformed investors holding a diversified portfolio will obtain a rate of return as generous as that achieved by experts. The random walk theory provides that an efficient market that trades on available information will fail to provide abnormal profits. A market will thus be deemed efficient only if we can posit a model for returns.

The EMH argues that there could not be abnormal returns, as competition among investors seeking abnormal profits should drive prices up to their correct value. Although the EMH does not assume all investors are rational, it assumes that markets are rational. The EMH also assumes that markets make unbiased future forecasts. However, the EMH is often unable to explain the excess volatility present in the market. Shiller (2003) argues that excess volatility may sometimes be better explained by "sunspots" or "animal spirits" or mass psychology rather than fundamental reasons. In contrast, behavioural finance assumes that in some circumstances financial markets are informationally inefficient and its participants are not always rational (Ritter, 2003). Grossman and Stiglitz (1980) also conclude that in a world with costly information, it is impossible for markets to be informationally efficient.

Thus, the less the availability of information in a market, the greater the inefficiency is. Since lack of information is caused in part by behavioural factors, it becomes necessary to incorporate such factors when studying inefficient markets. In their description of the Egyptian Stock Exchange (ESE),[8] Mauro and Sourial (1999, p.48) emphasize that "ESE stock returns are characterized by a distribution departing from the normal one, and by volatility that tends to change over time and be serially correlated … in turn implying the existence of deviations from market efficiency in the price of equities". This suggests that

[8] Currently abbreviated EGX.

the Egyptian market is highly susceptible to behavioural factors.

Furthermore, most of the finance and economic behavioural models to study the decision making of investors, economic agents, or financial managers are based largely in the US and other developed countries. Such research focuses fundamentally on what we understand about the US investor/agent and how they make their decisions. However, the US has a developed economy, and the findings there are likely to be both psychologically and culturally inappropriate for exact interpretation on emerging markets such as the ESE.

4.2.2 Political turmoil in Egypt

Vasile *et al.* (2011) argue that studying any crisis from a behavioural perspective allows us to understand how human psychology drives the financial actors' decisions. They note that success can be systematically compromised when anxiety, emotional pain, and other behavioural biases interfere with judgments and decisions about risk and reward.

Egypt has recently endured major political changes, starting with the removal of President Husni Mubarak in January 2011, to the presidential elections in June 2012, when Mohamed Morsi was elected President, to his removal from office in July 2013, and the election of current President El Sisi in June 2014. During this period the country suffered significant public disorder, sometimes involving bloodshed, putting severe stress on the economic and financial stability of the country and giving rise to behavioural and psychological impacts on decision makers as they struggled to understand, cope with and anticipate the implications of these political changes. The country also suffered from severe devaluation of the EGP in November 2016. While this may not be considered a crisis in the sense of political turmoil it still put a severe strain on the economy and may have affected managerial perception.

The crisis of 2008 and the turmoil in Egypt are similar in that they constitute a series of catastrophic events. Motivated by this similarity, this thesis investigates how the behavioural aspect, overconfidence/optimism (see Chapter 3), affected the managers decision-making during the period of Egyptian upheaval from 2011 to 2017, which I also posit can lead to an increase in default risk.

4.3 A Conceptual model for the study

The Egyptian turmoil of 2011 is a crisis that resembles the financial crisis of 2007-2008 in that there was severe instability and panic of big financial corporations collapsing. It stands to reason that all the psychological effects apply to the turmoil situation. As it was just discussed, most of the analysis that was done to study the financial crisis consider over confidence/optimism as the primary bias of interest. In particular, an overconfident individual remains overconfident even in a state of turmoil since uncertainty or volatility becomes heightened. In fact, as provided by Ben-David *et al.* (2013) and Eisenbach and Schmalz (2018) overconfidence becomes more pronounced during times of increased uncertainty or volatility having various effects on a firm.

Other biases in relation to the crisis period were also studied, such as herding, loss aversion, and panic. However, most of these managerial biases were discussed in a theoretical setting with little to no proxies provided for empirical testing (Malmendier and Taylor, 2015). The empirical testing of investor bias is a lot more widespread. The most popular method for measuring other biases in the literature is through the distribution of questionnaires or conducting interviews over an extended period. This method, however, is unsuitable for this research, as questionnaires and interviews should have been performed during the catastrophic events to measure the effects of volatility on managerial biases as in Ben-David *et al.* (2013). Shortcomings of the use of questionnaires in this research is discussed in more detail in section 4.5.1. Overconfidence/optimism remains the most widely tested bias in a corporate setting (Fairchild, 2005). Malmendier and Taylor (2015) explain that this is because overconfidence is the most damaging of all biases that can affect any decision maker.

The crucial financial and investment decisions of a firm are made by its top managers (Malmendier and Tate, 2005; 2008). Thus, firm financial decisions biases are in reality the biases of its managers. Chapter 3 discussed the implications of managerial overconfidence on corporate financial decisions found in the literature. Some of the implications that stem from being overly optimistic about the future, and an illusion of control, means that an overconfident manager overestimates return, underestimates volatility, and even when presented with negative feedback will ignore negative signals. This causes them to overinvest when there is an abundance of internal cashflow (retained earnings) or riskless debt, continue in negative NPV projects believing that circumstances will get better, initiate more mergers and acquisitions that are sometimes damaging to the firm, and hoard bad news.

The principal hypothesis of behavioural finance is that there may be irrational biases that affect the decision making process of managers and, in turn, affect the decisions and value of a firm as measured by: i. a manager’s decision to invest and the sensitivity of that bias to the availability of cashflow, ii. stock price crash risk, iii. and default risk. The latter measures are conceptualized as dependent variables, which are affected by managerial overconfidence (the primary independent variable). Additionally, a set of idiosyncratic and systematic control variables should also be considered, to test for the effect of the aforementioned variables net the effect of any outside factors. Finally, it is intended that this behavioural model will be integrated in other traditional non-behavioural models to study firm risk during catastrophic events in particular.

Based on this discussion and the literature review in Chapters 3, this thesis uses a behavioural model to test the following hypotheses:

H_1: managerial overconfidence increases investment decision sensitivity to cashflow.

H_2: there is a positive relationship between the level of managerial overconfidence and SPCR.

H_3: There is a positive relationship between managerial overconfidence and probability of default.

The thesis introduces those biases on all listed firms in the Egyptian and the UK Market.

4.4 Data Estimation Techniques

The models are estimated through regression analysis. Regression analysis is a statistical technique in which a possible relationship between a dependent variable and one or more independent variables is sought. The establishment of such a relationship can then be used to predict values of the dependent variable corresponding to given values of the independent variables. Thus, the objective of regression analysis is both scientific description and prediction (Mooi and Sarstedt, 2011). Under regression analysis there are different estimation techniques, in the following sections I will discuss the techniques relevant to this study.

4.4.1 Panel data analysis

To test the hypotheses outlined above, panel data analysis techniques are adopted. Panel data allow for the analysis of a number of firms over time, providing multiple observations on each firm in the sample. One of the major advantages of panel data is that it is two dimensional (cross-sectional and longitudinal). It employs a large number of data points, thereby increasing the degrees of freedom and reducing collinearity among explanatory variables (Hsiao, 2003). Furthermore, by allowing time or firm specific effects in the specification of panel data, the bias resulting from omitted variables is reduced through differencing. Panel data can either be balanced or unbalanced. Unbalanced data is actually very common in general. Given the nature of the data, I expect to have an unbalanced data model as it is extracted from financial statements and trading activity. Reasons for missing data include later entry into the stock market, mergers and acquisitions, bankruptcy among others. However, the degree of imbalance should have little impact on estimation accuracy for most methods of panel regression (Flannery and Hankins, 2013).

The two main panel data analysis models, namely fixed effects and random effects models, will be discussed briefly in the next two subsections, stating the advantages and disadvantages of each model.

As for notation, the subscript i is used to indicate a firm index, the subscript t to indicate a time step or instant, the letter x to refer to explanatory, or independent vector variables, the letter y to indicate a dependent variable, the letter u to indicate random market effects, the parameter α to gather all effects not explainable by the independent variables and the parameter β to indicate the weight of contribution of the independent variable in explaining the outcome. The number of firms being studied is denoted by n while the number of time steps is denoted by T. For clarity of discussion, we assume here that we have balanced data.

4.4.1.1 Fixed Effects Model (FE)

The fixed effects model captures all variables that vary across firms but remain constant across time, thus allowing for heterogeneity across firms by including a different intercept α_i for each firm. The regression model under the FE model is given by:

$$y_{it} = \beta_0 + x'_{it}\beta_1 + \gamma_i + u_{it}, \tag{4.1}$$

where β_0 is the firm specific intercept, x_{it} is a vector of explanatory variables and β_1 is a parameter vector, γ'_i is a vector of time invariant unobserved heterogeneities across firms.

There are several methods for parameter estimation in the literature, either using OLS of the dummy regression model, or OLS using firm demeaned data:

1. The least squares dummy variable (LSDV). Two main methods of LSDV are used in the literature:

   a. The first method adds a dummy variable (usually binary) equivalent to the number of firms, for all time invariant variables i.e., variables that change across firms but remain constant over time. More explicitly, the data model (4.1) and individual level model takes the form

$$y_{it} = \beta_0 + x'_{it}\beta_1 + \gamma_i + u_{it},$$

$$y_i = \beta_0 i_k + X_i\beta_1 + E_i\gamma_i + u_i,$$

   where

$$E_i = i_k,$$

   while the full model takes the form

$$y = \beta_0 i_{kn} + X\beta_1 + E\gamma + u, \tag{4.4}$$

where

$$\boldsymbol{E} = \textbf{blockdiag}(\boldsymbol{E_1}, \boldsymbol{E_2}, \dots, \boldsymbol{E_n}),$$

$$\boldsymbol{\gamma} = [\boldsymbol{\gamma_1} \quad \boldsymbol{\gamma_2} \quad \cdots \quad \boldsymbol{\gamma_n}]'.$$

The columns of the $Tn \times n$ matrix E are called dummy variables. The vector γ is a parameter vector that can now be approximated by least squares if desired.

Equation (4.4) is also called the one-way model since we allow only cross-sectional effects to be present.

b. Alternatively, we could also add longitudinal dummy variables. The model (4.1) in this case becomes

$$y_{it} = \beta_0 i_{kn} + X\beta_1 + E\gamma + F\delta + u, \tag{4.5}$$

where

$$\boldsymbol{F} = [\boldsymbol{I_T}, \boldsymbol{I_T}, \dots, \boldsymbol{I_T}]',$$

$$\boldsymbol{\delta} = [\boldsymbol{\delta_1} \quad \boldsymbol{\delta_2} \quad \dots \quad \boldsymbol{\delta_T}]'.$$

The columns of the $Tn \times T$ matrix F are time dummy variables. The vector δ is a parameter vector that can also be estimated by least squares if desired.

Equation (4.5) is also called the two-way model since we allow cross-sectional as well as longitudinal effects to be present.

2. The within transformation, which is done by subtracting the time mean of each entity away from the variables in Equation 4.1 to arrive at demeaned variables. Thereby dropping β_0 and γ_i, giving us:

$$y_{it} - \bar{y}_i = \beta_1(x'_{it} - \overline{x'}_i) + u_{it} - \bar{u}_i,$$

3. The between estimator, which runs a cross sectional regression on the time averaged value of variables, thereby dropping any variables that are constant overtime, giving us:

$$\bar{y}_i = \beta_1 \overline{x'}_i + \bar{u}_i$$

4. The first difference estimator, where the first difference is taken from each variable, thereby dropping any variables that are constant overtime, giving us:

$$\Delta y_{it} = \beta_1 \Delta x'_{it} + \Delta u_{it}$$

The choice between different estimators will depend on the data characteristics. For example, if errors are serially correlated, then first differencing estimators or within estimators may be appropriate. This is because while the errors themselves are serially correlated the first differenced errors will be uncorrelated.

LSDV method may not be appropriate when n is very large as the number of parameters that need estimation would now be $n + k$. Where n is the number of firms, and k are the parameters of other explanatory variables included in the model.

4.4.1.2 The Random Effects Model (RE)

Also known as the error component model. Here the market effects variable u_{it} in model (4.1) is written as

$$u_{it} = \varepsilon_i + v_{it}, \tag{4.6}$$

where ε_i is a random intercept which measures the random deviation of each entity's intercept from the global intercept α_0. Under the random effect method, the component ε_i cannot be correlated with the explanatory $T \times k$ matrix X_i. However, as the model still suffers from serial autocorrelation, generalised least squares (GLS) should then be used instead of OLS for the transformed data.

While RE model produces more efficient estimates, these estimates may be biased if the assumptions do not hold true. The main assumptions are:

I. ε_i has a zero mean,

II. ε_i is independent of v_{it},

III. ε_i is independent of x_{it},

IV. ε_i has a constant variance.

To test whether to use the FE or the RE method the Hausman (1978) test is usually performed. Its χ^2 distributed test statistic is

$$H = \left(\hat{\beta}^I - \hat{\beta}^{II}\right)' \left[\mathrm{var}\left(\hat{\beta}^I\right) - \mathrm{var}\left(\hat{\beta}^{II}\right)\right]^{-1} \left(\hat{\beta}^I - \hat{\beta}^{II}\right), \tag{4.7}$$

where $\hat{\beta}^I, \hat{\beta}^{II}$ are the estimated parameters using FE and RE methods, respectively. The null hypothesis for the Hausman test is that the FE method is not appropriate. A p value is calculated and if $p > 0.05$, then RE is more appropriate, and if $p < 0.05$, then FE method is more appropriate.

4.4.2 Dynamic panel data

Based on model characteristics, we may sometimes need to use the Generalized Method of Moments (GMM) as an estimator for panel data models. GMM is considered one of the most popular estimation methods in applied econometrics (Hansen, 2014). In this section I will briefly discuss dynamic linear models estimated by GMM.

The dynamic model with lagged dependent variables can be stated as:

$$y_{it} = \delta y_{it-1} + x'_{it}\beta + v'_t\gamma + u_i + \varepsilon_{it} \tag{4.8}$$

v'_t are a set of variables that vary with time but are constant across firms, u_i is the individual effects and ε_{it} is the idiosyncratic error.

Equation (4.8) can be re-written as:

$$y_{it} = w'_{it}\rho + u_i + \varepsilon_{it}, \tag{4.9}$$

Where

$$\boldsymbol{w_{it}} = \begin{pmatrix} \boldsymbol{y_{it-1}} \\ \boldsymbol{x_{it}} \\ \boldsymbol{v_t} \end{pmatrix}, \ \ \boldsymbol{\rho} = \begin{pmatrix} \boldsymbol{\delta} \\ \boldsymbol{\beta} \\ \boldsymbol{\gamma} \end{pmatrix}, \tag{4.10}$$

$$i = 1,2, \dots, N, \qquad t = 1,2, \dots, T, \quad k = 1 + k_0 + d.$$

We assume that the errors u_i and ε_{it} are mutually independent and ε_{it} are serially uncorrelated with mean zero. Our model is an AR(1) (Autoregressive) as y_{it} depends on just one lag value of itself. In order to deal with the fixed effects in equation (4.8) the within transformation is applied to eliminate the individual effects u_i. Then we have:

$$\Delta y_{it} = \Delta w'_{it}\rho + \Delta\varepsilon_{it}. \tag{4.11}$$

However, the transformation introduces endogeneity

$$E(\Delta y_{it}\Delta\varepsilon_{it}) = E(y_{it-1} - y_{it-2})(\varepsilon_{it} - \varepsilon_{it-1}) \tag{4.12}$$

$$= -E(y_{it-1}\varepsilon_{it-1}) = -\sigma_\varepsilon^2$$

violating the assumption of independence and producing estimates that are inconsistent when T is finite.

To deal with this problem, Instrumental Variables (IV) are introduced. Anderson and Hsiao (1982) were the first to suggest the choice of y_{it-2} as an acceptable IV as it is correlated with y_{it-1} yet uncorrelated with ε_{it}. While this choice of an IV was considered a breakthrough, it relies on two critical assumptions. The first assumption is that the dynamics are correctly specified so that ε_{it} is serially uncorrelated. Thus for example if an AR(1) model is used, and the true model is an AR(2), y_{it-2} would not be a valid IV as it will be biased. Furthermore, this choice of IV requires that $E(y_i \Delta y_{i2}) \neq 0$ which can also prove to be problematic. These assumptions can thus affect the validity and accuracy of the estimators and thus the Arellano-Bond Estimator was introduced in 1991.

4.4.2.1 Arellano-Bond estimator

The transformed individual level and full models are, respectively:

$$\Delta \boldsymbol{y_i} = \Delta W_i \rho + \Delta \boldsymbol{\varepsilon_i} \tag{4.13}$$

$$\Delta \boldsymbol{y} = \Delta W \rho + \Delta \boldsymbol{\varepsilon}$$

As discussed in the previous section, the model is endogenous and instruments variables are needed. The instruments introduced by Arellano and Bond have the following form:

The instruments introduced by Arellano and Bond have the following form:

$$
\boldsymbol{Z_{it}} = \begin{pmatrix} \boldsymbol{y_{i1}} \\ \boldsymbol{y_{i2}} \\ \vdots \\ \boldsymbol{y_{it-2}} \\ \boldsymbol{x_{i1}} \\ \vdots \\ \boldsymbol{x_{it-1}} \\ \boldsymbol{v_1} \\ \vdots \\ \boldsymbol{v_{t-1}} \end{pmatrix},
$$

$$
\boldsymbol{Z_i'} = \begin{pmatrix} \boldsymbol{Z_{i3}} & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{Z_{i4}} & \cdots & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \cdots & \boldsymbol{Z_{iT}} \end{pmatrix}.
$$

Observe that the number of rows in Z_{it} is

$$
n_t = (t-2) + k_0(t-1) + d(t-1)
$$

$$
= (k_0 + d + 1)t - (k_0 + d + 2)
$$

$$
= kt - (k+1).
$$

Thus, Z_i' has a number of rows $\ell = (T-2)\left(\frac{T+1}{2}k - 1\right)$. To show this, we note that the number of rows in Z_i' is the sum of the number of rows in $Z_{i3}, Z_{i4}, \dots, Z_{iT}$. We calculate

$$
\ell = \sum_{t=3}^{T} n_t
$$

$$
= \sum_{t=3}^{T} [kt - (k+1)]
$$

$$
= k \sum_{t=3}^{T} t - (k+1)(T-2)
$$

$$
= \ k \frac{(T+3)(T-2)}{2} - (k+1)(T-2)
$$

$$= (T-2)\left(\left(\frac{T+3}{2}-1\right)k-1\right)$$

$$= (T-2)\left(\frac{T+1}{2}k-1\right).$$

Furthermore, the number of columns in $Z_i'$is $(T-2)$. In other words, the dimension of Z_i' is $\ell \times (T-2)$.

The moment conditions are:

$$E\big(Z_i'(\Delta \boldsymbol{y_i} - \Delta W_i \rho)\big) = 0. \tag{4.14}$$

There are ℓ equations for the k parameters of ρ. Obviously, $\ell > k$ for $T > 2$.

In this case, we have an overdetermined system so that GMM must be used to estimate ρ.

4.4.2.2 Efficient Estimators

The GMM method amounts to minimizing a weighted norm of $Z_i'(\Delta \boldsymbol{y_i} - \Delta W_i \rho)$. Efficient estimators set the norm weight, $w = \Omega^{-1}$, where

$$\Omega = \mathrm{var}(Z_i'\Delta \boldsymbol{\varepsilon_i}) = E(Z_i'\Delta \boldsymbol{\varepsilon_i} \Delta \boldsymbol{\varepsilon_i}' Z_i). \tag{4.15}$$

The resulting estimate is:

$$\hat{\rho}_{gmm} = (\Delta X' Z \Omega^{-1} Z' \Delta X)^{-1} (\Delta X' Z \Omega^{-1} Z' \Delta \boldsymbol{y}) \tag{4.16}$$

When ε_{it} are homoscedastic, then

$$\Omega = \mathrm{E}(Z_i' H Z_i)\sigma_\varepsilon^2 \tag{4.17}$$

$$\boldsymbol{H} = \begin{pmatrix} \mathbf{2} & \mathbf{-1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{-1} & \mathbf{2} & \mathbf{-1} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{-1} & \mathbf{2} & \mathbf{-1} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{-1} & \mathbf{2} \end{pmatrix}.$$

The variance matrix Ω is yet to be estimated. There are several ways to estimate it. The first estimate is known as the one step GMM Arellano-Bond estimator.

$$\hat{\Omega}_1 = \sum_{i=1}^{n} Z_i' H Z_i \tag{4.18}$$

So that,

$$\hat{\rho}_1 = (\Delta W' Z \hat{\Omega}_1^{-1} Z' \Delta W)^{-1} (\Delta W' Z \hat{\Omega}_1^{-1} Z' \Delta \boldsymbol{y}) \tag{4.19}$$

The Var $(\hat{\rho}_1)$ is estimated by:

$$\mathrm{Var}\,(\hat{\rho}_1) = \left(\Delta W' Z \hat{\Omega}_1^{-1} Z' \Delta W\right)^{-1} (\Delta W' Z) \hat{\Omega}_1^{-1} (Z' \Sigma Z)$$

$$\hat{\Omega}_1^{-1} (Z' \Delta W) \left(\Delta W' Z \hat{\Omega}_1^{-1} Z' \Delta W\right).$$

In case of homoscedasticity it reduces to:

$$\hat{V}_1^0 = (\Delta W' Z \hat{\Omega}_1^{-1} Z' \Delta W)^{-1} \hat{\sigma}_\varepsilon^2, \tag{4.20}$$

where

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{n} \sum_{i=1}^{n} \widehat{\Delta \boldsymbol{\varepsilon}_i}' \, \widehat{\Delta \boldsymbol{\varepsilon}_i},$$

$$\widehat{\Delta \boldsymbol{\varepsilon}_i} = \Delta \boldsymbol{y}_i - \Delta W_i \hat{\rho}_1.$$

A two-step method is given by:

$$\hat{V}_1 = (\Delta W' Z \widehat{\Omega}_1^{-1} Z' \Delta W)^{-1} (\Delta W' Z \widehat{\Omega}_1^{-1} Z' \hat{\Omega}_2 Z \hat{\Omega}_1^{-1} Z' \Delta W)(\Delta W' Z \widehat{\Omega}_1^{-1} Z' \Delta W)^{-1} \quad (4.21)$$

Where

$$\hat{\Omega}_2 = \sum_{i=1}^{n} Z_i' \, \widehat{\Delta \boldsymbol{\varepsilon}_i} \widehat{\Delta \boldsymbol{\varepsilon}_i'} Z_i$$

$$\hat{\rho}_2 = (\Delta W' Z \widehat{\Omega}_2^{-1} Z' \Delta W)^{-1} (\Delta W' Z \widehat{\Omega}_2^{-1} Z' \Delta \boldsymbol{y})$$

Equation 4.21 is known as the two step GMM Arellano-Bond estimator. An appropriate robust covariance estimator is given by:

$$\hat{V}_2 = (\Delta W' Z \widehat{\Omega}_2^{-1} Z' \Delta W)^{-1} (\Delta W' Z \widehat{\Omega}_2^{-1} \hat{\Omega}_3 Z \hat{\Omega}_2^{-1} Z' \Delta W)(\Delta W' Z \widehat{\Omega}_2^{-1} Z' \Delta W)^{-1} \quad (4.22)$$

where

$$\hat{\Omega}_3 = \sum_{i=1}^{n} Z_i' \, \widehat{\Delta \boldsymbol{\varepsilon}_i} \widehat{\Delta \boldsymbol{\varepsilon}_i'} Z_i,$$

$$\widehat{\Delta \boldsymbol{\varepsilon}_i} = \Delta \boldsymbol{y}_i - \Delta X_i \hat{\rho}_2.$$

4.4.3 Data with binary outcome

The estimation methods discussed in the previous section are useful for variables that are continuous. However, one of the SPCR models used in this thesis has a dependent variable that takes a value of either 1 or 0, the appropriate estimation techniques for models with binary outcome is the Logit or Probit model.

4.4.3.1 The Logit and Probit Model

The Logit model applies the transformation:

$$\pi_i(\beta) = \frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}}, \tag{4.23}$$

thus producing values in the range (0,1). The Probit model applies the transformation:

$$\pi_i(\beta) = \int_{-\infty}^{x_i'\beta} \phi(z)dz, \tag{4.24}$$

where $\phi(\cdot)$ is the joint probability density function for x_i. Both transformations are nonlinear and ordinary least squares methods are very difficult to apply for parameter estimation. Instead, maximum likelihood estimations are used.

Both models produce very similar results, and there is no definite rule to choose between them. I will use the Logit model, following (Kim *et al.*, 2016). The likelihood function for n independent binomially distributed variables is

$$\log L(\beta) = \sum \{y_i \log(\pi_i) + (n_i - y_i)\log(1 - \pi_i)\}. \tag{4.25}$$

This model allows us to interpret the sign of the coefficients but not the magnitude of change as with the linear regression model. Instead we can interpret the results in terms of marginal effects. Marginal effects, however, depend on a specific value of x. We may choose the mean value of x, or we may also view the partial effects for discrete variables, which predict probabilities for the two discrete value of variables (overconfident vs. non-overconfident) and record the differences.

4.4.4 Additional testing

When examining data, one must consider two important problems that may affect the results, namely outliers and multi-collinearity (Alexander, 2008). Outliers can significantly influence regression results by moving the regression line either up or down. To check for outliers, the minimum and maximum values of each variable are calculated to determine if unexpectedly high or low values occur. Researchers frequently consider values more than three standard deviations away from the mean as potential outliers (Leys *et al*., 2013). Outliers may also be observed using a scatter plot to determine if there are any extreme values. To avoid model bias, the outliers are removed, and the model is run without those observations.

Multicollinearity is present when two independent variables are highly correlated. One way to identify multicollinearity is to create a correlation matrix and try to identify which variables are strongly correlated. Another way to identify multicollinearity is to calculate the tolerance, or its reciprocal, the variance inflation factor (VIF). VIF values above 10 indicate the existence of multicollinearity (Voss, 2004). Remedies for multicollinearity include the removal of one of the variables and then running a revised regression model or transform one of the variables by taking its log form (Mooi and Sarstedt, 2011).

The investment sensitivity to cashflow model has an interaction variable, where it is hypothesized that the managerial overconfidence will affect the magnitude of cashflow effect on investment. This poses a problem however, as by construction the interaction term may be highly correlated with either managerial overconfidence or cashflow. One way to remedy this is to demean the interaction term.

Finally, it is important to check for the stability or the internal validity of the regression model by splitting the data into two parts (called split-sample validation) and running the regression model again on each subset of data (Steyerber et al., 2001). Using such an approach, approximately 70% of the data are randomly chosen to estimate the regression model and the rest are used for comparative purposes. If the new regression produces similar effects, with the overall relationship between the dependent and independent variables being statistically significant, the R^2 within 5% (plus or minus) the R^2 for the tested model, and the results of the statistical significance tests for the coefficients of the independent variables for both analyses are the same, it may be concluded that the model is stable. Thus, in different models we may choose to re-run the model over a certain period of time to check for internal validity. External Validity, on the other hand, is more difficult to test, it measures the generalizability of the results. Generally, a strong referencing system of the model used in the study will support the external validity as the model will have been tested and the findings supported by other authors repeatedly.

4.5 Data

The research is conducted primarily by means of a behavioural model applied to listed firms in Egypt and the UK from 2005 to 2018. The Egyptian political unrest started in January 2011 and ended with the presidential election of El Sisi in 2014, followed by a devaluation of the Egyptian pound in November 2016, thus the data covers the effects before the events, during the events, and till stability is restored, roughly in 2018. The start date was chosen as 2005 to control for any effects that may have been caused by the global financial crisis of 2008.

There are 162 firms listed on the Egyptian Stock Exchange (EGX) and the Nile Stock Exchange, excluding firms from the financial sector. However, my total population consists of only 102 firms for which there were complete records (from 2005-2018). Similarly, complete data for the UK was available for 777 firms from the total population. Data were collected from financial statements of the constituent firms for both Egypt and the UK from *Bloomberg*. Data analysis is performed using MATLAB and Stata. MATLAB is used to organize the data, and for variable measurement (as SPCR and PD discussed in more detail in Chapters 6 and 7), all regressions are then run on Stata. Missing data are treated in two ways. In case where there is a linear trend, as in the case of missing returns data used to calculate SPCR or PD, linear interpolation is used. Linear interpolation is a curve fitting method which establishes a linear relationship among known data points, and then uses this relationship to estimate unknown or missing values. However, where there is missing financial statement data within our sample, Stata automatically discards the row, giving us fewer observations. Following Malmendier and Tate (2005), and to ensure that outliers do not contaminate our results we trim our data at 1% level. Outliers are removed and left blank, i.e. treated as missing observations.

4.6 Overconfidence Proxies

Most existing studies examine overconfidence[9] in terms of shareholder behaviour. The empirical tools used to study overconfidence (in terms of overly tight probability distributions, underestimation of price volatilities, and/or overvaluation of own trading performance in relation to the average market return) are not easily transferrable into corporate settings. Several researchers, such as Malmendier and Tate (2005, 2008) and Huang *et al.* (2013) among others, use option exercise behaviour as a proxy for

[9] Theoretical models distinguish optimism and overconfidence, where optimism is modelled as an overestimation of return while overconfidence modelled as an underestimation of risk. However, psychological and behavioural research reveals that these biases are closely related and thus do not need separate proxies to distinguish between them for empirical testing. Overconfidence and optimism are thus used interchangeably in this thesis.

overconfidence. It is not possible though to use this proxy in the Egyptian market since it does not have an option market. Further, there are several reasons why the Malmendier and Tate (2005) option-based measure may not be appropriate for the UK as well. There is a significant difference in the structure of executive remuneration between the UK and the US. Option grants of UK CEOs account for only a small portion of their total portfolio compared to the US CEOs (Conyon and Murphy, 2000), thus managers have a less pressing need to diversify by exercising their options early. Further, data availability of the portfolios of CEOs in the UK is not widely accessible as it is in the US.

Another popular method to measuring optimism in the literature is the distribution of questionnaires in a timely manner (Ben- David *et al*. 2008; Azouzi and Anis, 2012; Mohamed, 2012). This approach, however, is also not feasible for this study, because of the extreme reluctance by Egyptian CEOs to participate in a survey due to the political instability that the country has witnessed during the past 10 years. Furthermore, the response rate to questionnaires in Egypt was found to be low (Dennis, 2003), with only a 25 per cent response rate in a study by Hatab and Hess (2013). Further, this study aims to study the effect that external instability may have on managerial overconfidence, questionnaire analysis would have been possible in this thesis only if questionnaires were distributed during the period of the turmoil and not in the aftermath.

4.6.1 Overconfidence measure based on financial and investment activities of the manager

Given the relative shortage of the data available in the Egyptian market, the measure of overconfidence used in this study will be based on the exaggerated *activities of the manager* as proposed by Schrand and Zechman (2012) and Campbell *et al*. (2011).

Our first proxy for overconfidence is obtained from the work of Schrand and Zechman (2012). Their proxy is measured as a firm-specific score calculated from the investing and financing activities of the firm. They justify the choice of this proxy as investment and financing activities have been consistently found to be related to managerial overconfidence as presented in Chapter 3. The first component of the score is based on investment level, calculated as total asset growth on sales growth. The firm will be given a score of 1 in a given year if the firm investment level is in excess of the industry median level for the same year. Overconfident managers are more likely to overestimate the returns from investment while simultaneously underestimating risk, causing them to overinvest, particularly when there is an abundance of internal cashflow / retained earnings (Malmendier and Tate, 2005). The second component is the net dollar acquisitions made by the firm. The firm will be given a score of 1 in a given year if its net dollar acquisitions are greater than the industry median level for the same year. Acquisitions are taken as the net value of acquisitions obtained from the statement of cashflows. Malmendier and Tate (2008) and Ben-David *et al.* (2010) among others, find that overconfident managers engage in more mergers and acquisitions, and may even overpay for their acquisitions to the point where it may be damaging for the firm. The third component is the firm debt to equity ratio. The firm will be given a score of 1 if its debt to equity ratio is greater than the industry median level for a given year. An overconfident manager views firm equity as undervalued by the public, when there is a financing deficit, an overconfident manager will be more likely to take on more debt rather than issue undervalued stocks (Heaton, 2002). The fourth component is based on whether the firm uses convertible debt or preferred stock; the firm will be given a score of 1 if the firm uses either convertible debt or preferred stock. Schrand and Zechman explain that overconfident managers will choose risky debt, where risky debt is measured as a debt with longer duration. If a firm totals a score of 2 or higher in a given year, its manager will be considered overconfident. This measure of overconfidence is denoted SZOC1_{it}.

Schrand and Zechman further expand their measure by including a fifth component which is dividend yield, they give the firm a score of 1 if its dividend yield is equal to zero. This is due to an overconfident manager unwillingness to payout dividends and preserve cash for future investment opportunities. Finally, if the firm totals a score of 3 or more, its manager is considered overconfident. It may be argued that dividend policy could proxy for firm characteristics rather than managerial overconfidence. For example, a new firm with more investment opportunities, may be unlikely to pay out dividends and preserve cash for investments compared to a well-established firm requiring less investment needs. Therefore, Schrand and Zechman separate dividend policy in a new measure. They further state that while the same issue may be argued under the debt/equity ratio, the latter has shown a tendency to follow the industry norm. I denote this second measure of overconfidence as SZOC2_{it}. Furthermore, we may notice that Schrand and Zechman prefer to use a binary measure of overconfidence based on several investing and financing activities found to be related to managerial overconfidence in literature rather than a comprehensive score. This is because while one activity may be related to firm policy, firm characteristics, or previous history, and not conclusive of managerial overconfidence. A composite of several activities being exaggerated at the same time is more likely to be due to the consistent impact of an overconfident manager.

Schrand and Zechman (2012) argue that while the above proxy for overconfidence may be associated with weaker governance, the latter gives a greater propensity for overconfidence bias to be pronounced. Finally, their proxy was found to have significant correlation with the option exercise-based proxy proposed by Malmendier and Tate (2005).

One criticism of this proxy is that it can be related to decisions taken by previous CEOs. For example, capital structure and dividend policies are usually considered sticky, and thus the observed level in the current period may be related to the decisions made by a previous CEO. I will thus use another measure of overconfidence introduced by Campbell *et al.* (2011) which focuses solely on the investment levels observed in relation to industry mean. Investment policies are arguably less sticky than capital structure and dividend policies (Kim *et al.*, 2016).

Campbell *et al.* (2011) propose a measure of CEO optimism that is not directly related to compensation. Their model predicts a theoretical link between CEO optimism and the firm investment level, and they argue that the CEO investment choice decreases with risk aversion and increases with optimism. A risk averse CEO with low optimism underinvests, i.e. chooses investment below the level that maximizes firm value. Meanwhile, a moderately optimistic CEO will choose to invest at a level that maximizes shareholder value. Thus, the firm investment level will increase as CEO optimism increases, offsetting the underinvestment from CEO risk aversion characteristic. Optimism levels below (above) value-maximizing level of optimism leads the CEO to underinvest (overinvest), causing firm value to be concave in relation to CEO optimism. They thus propose a measure of CEO optimism based on the ratio of capital expenditure CE_{it} to beginning of year net property, plant and equipment $\mathrm{PPE}_{i,t-1}$.

$$\mathrm{OPT}_{it} = \frac{\mathrm{CE}_{it}}{\mathrm{PPE}_{i,t-1}} \tag{4.26}$$

Campbell *et al.* (2011) specifically classify a CEO as highly optimistic if the firm industry-adjusted investment OPT_{it} in Equation (4.26) is above the 80$^{\text{th}}$ percentile of all firms for two consecutive years. The reason for specifying two consecutive years is that investment can be "lumpy" in time, and they do not wish to classify a CEO as highly optimistic simply for choosing to bunch investment in a particular year. Conversely, they classify CEOs as having low optimism if the firm industry-adjusted investment is below the 20$^{\text{th}}$ percentile of all firms for two consecutive years[10]. The CEOs that do not fall into these two categories, are classified as moderately optimistic. Their measure of overconfidence is denoted as $\mathrm{OPT80}_{it}$ and $\mathrm{OPT20}_{it}$ respectively.

4.6.2 Overconfidence measure based on insider trading

I will add a third measure of CEO overconfidence for the UK market; the net stock purchase measure, denoted $\mathrm{PURCHASE}_{it}$. Data for this measure is not available for the Egyptian market and therefore is not applicable there. This measure was introduced by Malmendier and Tate (2005) and developed by Campbell *et al.* (2011). The logic behind this measure is that overconfident CEOs may think a firm's value perceived by the market is much lower than the value perceived by themselves, so they have greater propensity to purchase stocks as net buyers. By increasing the net purchases of their firm's shares, they are putting themselves at a greater risk as they fail to diversify their idiosyncratic risk. This measure is also in line with the investor bias discussed by Odean (1998a, 1998b) where overconfidence

10 Note that OPT20 is not a measure of overconfidence, rather a measure of the "lack of confidence" or pessimism of the manager.

in investors can lead to higher trading volume in financial markets. Odean argues that overconfident investors will trade more aggressively and hold less diversified portfolios leading to a lower expected utility than the rational trader. The same logic can be applied to overconfident CEOs. The measure employed is based on insider trading activity of a firm.

Stock purchase measure may be specifically appropriate for the UK market for several reasons. First, regulations of insider trading are much stricter in the UK than it is in the US. This makes it very difficult for managers to benefit from purchasing stocks based on insider information. Further, data for this measure is widely available making it a convenient measure to use.

Following the work of Malmendier and Tate (2005), Campbell *et al.* (2011) and Ahmed and Duellman (2012) I will define net purchases as stock purchases minus stock sales, both defined in units of stocks. The stock purchase measure of overconfidence is classified as a dichotomous variable where PURCHASE is set to equal one if the CEO's net purchases are in the top 80^{th} percentile of net purchases by all CEOs in that year and must increase the CEOs ownership of the firm by 10% during the fiscal year, zero otherwise. This measure labels a manager as overconfident if the amount of net purchases is large in absolute terms and substantially increases the CEOs ownership in the firm.

The conditions for the PURCHASE measure may be a bit restrictive. Therefore, an alternative measure to stock purchases will also be used, which is the net purchase ratio NPR (Doukas and Petmezas, 2007; Billet and Qian, 2005; Ataullah *et al.*, 2017). This is a relative measure, and so is relatively logical and simple, calculated as:

$$NPR=\frac{\text{insider purchase - insider selling}}{\text{insider purchase + insider selling}} \quad (4.27)$$

The NPR ranges from -1 to 1, where a higher value of NPR implies that managers are buying more shares and thus have more overconfidence. Similar to the PURHCASE method, NPR purchases and sales are both defined in units of stock.

4.6.3 Overconfidence proxies' descriptive statistics

All the overconfidence proxies used in this thesis, except NPR, are dichotomous variables with a value of 1 for managerial overconfidence and 0 otherwise. Similarly, OPT20 is a variable that measures pessimism or under confidence. OPT20 is also a dichotomous variable, where 1 signifies managerial pessimism and 0 otherwise. NPR is a relative measure of overconfidence with a value ranging from -1 to 1, with positive values closer to 1 signifying increased managerial overconfidence and negative values closer to -1 signifying decreased confidence. The descriptive statistics for the overconfidence variables are presented in Table 4.1.

Table 4.1 Overconfidence proxies' descriptive statistics

	Egypt				UK			
Variables	**Mean**	**Std. Deviation**	**Min**	**Max**	**Mean**	**Std. Deviation**	**Min**	**Max**
SZOC1	0.066	0.248	0	1	0.410	0.492	0	1
SZOC2	0.039	0.193	0	1	0.289	0.454	0	1
OPT80	0.126	0.333	0	1	0.184	0.388	0	1
OPT20	0.349	0.982	0	1	0.154	0.361	0	1
PURCHASE	-	-	-	-	0.144	0.351	0	1
NPR	-	-	-	-	0.181	0.923	-1	1

This table presents the descriptive statistics for the overconfidence proxies used in this study.
SZOC1, SZOC2, OPT80, PURCHASE and NPR are measures of overconfidence.
OPT20 is a measure of pessimism.

As we can see from Table 4.1 the mean value of overconfidence proxies SZOC1, SZOC2 are 6.6% and 3.9%, respectively, for the Egyptian market. These percentages are significantly lower than 41% and 28.9% for the UK market. The mean value of SZOC1 and SZOC2 for the Egyptian market are also significantly lower than those reported by Schrand and Zechman (2012) of 61% and 53% for the US. The low mean value of overconfidence for Egypt may be justified as due to the ensuing political instability, where managers were pessimistic rather than optimistic. However, also also note that the Schrand and Zechman (2012) measurement of overconfidence is biased towards a developed market. For example, in my data sample for the Egyptian market, there were no companies with net acquisitions greater than zero, there were no companies that used convertible debt, and even the issuance of preferred stock is not a common practice in the Egyptian market. Thus the mean values of SZOC1, SZOC2 being very low for the Egyptian market may be as a consequence of the nature of the measurement being created for more developed markets.

Similarly, the mean value of the proxy of high optimism OPT80 for the Egyptian and the UK market at 12.6% and 18.4%, respectively, are lower than the value reported by Campbell *et al.* (2011) of 35.5% for the US market. Meanwhile, the value of low optimism OPT20 of 34.9% for the Egyptian market, is comparable to that of Campbell *et al.* of 34.7%, but remains lower for the UK market with 15.4%. The mean value of PURCHASE measure of overconfidence is 14.4% which is lower than the 26.1% reported in the US market by Ahmed and Duellman (2012). Finally, the mean value for NPR 0.181, although close to 0 remains a positive average figure, signifying that on average managers in the UK were more confident than pessimistic.

Figure 4.1 shows the average value of the overconfidence proxy for each industry in the Egyptian market. I require there to be at least five companies in an industry to be able to make meaningful comparative measures of overconfidence with industry average. There are industries in the Egyptian market specifically where there are just one or two companies, those companies (industries) were thus dropped[11]. The first thing we notice is that managerial pessimism, as measured by OPT20, was higher for all industry groups than managerial overconfidence. This is logical as the mean OPT20 was generally high compared to other overconfidence measures. Meanwhile, OPT80 generally has a higher mean overconfidence value than either SZOC1 or SZOC2. This makes sense as the Schrand and Zechman (2012) measures of overconfidence, SZOC1 and SZOC2, are a composite score, requiring several criteria to be met and is thus a more stringent measure of overconfidence. The industry with the highest average overconfidence is the healthcare industry according to SZOC2 and OPT80 measures of overconfidence. While the mean values of pessimism are relatively close across all industry groups, the industry with the highest pessimism is the consumer discretionary industry. This further supports the argument that, due to the political instability in Egypt, average values of managerial pessimism increased across the market approximately equally.

[11] Energy, information technology and utilities industry were excluded.

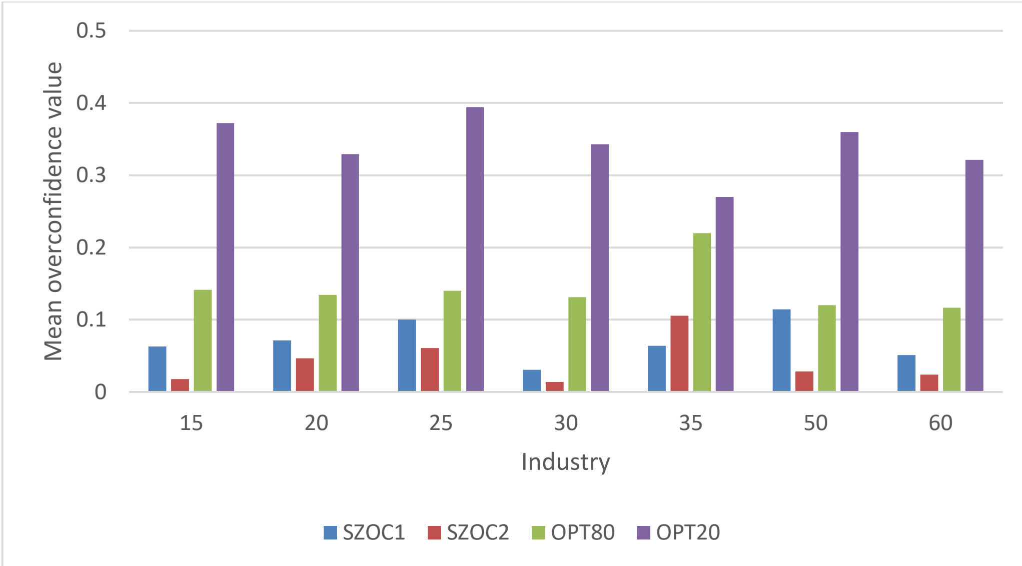

Figure 4.1 Mean overconfidence per industry in Egypt

10 – Energy
15 – Materials
20 – Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 – Information Technology
50 - Communication Services
55 - Utilities
60 - Real Estate

Next, I present a trend of the average overconfidence measures per year for the Egyptian market, to form a clearer picture of whether the political turmoil could have influenced managerial overconfidence. The results are presented in Figure 4.2. As we can see, the overconfidence proxies, follow a similar trend, perhaps most apparent from SZOC1 and SZOC2. Managerial overconfidence was on an increasing trend until 2011 and then started to decrease onward until 2018. Similarly, we can see that the measure of pessimism OPT20 was on a downward trend until 2011 and started to increase after that. These results imply that the political turmoil and instability in Egypt, which started in early 2011, likely resulted in increased managerial pessimism rather than increased overconfidence. This contrasts the hypotheses by Ben-David *et al.* (2013) and Eisenbach and Schmalz (2015) where they theorize that managerial overconfidence increases during times of instability rather than decreases.

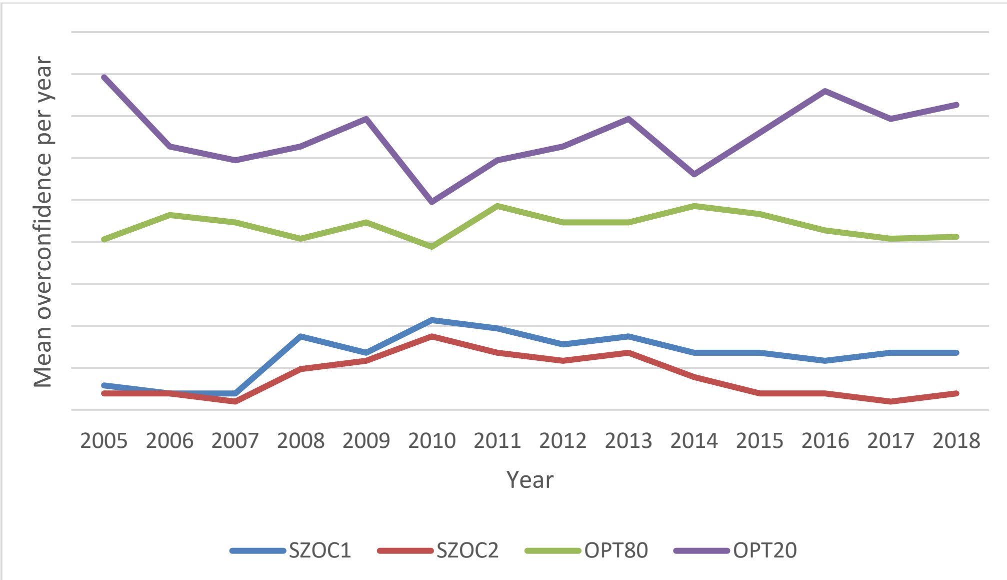

Figure 4.2 Mean overconfidence per year in Egypt

Figure 4.3 presents the average overconfidence proxy broken down by industry for the UK market. We can see that the mean value for SZOC1, SZOC2 and OPT80 usually follow a similar trend. Further, we can see that, the OPT80 and OPT20 Campbell *et al.* (2011) measures of overconfidence, show that on average OPT80 (measure of overconfidence) was greater than OPT20 (measure of pessimism) in most industries except for the energy and utilities industry, where managerial pessimism had a higher mean value than managerial overconfidence. The measure of overconfidence with the lowest mean across all industries is the PURCHASE measure. This is expected, because there are several conditions that need to be fulfilled for a manager to be considered overconfident under the PURCHASE measure, making it the most restrictive measure of the overconfidence considered in this study. The major discrepancy one can note is related to the NPR measure of overconfidence; we can note that mean value of overconfidence is negative for the consumer staples. This indicates that this is the industry with the lowest average managerial overconfidence. This does not necessarily hold true for other measures of overconfidence. Nonetheless, most measures of overconfidence are closely related, with all measures of overconfidence positively correlated together, and negatively correlated with OPT20 (the measure of pessimism).

Figure 4.3 Mean overconfidence per industry in the UK

10 – Energy
15 – Materials
20 – Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 – Information Technology
50 - Communication Services
55 - Utilities
60 - Real Estate

4.7 Conclusion

This chapter starts by justifying the use of the Egyptian market as the main market of this study, followed by an overview of the conceptual model of study and the testable hypotheses. The estimation techniques, namely panel data analysis, are also discussed in detail.

Information on data, including the time period and markets used for analysis, and where the data is collected from is detailed. The different overconfidence proxies used in the literature are discussed, followed by a justification of why some proxies may be inapplicable for this study. Finally, a detailed discussion of the overconfidence proxies used in this study is provided, as well as an analysis of the descriptive statistics and trends noticed in the overconfidence studies for Egypt and the UK

The information regarding the estimation method, data collection and overconfidence proxies discussed above will be applied to three separate models to identify whether there is an effect of behavioural biases of agents on decision-making and firm risk during catastrophic events. In the upcoming empirical study chapters, I will start with a brief introduction of the relevant model, re-state the hypotheses, present the model and discuss the factors used to control for external and internal environment followed by an analysis of the results.

Chapter 5

Managerial Overconfidence and Investment Decisions

5.1 Introduction

Previous studies have considered several motivations that cause investment distortion across firms. In Chapter 2, I discussed the traditional theories used to explain investment distortions which stemmed mainly from firm or industry characteristics. One of the main factors that may constrain investment is the amount of funding available. Amongst those the most prominent theories are that managers follow a Pecking Order, discussed in detail in Chapter 2, whereby managers prefer to finance their investments internally (through retained earnings) than external financing. However, if they must access the external market for funds, they prefer debt over equity (Myers and Majluf, 1984). While empirical evidence confirms the existence and robustness of investment-cashflow sensitivity after controlling for investment opportunities, explaining this sensitivity solely in terms of capital market imperfections remains controversial (Myers, 2001; Malmendier and Tate, 2005).

Researchers look at alternative explanations that focus on managerial characteristics as a reason for investment discrepancies. Those managerial characteristics can be broken down into three main categories: agency theory, asymmetric information between corporate insiders and the capital market, and managerial overconfidence. Under asymmetric information, managers acting in the interest of shareholders will not invest unless there is sufficient cashflow; they try to restrict external financing so as not to dilute the shares of the company. Under the agency theory, there is a misalignment of managerial and shareholders interest (Myers and Majluf, 1984; Jensen and Meckling, 1976). Managers may overinvest to serve their personal interest, such as the privileges of being in large empires. As the capital market and firm regulations may limit managerial access to external financing, overinvestment of self-serving managers increases with the increase in cashflow. On the other hand, overconfident managers overestimate returns on investment while simultaneously believing that their firm is undervalued (Hackbarth, 2008). Given sufficient internal cashflow they will overinvest, but when these funds are depleted, they will be reluctant to tap the external market, believing that any new equity issued will be undervalued by the market even when these investments are desirable. Thus the main difference between the agency theory and managerial overconfidence is that under the agency theory a manager is consciously overinvesting to reap private benefits while an overconfident manager overestimates the value of a project and thus will overinvest believing that he is acting in the best interest of shareholders. However, once in need of external funding, overconfident managers will be least willing to issue new equity and may even choose not to invest in positive NPV projects believing that they will undervalue the firm.

Thus, overconfident managers will be more likely to overinvest when there is excess internal cashflow (retained earnings). Further overconfident managers view their equity as being undervalued by the market and may forgo investment if internal funds or debts are not available. This means that investment sensitivity to cashflow is likely to be exacerbated in equity dependent firms.

Following the work of Malmendier and Tate (2005) I will test my prediction using a regression model. The next section presents the regression model followed by a brief discussion of the descriptive statistics and a more detailed analysis of the results. Empirical testing will be done on both the Egyptian and the UK market to allow for better comparison, as discussed in Chapter 4.

5.2 Regression model

Following Malmendier and Tate (2005) the following regression model will be tested:

$$INV_{it} = \alpha_i + \beta_1 CF_{it} + \beta_2 Q_{it-1} + OC'_{it-1}\beta_3 + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it-1} + CF_{it}.OC'_{it-1}B_6 + CF_{it} \cdot x'_{it}B_7 \quad (5.1)$$

where

INV is investment; measured as capital expenditures normalized by the beginning of the year property plant and equipment.

CF is cashflow before extraordinary items plus depreciation; normalized by the beginning of the year PP&E, we expect to find a positive relationship between cashflow and investment, where increased internal cashflow will allow firms to take advantage of investment opportunities.

Q is the Tobin's q-ratio; measured as market value of assets over book value of assets. Market value of assets is defined as total assets plus market value of equity minus book value of equity. Book value of assets is the total assets obtained from the balance sheet. Tobin's Q here is an approximate measure of firm performance, firms that are performing well are expected to have increased levels of investment.

OC is the vector of overconfidence measures (see below). As mentioned in section 5.1, overconfidence in managers causes them to overestimate returns while simultaneously underestimating risk, this will cause managers to overinvest.

x_{it} is a vector of additional control factors which include:

Firm size, denoted SIZE_t, calculated as log of market capitalization. Larger firms are expected to have better investment opportunities, and thus I expect a positive relationship between firm size and investment.

Return on assets, denoted ROA_t, calculated as net income divided by total assets. I expect a positive relationship between ROA and investment as firms with higher ROA, are performing better, and thus more likely to be able to invest.

Leverage, denoted LEV_t, calculate as total debt divided by total assets. I expect a negative relationship between leverage and investment, where firms with high levels of debt may be financially constrained and thus unable to increase investment.

Finally, I will also add firm fixed effects, year fixed effects and the interaction of cashflow with industry (the effects of year fixed effects and industry are explained in more detail below).

OC is a vector of overconfidence measures that includes SZOC1, SZOC2, OPT80, OPT20, PURCHASE and NPR. The model hypothesis is that an overconfident manager's decision to invest is altered by the amount of internal cashflow (retained earnings). Therefore, an interaction term, CF.OC, cashflow multiplied by overconfidence is included in the model. I expect a positive relationship between the interaction term, CF.OC and investment. Further, cashflow is expected to have a moderating effect on other variables as well, thus the model also includes interaction terms between cashflow and the other variables.

SZOC1 and SZOC2 are the Schrand and Zechman (2012) measures of overconfidence. They measure overconfidence based on a composite score calculated from different firm-specific activities. In regard to SZOC1, a manager is considered overconfident if any two of the following four requirements holds true: the rate of investment, or volume of acquisition, or debt to equity ratio, are greater than the industry median for that year, or if the firm uses convertible debt or preferred stock. In regard to SZOC2, a manager is considered overconfident if any three of the following five components holds true: the rate of investment, or rate of acquisition, or the debt to equity ratio, are greater than the industry median for that year, or if the firm uses convertible debt or preferred stock, or if the dividend yield is greater than 0. OPT80 and OPT20 are the Campbell *et al.* (2011) measure of overconfidence and pessimism or "under confidence". Regarding OPT80, a manager is considered as overconfident if their investment activities are above the 80^{th} percentile of all firms, within the same industry, for two consecutive years. Similarly, regarding OPT20, a manager is considered as pessimistic if their investment activities are below the 20^{th} percentile for all firms for two consecutive years.

PURCHASE and NPR are based on the stock purchase activities or insider trading of the firm. Under the PURCHASE measure a manager is considered overconfident if net purchases, defined in units of stocks, are in the top 80^{th} percentile of net purchases by all CEOs in that year. Further, those purchases must increase the CEOs ownership of the firm by 10% during the fiscal year. The NPR is a measure of overconfidence with a value that varies from -1 to 1 and is calculated as

NPR= (insider purchase - insider selling)/ (insider purchase + insider selling)

The method of measuring overconfidence and a few control variables are different from Malmendier and Tate (2005). I had to slightly alter my model due to data unavailability in the countries chosen for empirical testing. Malmendier and Tate (2005) perform their test on the US market, and have detailed information about personal CEO data, this data is not available in the Egyptian market or the UK market.

I use a fixed-effects Panel regression. Serial correlation and heteroskedasticity are dealt with by clustering observations by firm in order to produce robust standard errors that control serial correlation. I also include an interaction term between industry dummy and cashflow, to capture any change in effects after considering the effects of the industry group. The reasoning for including year fixed effects and industry interaction with cashflow is explained in more detail in Section 5.3.

The overconfidence measures here are lagged by one year for two main reasons. First, this will allow a year for overconfidence bias to influence investment decision of managers. An additional important consideration is reverse causality. It may be argued that firms with higher risk or lower firm value tend to employ overconfident CEOs, whereby increase in investment may be a result of firms trying to improve firm value. That is firms with low firm value and have several investment opportunities available to them, may hire an overconfident manager to mitigate this problem. Further as in Malmendier and Tate (2005), Tobin's Q is also lagged, this is because Tobin's Q is an approximate measure of firm performance. Firm's that perform better in the previous year $t-1$ are likely to increase investment in current period t.

Regression for the Egyptian market is performed in EGP and equivalent USD. With the start of the Egyptian revolution in 2011, inflation was at 11.09% as measured by the average consumer price index and remained relatively stable during the period 2012-2016. However, during the period 2005-2016 the EGP was on a managed float. In November 2016, the Central Bank of Egypt (CBE) decided to allow the Egyptian pound to float freely which led to the devaluation of the Egyptian pound by 32.3% and caused inflation to soar 23.53% in 2017. To counter the effects of expected inflation, the CBE raised interest rates by 300 basis points to encourage people to save more and spend less. I expect that firm investment decisions may have been affected in 2017-2018 and while investment levels in EGP amount may have remained the same, or decreased slightly, their equivalent in dollar amount would have significantly decreased. Therefore, regression for the Egyptian market is performed both in EGP and equivalent USD to control for the combined effects of currency devaluation and inflation. The main conclusions for both regressions remain very similar in terms of variable significance and signs of coefficients. Results presented here are in USD, regression results for the Egyptian pound are included in Appendix A5C. The focus of my analysis will be the results of the regression done in the USD.

5.3 Descriptive statistics and correlation matrix

Tables 5.1 and 5.2 provide summary of the descriptive statistics for the model variables in Egypt and the UK respectively. The values presented are similar to the results presented by Malmendier and Tate (2005). The UK is a larger, more developed, economy and as such the mean value of investment at 245.05 (in GBP Million), is expectedly higher for the UK than for Egypt at 142.41 (in GBP Million), even when normalized by capital. It might be important to note that the descriptive statistics included in Table 5.1 and 5.2 are for the final sample that goes into the model regression, rather than the total available sample[12]. Thus, variable statistics change slightly with change in sample size than the statistics discussed in section 4.6.3. However, conclusions remain where the mean value of the different overconfidence

[12] Missing observations are removed as mentioned in Section 4.5.

proxies is normally higher for the UK than for the Egyptian market. This might be due to the time of political instability where managers became increasingly pessimistic rather than overconfident. This is specifically true for SZOC1, SZOC2 where their values of 7.1% and 4.2%, respectively, for the Egyptian market is significantly lower than 47.4% and 34.8% for the UK market. However, here the mean value of the proxy of high optimism OPT80 for the Egyptian market, 13.1%, is lower than the UK market with 19.5%. Finally, the value of low optimism OPT20 is 27.5% for the Egyptian market, significantly higher than the UK market with 18.2%. All the above discrepancies point to an increase in managerial pessimism in the Egyptian market relative to the UK market. It is also interesting to note that the minimum ROA for the UK is significantly lower than that of Egypt, signifying that in the UK sample there is a firm with significantly low earnings (losses). Finally, although the minimum for Size comes out as negative, this is only due to the way size is defined as log of market capital, whereby the log of any number less than 1[13] is negative.

Table 5.3 shows a more detailed summary of investment and cashflow, tabulated by the different overconfidence measures. Investment and cashflow, in Table 5.3, are normalized by capital. As we can see, for both Egypt and the UK, the mean value of normalized investment is always much higher for the group of firms with overconfident managers than that of non-overconfident ones. For example, under the SZOC1 measure of overconfidence the mean level of investment for the overconfident group for Egypt and the UK is 0.364 and 0.371 respectively, while the mean value for the non-overconfident group is 0.146 and 0.069 respectively. While this is not enough to conclude a true causal relationship between

[13] Data procured from Bloomberg is given in millions, i.e. firms with equity size less than one, would be indicative of an equity value less than one million.

overconfidence and increased investment, it provides initial hints in support of previous literature (Hirshleifer and Luo, 2001; Baker *et al.*, 2004; Malmendier and Tate, 2005). The mean value of normalized earnings is not necessarily higher for overconfident firms. These results make sense since investment decisions are made by top management and thus these decisions can be affected by personal psychological biases. Earnings, on the other hand, depend on numerous factors, some of which cannot be influenced by managers.

Correlations are shown in Table A5A1 and Table A5A2 of Appendix A5A. As expected, the correlation between investment and cashflow, Q, and the overconfidence measures are positive, although not highly correlated. Investment and cashflow are highly correlated at 0.799 for the UK while having a more moderate correlation of 0.584 for Egypt. Meanwhile Tobin's Q is more highly correlated for Egypt at 0.618, while being only weakly correlated at 0.139 for the UK. We can see that the overconfidence variables are all positively correlated with each other, and negatively correlated with OPT20 (the measure of pessimism). The highest correlations of overconfidence exist between SZOC1 and SZOC2, at a value greater than 0.7, for both the Egyptian and the UK markets; this is reasonable as they are both from a similar composite score. I intend to remedy this problem by always including only SZOC1 or SZOC2 in my model. We can see that none of the other variables are highly correlated, so there is no concern about perfect multicollinearity.

Table 5.1 Descriptive statistics for Egypt

Variable	Obs	Mean	Std. Dev.	Min	Max
Assets	1,321	2734.674	6902.850	22.842	94952
PP&E	1,321	1173.674	2969.217	0.520	28753
Investment	1,321	142.409	564.094	0	0
Investment normalized by PP&E	1,321	0.123	8.016	0	291
Investment normalized by assets	1,321	0.046	0.107	0	0
Cashflow	1,321	296.214	1972.183	-4849.400	66944
Cashflow normalized by PPE&E	1,321	0.102	0.161	-1.048	2.339
Cashflow normalized by assets	1,321	0.160	1.461	-37.288	6.994
Q	1,321	1.599	1.729	0.284	40.768
SZOC1	1,321	0.071	0.257	0	1
SZOC2	1,321	0.042	0.200	0	1
OPT80	1,321	0.131	0.422	0	1
OPT20	1,321	0.275	0.380	0	1
Size	1,321	6.371	1.720	1.546	11.661
LEV	1,321	0.483	0.383	0.005	5.856
ROA	1,321	6.961	13.574	-15.214	16.857

Monetary amounts are in EGP(Million).
Assets is the book value of total assets. Investment is defined as capital expenditure. Cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC1, SZOC2 and OPT80 are measures of overconfidence. OPT20 is a measure of pessimism. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity.

Table 5.2 Descriptive statistics for the UK

Variable	Obs	Mean	Std. Dev.	Min	Max
Assets	8586	3940.330	26384.130	0.073	748808
PP&E	8586	1565.962	13572.360	0	695081
Investment	8586	245.052	2250.417	0	78355
Investment normalized by PP&E	8586	1.935	50.639	0	3175.482
Investment normalized by assets	8586	0.045	0.075	0	1.904
Cashflow	8586	338.151	2747.406	-19270.640	45046.950
Cashflow normalized by PP&E	8586	-7.850	347.134	-7875.556	16303
Cashflow normalized by assets	8586	0.002	0.372	-17.193	2.597
Q	8586	3.338	46.663	0	1469.958
SZOC1	8586	0.474	0.499	0	1
SZOC2	8586	0.348	0.476	0	1
OPT80	8586	0.195	0.396	0	1
OPT20	8586	0.182	0.386	0	1
PURCHASE	8586	0.166	0.372	0	1
NPR	8586	0.061	0.923	-1	1
ROA	8586	-2.914	30.936	-45.393	12.782
Size	8586	4.462	2.451	-4.645	13.547
Lev	8586	0.118	0.333	0.001	20.485

Monetary amounts are in GBP(Million).

Assets are book value of total assets. Investment is defined as capital expenditure. Cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC1, SZOC2, OPT80, PURHCASE and NPR are measures of overconfidence. OPT20 is a measure of pessimism. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity.

Table 5.3 Investment and cashflow tabulated by overconfidence measures

		Egypt					
		Summary of INV			Summary of CF		
	Group	Mean	Std. Dev.	Freq.	Mean	Std. Dev.	Freq.
SZOC1	0	0.146	8.063	1,303	0.156	1.507	1,230
	1	0.364	0.992	95	0.223	0.509	94
SZOC2	0	0.129	7.949	1,342	0.159	1.488	1,269
	1	0.297	0.269	56	0.200	0.420	55
OPT80	0	0.059	0.184	1,080	0.158	1.320	1,018
	1	0.694	16.360	317	0.165	1.853	305
OPT20	0	0.138	8.558	1,158	0.168	1.544	1,091
	1	0.014	0.052	240	0.123	0.970	233
		UK					
		Summary of INV			Summary of CF		
	Group	Mean	Std. Dev.	Freq.	Mean	Std. Dev.	Freq.
SZOC1	0	0.069	2.173	5,607	-0.190	26.371	5,507
	1	0.371	12.458	4,442	-0.081	29.975	4,418
SZOC2	0	0.198	10.050	6,906	-0.441	33.536	6,794
	1	0.213	2.432	3,143	0.508	7.066	3,131
OPT80	0	0.099	2.173	9,234	0.088	18.959	9,111
	1	1.363	28.715	815	-2.703	74.543	814
OPT20	0	0.224	9.016	8,804	-0.132	29.604	8,734
	1	0.051	0.486	1,245	-0.206	11.020	1,191
PURCHASE	0	0.224	9.158	8,526	-0.160	30.380	8,415
	1	0.082	0.777	1,523	-0.030	4.633	1,510
NPR	1	0.073	0.870	682	0.037	5.588	891
	2	0.142	1.284	2,019	0.285	9.731	1,796

INV is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E.
SZOC1, SZOC2, OPT80, PURCHASE and NPR are measures of overconfidence.
OPT20 is a measure of pessimism.
Group definition: 0 not overconfident, 1 overconfident
NPR group definition: 1 negative NPR values signifying lower overconfidence, 2 positive NPR values signifying higher degrees of overconfidence.

I will now consider how investment may vary by industry or year. Figure 5.1 presents the mean level of investment distributed according to industry. It may be important to note that the definition of investment employed is capital expenditure divided by lagged property plant and equipment. This is because the value of investment in relation to the existing PP&E is more meaningful than just the dollar amount of investment. As expected, certain industries[14] have a higher level of capital expenditure than their competitors for both Egypt and the UK. This is because some industries, by nature, are more capital intensive than others. Figure 5.1 indicates that the energy and material industry lead in the level of capital expenditure for the UK. In Egypt, while the level of investment is understandably a lot lower than the UK, it seems to be led by the materials industry.[15]

Figure 5.2 presents the mean industry investment per year, in Egypt. We expect that the investment level during certain years may have been affected by the political and economic circumstances of the country. In fact, if we look at Figure 5.2, we can see that capital expenditure was on a rising trend in Egypt until 2007, then with the global financial crisis it started to decrease. It declined even further with the start of the Egyptian turmoil in 2011, and was starting to recover in 2013, but then due to continued turmoil with the overthrowing of president Morsi and the devaluation of the Egyptian pound, the investment level decreased to an all-time low in 2016. Cautioned by this information I will include industry and year fixed effects to my regression.

[14] Industry classifications were made according to GICS (Global Industry Classification Standard) obtained from Osiris.
[15] There are 3 industries in the Egyptian market with no listed companies, or only one listed company, which had to be excluded as overconfidence measures could not be determined.

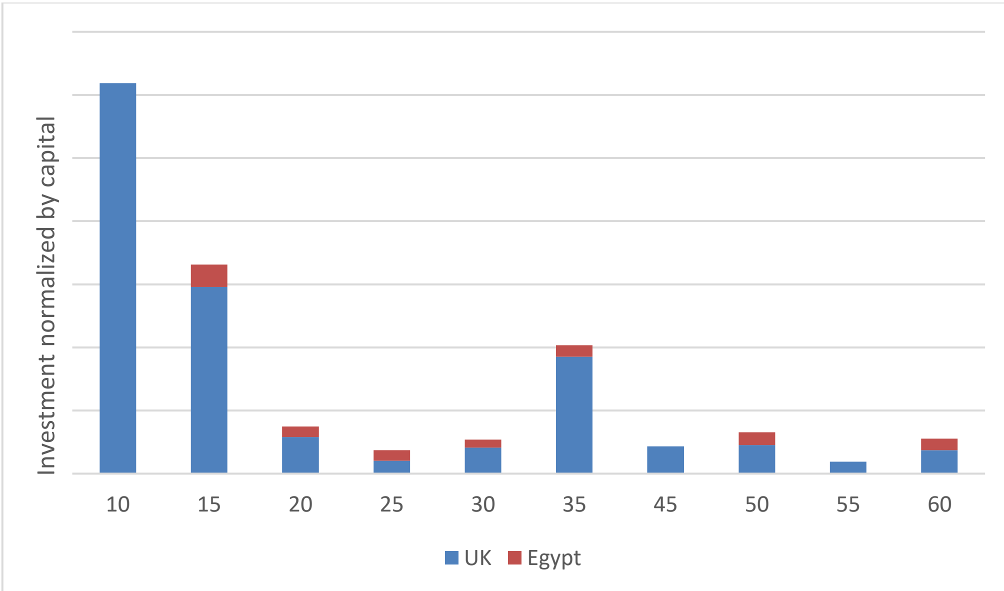

Figure 5.1 Mean investment per industry

10 – Energy
15 – Materials
20 – Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 – Information Technology
50 - Communication Services
55 - Utilities
60 - Real Estate

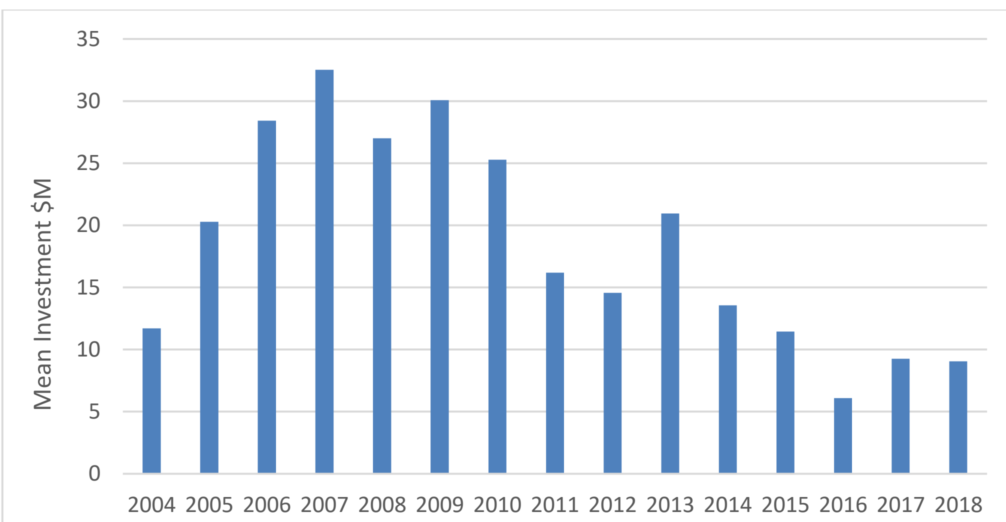

Figure 5.2 Mean investment per year (Egypt)

5.4 Regression results and analysis

Table 5.4 provides the results for the baseline regression against investment for Egypt and the UK. The first two columns present the basic relationship between cashflow, Tobin's Q and investment. Cashflow and Tobin's Q are considered the most popular variables affecting investment as established in previous literature. Since I have panel data, it makes sense to utilise the advantages of panel data and use fixed effects analysis. However, the results presented in Table 5.4 include both FE and standard OLS regression without FE. As we can see for both Egypt and the UK, the relationship between investment and cash flow is positive and significant, where firms with higher cash have a better ability to invest. The coefficient for cashflow in the fixed effects model without controls is higher in the UK with a coefficient of 0.181 than for the Egyptian market with a coefficient 0.024. Signifying that the availability of cash has a greater influence on investment for the UK market than for the Egyptian market. Nonetheless both coefficients are positive and significant at 1% level. The relationship between investment and Tobin's Q is also positive and significant, where firms with higher Tobin's Q are better able to invest.

The third column presents the results of a FE regression of investment against cashflow, Tobin's Q and the rest of the control variables. This regression includes controls but excludes overconfidence proxies, this to form the basic relationship between investment and control variables. The basic regression will be beneficial when making comparisons with models where overconfidence proxies are included. Firstly, one can note that as control variables are added the coefficient of cashflow increased to 0.452 for Egypt and 0.488 for the UK and remains highly significant for both markets at 1%. This is reasonable as cash is not only an independent but also a moderator variable making it a crucial variable in the model. As in

Malmendier and Tate (2005) we can see from Table 5.4 that the interaction between Cashflow (CF) and Tobin's Q is significant and positive (with a coefficient = 0.047 and p-value = <0.001 for Egypt and a coefficient = 0.0001 and p-value = 0.015 for the UK), indicating that the effect of Q on investment increases with increasing cash flow. This makes sense as more successful companies (higher Tobin's Q) are more responsive to investment opportunities especially with increase in cash flow. However, note that while Tobin's Q remains positive with a coefficient of 0.001 for the UK, it is now significant only at 10%.

Furthermore, as we can see from Table 5.4, the effect of leverage alone on investment is negative for both markets. Firms with higher levels of debt will tend to invest less. However, also note that, leverage for the UK market is highly significant at 1% level and with a coefficient of -0.004. For Egypt, the coefficient for leverage is -0.0001, while that holds the expected sign, it is insignificant with a probability of 0.317. However, the interaction between cashflow and leverage is positive. This means that firms with higher leverage will tend to increase their investment if they have increased cash flow. My interpretation of this is that these firms would feel safer paying back their debt, i.e. they are more confident in paying back parts of their debt and interest as it comes due. A firm is most concerned with current cash needs, driven by short-term debt as it can cause default. Again, the interaction term while highly significant for the UK at 1% level, is insignificant for the Egyptian market although it presents the expected coefficients sign.

Size is significant and positive for the UK (coefficient = 0.552, p-value = 0.014) signifying that larger firms have higher levels of investment. However, size and cash flow interaction term (coefficient = -0.202, p-value = <0.001) while significant has a negative coefficient, indicating that larger firms invest less as their cash flow increases. While this result is somewhat puzzling, it may be reasoned that large firms are better able to get leverage at lower rates, having already set up their credit worthiness in the market, and thus do not necessarily depend on internal cashflow when making investment decision. These results are also in line with those presented by Malmendier and Tate (2005). The next subsections discuss the effect of each managerial overconfidence measure separately on investment sensitivity to cashflow.

Table 5.4 Baseline regression

Egypt			
Variables	No FE, No Controls	FE, No Controls	FE, Controls
CF_t	0.028 (<0.001)	0.024 (<0.001)	0.452 (<0.001)
Q_{t-1}	0.053 (0.007)	0.076 (0.002)	0.071 (0.001)
ROA_t	-	-	0.698 (0.039)
$SIZE_t$	-	-	-0.160 (0.120)
LEV_t	-	-	-0.0001 (0.137)
$CF_t.Q_{t-1}$	-	-	0.047 (<0.001)
$CF_t.ROA_t$	-	-	0.203 (<0.001)
$CF_t.SIZE_t$	-	-	0.306 (<0.001)
$CF_t.LEV_t$	-	-	0.0001 (0.442)
Intercept	-	-	0.164 (0.070)
Firm FE	No	Yes	Yes
Year FE	No	Yes	Yes
Industry FE	No	No	No
R-Sq	0.276	0.277	0.472
Rho	-	0.128	0.229
UK			
CF_t	0.181 (<0.001)	0.181 (<0.001)	0.488 (<0.001)
Q_{t-1}	0.003 (<0.001)	0.007 (<0.001)	0.001 (0.055)
ROA_t	-	-	0.0003 (0.751)
$SIZE_t$	-	-	0.552 (0.014)
LEV_t	-	-	-0.004 (<0.001)
$CF_t.Q_{t-1}$	-	-	0.0001 (0.015)
$CF_t.ROA_t$	-	-	0.0002 (<0.001)
$CF_t.SIZE_t$	-	-	-0.202 (<0.001)
$CF_t.LEV_t$	-	-	0.0002 (0.006)
Intercept	-	-	0.212 (0.066)
Firm FE	No	Yes	Yes
Year FE	No	Yes	Yes
Industry FE	No	No	No
R-Sq	0.360	0.359	0.778
Rho	-	0.144	0.153

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + x'_{it} B_3 + \beta_4 CF_{it} \cdot Q_{it-1} + CF_{it} \cdot x'_{it} B_5$

Regression for Egypt performed in USD and for the UK in GBP. This table presents baseline regression of Investment against cashflow, overconfidence and other control variables. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. The number of firms i for Egypt is 102 is and for the UK is 761, the time period t is from the year 2005 to 2018 for both markets, the number of observations n for Egypt is 1321 and for the UK is 8586. Expected coefficient signs are described in section 5.2.

The R^2 reported in the table above is the overall R^2. When performing panel data analysis, it is important to consider the value of rho rather than just the overall R^2. Whereas pooled regression often refers to R^2 as the proportion of variance in the dependent variable explained by the independent variables, under fixed effects rho refers to the proportion of variation explained by the firm-specific term (the term that changes across firms but does not vary with time), under random effects rho is used to refer to the fraction of total variance due to ε_i (variation in the error term that changes across firms and time)

Rho is known as the intraclass correlation and is measured as:

$$rho = \frac{(sigma\_u)^2}{(sigma\_u)^2 + (sigma\_\varepsilon)^2}$$

Where

sigma _ u = standard deviation of residuals within groups u_i;

sigma _ ε = standard deviation of residuals (overall error term) ε_i.

The next subsections will discuss how each of the overconfidence measures and its interaction with cashflow affect investment level.

I. Overconfidence proxies SZOC

SZOC1 and SZOC2 are composite scores for overconfidence proposed by Schrand and Zechman (2012) based on different firm-specific activities and its comparison with all firms in the same industry. The activities include investing, acquisition, debt to equity, convertible debt or preferred stock, and dividend yield. They are discussed in Section 5.2 and discussed in more detail in Section 4.6. Tables 5.5 and 5.6 present the result of the effect of SZOC1 and its interaction with cashflow against investment for Egypt and the UK respectively. Tables 5.7 and 5.8 present the results of the effect of SZOC2 on investment and its sensitivity to cashflow for Egypt and the UK respectively.

Within the Egyptian market we can note from Table 5.5 that in the first column, SZOC1 has a coefficient 0.568 and is significant at a 1% level, while its interaction with cashflow has a coefficient of -0.102 and is insignificant. These sign coefficients provide unexpected results, as it would mean that overconfidence bias reduces the managers likelihood to invest as more cash becomes available. This is contrary to the hypothesis, the findings for the UK market and the findings by Malmendier and Tate (2005). Further once controls are added, the value of SZOC1 and its interaction with cashflow become insignificant. Thus, SZOC1 is only significant when there are no controls, this is probably due to model under-specification, as both variables (SZOC1 and the interaction term) are insignificant when controls are added, regardless of how serial autocorrelation is controlled for, as can be seen from columns 3 and 4 of Table 5.5, and therefore I conclude that managerial overconfidence as measured by SZOC1 is insignificant. Similarly, in Table 5.7 SZOC2 and its interaction with cashflow remain insignificant for the Egyptian market with or without controls and regardless of how autocorrelation is controlled for. The results for cashflow, Tobin’s Q and the other control variables remain very similar to the baseline regression in terms of signs of coefficients and significance levels. For example, cashflow remains significant at a 1% level with the different model specifications in Table 5.7. However, once I control for serial autocorrelation, several control variables now turn insignificant. I speculate that this may be due to the method used to control for serial autocorrelation, which is clustering observations by firm id. I will discuss this in more detail in what follows. It is also interesting to note that the model which includes

SZOC1 as an overconfidence measure is very similar to the model where SZOC2 is included. The results presented in Appendix A5C1 and A5C2, where regression is performed using EGP instead of the equivalent USD show similar results. Cashflow and Tobin's Q behave similarly and SZOC1, SZOC2 and their interaction with cashflow are also insignificant.

On the other hand, and interestingly, the UK market shows a significant negative relationship between overconfidence and investment, and a positive significant relationship of the interaction between overconfidence, cashflow and investment for both SZOC1 and SZOC2. For example, in the first column of Table 5.6, we can see that SZOC1 is significant with a p-value of 0.04 and a coefficient of -0.361, while the interaction term is highly significant at the 1% level with a coefficient of 0.23. I tried testing this model without adding the interaction term between SZOC1 and cashflow, and SZOC1 showed a significant positive coefficient of 0.024 and a p-value of 0.043. Thus, if we do not consider the effect of cash as a moderator variable, the coefficient of the overconfidence variable results positive, signifying that overconfident managers will increase investment. However, once cash is included as a moderator, one can clearly see that investment increases only due to the availability of excess cash. This interaction term in fact is highly significant at 1% level in the models where I control for serial autocorrelation. The UK results do give evidence of previous theoretical findings in the literature such as Malmendier and Tate (2005), Campbell et al. (2011) and Oran (2013) where it is theoretically deduced that overconfident managers do not take advantage of investment opportunities unless there is an abundance of internal cashflow (retained earnings). If overconfident managers have to tap into the external market to finance their investments, they will view any debt as risky, and their company stock as undervalued, and are thus likely to pass on investment opportunities even if they provide positive NPV.

In fact, the SZOC measures of overconfidence remained significant even when standard errors were clustered by firm, or when I included interactions of CF and industry. Again, both models present very similar results whether SZOC1 or SZOC2 are used. The more puzzling element though is that Tobin's Q turns insignificant when overconfidence proxies and controls are added, regardless of how autocorrelation is controlled for. This may be because Tobin's Q is arguably not always the best proxy for measuring firm performance. Bartlett and Partnoy (2018) argue that as Tobin's Q uses the book value of assets (denominator) in its measurement, it is likely to produce biased estimates. This is due to certain assets being omitted as intangible assets, or other firm-specific details which may systematically alter Tobin's Q (e.g. the level of current assets, depreciation among others).

Table 5.5 The effect of the interaction of cashflow and SZOC1 on investment (Egypt)

	Egypt			
Variables	OC, FE, No Controls	OC, FE, Controls	Std. Errors Cluster by Firm	Industry-CF Interaction, Firm FE
CF_t	0.053 (<0.001)	0.504 (<0.001)	0.504 (0.043)	0.050 (0.002)
Q_{t-1}	0.078 (<0.001)	0.062 (0.007)	0.062 (0.109)	- 0.017 (0.362)
ROA_t	-	1.119 (0.011)	1.119 (0.430)	0.333 (0.319)
SIZE_t	-	-0.161 (0.145)	-0.161 (0.030)	0.041 (0.062)
LEV_t	-	-0.0001 (0.680)	-0.0001 (0.002)	-0.0001 (0.027)
$\mathrm{CF}_t.\mathrm{Q}_{t-1}$	-	0.059 (<0.001)	0.059 (0.343)	0.011 (0.798)
$\mathrm{CF}_t.\mathrm{ROA}_t$	-	0.418(<0.001)	0.418 (0.433)	0.055 (0.267)
$\mathrm{CF}_t.\mathrm{SIZE}_t$	-	0.303 (<0.001)	0.303 (0.278)	-0.005 (0.668)
$\mathrm{CF}_t.\mathrm{LEV}_t$	-	-0.0001 (0.153)	-0.0001 (0.485)	-0.0001 (0.297)
$\mathrm{SZOC1}_{t-1}$	0.568 (<0.001)	0.566 (0.501)	0.566 (0.115)	0.537 (0.123)
$\mathrm{CF}_t.\mathrm{SZOC1}_{t-1}$	-0.102 (0.606)	-0.059 (0.760)	-0.059 (0.973)	-0.286 (0.081)
Intercept	0.012 (0.809)	0.116 (0.226)	0.116 (0.168)	0.120 (0.275)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.364	0.399	0.399	0.577
Rho	0.100	0.126	0.126	0.131
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 SZOC1_{it-1} + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.SZOC1_{it-1} + CF_{it} \cdot x'_{it}B_7$

Regression is performed in USD. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC1 is the Schrand and Zechman (2012) measure of overconfidence. OC is overconfidence and FE is fixed effects. x'_{iT} in the equation is the vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 102, the time period t is from the year 2005 to 2018, the number of observations n is 1321. Expected coefficient signs are described in section 5.2.

Table 5.6 The effect of the interaction of cashflow and SZOC1 on investment (UK)

Variables	OC, FE, No Controls	OC, FE, Controls	Std. Errors Cluster by Firm	Industry-CF Interaction, Firm FE
CF_t	0.243 (<0.001)	0.173 (<0.001)	0.173 (0.001)	0.175 (0.008)
Q_{t-1}	0.002 (0.020)	-0.001 (0.789)	-0.001 (0.595)	-0.002 (0.797)
ROA_t	-	-0.001 (<0.001)	-0.001 (0.882)	-0.0004 (0.910)
SIZE_t	-	0.151 (<0.001)	0.151 (0.353)	0.159 (0.338)
LEV_t	-	-0.0003 (0.079)	-0.0003 (0.916)	-0.006 (0.922)
$\mathrm{CF}_t.\mathrm{Q}_{t-1}$	-	0.0001 (0.617)	0.00001 (0.307)	-0.0004 (0.370)
$\mathrm{CF}_t.\mathrm{ROA}_t$	-	0.0002 (<0.001)	0.0002 (0.450)	1.8E-05 (0.498)
$\mathrm{CF}_t.\mathrm{SIZE}_t$	-	0.105 (<0.001)	0.105 (<0.001)	-0.106 (0.002)
$\mathrm{CF}_t.\mathrm{LEV}_t$	-	-0.0001 (0.660)	-0.0001 (0.893)	-3.130 (0.902)
$\mathrm{SZOC1}_{t-1}$	-0.361 (0.040)	-0.069 (0.041)	-0.069 (0.016)	-0.041 (0.059)
$\mathrm{CF}_t.\mathrm{SZOC1}_{t-1}$	0.230 (<0.001)	0.316 (0.501)	0.316 (<0.001)	0.099 (<0.001)
Intercept	0.090 (<0.001)	-0.668 (0.046)	-0.668 (0.322)	-0.029 (0.303)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.879	0.914	0.914	0.915
Rho	0.152	0.156	0.156	0.157
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 SZOC1_{it-1} + x'_{it} B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.SZOC1_{it-1} + CF_{it} \cdot x'_{it} B_7$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC1 is the Schrand and Zechman (2012) measure of overconfidence. OC is overconfidence and FE is fixed effects. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

Table 5.7 The effect of the interaction of cashflow and SZOC2 on investment (Egypt)

Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	0.053 (<0.001)	0.505 (<0.001)	0.505 (<0.001)	0.049 (<0.001)
Q_{t-1}	0.073 (0.001)	0.057 (0.014)	0.057 (0.067)	-0.008 (0.595)
ROA_t	-	1.019 (0.021)	1.019 (0.136)	0.282 (0.391)
SIZE_t	-	0.165 (0.136)	0.165 (0.041)	0.025 (0.896)
LEV_t	-	0.0002 (0.186)	0.0002 (0.068)	0.0001 (0.036)
$\mathrm{CF}_t.\mathrm{Q}_{t-1}$	-	0.059 (<0.001)	0.059 (0.383)	0.001 (0.94)
$\mathrm{CF}_t.\mathrm{ROA}_t$	-	0.415 (<0.001)	0.415 (0.407)	0.044 (0.328)
$\mathrm{CF}_t.\mathrm{SIZE}_t$	-	0.304 (<0.001)	0.304 (0.467)	-0.004 (0.719)
$\mathrm{CF}_t.\mathrm{LEV}_t$	-	-0.0001 (0.160)	-0.0001 (0.251)	0.0001 (0.024)
$\mathrm{SZOC2}_{t-1}$	0.152 (0.404)	0.069 (0.703)	0.069 (0.194)	0.064 (0.288)
$\mathrm{CF}_t.\mathrm{SZOC2}_{t-1}$	-0.071 (0.730)	0.088 (0.661)	0.088 (0.230)	-0.148 (0.163)
Intercept	0.054 (0.261)	0.155 (0.107)	0.155 (0.239)	-0.104 (0.428)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF F	No	No	No	Yes
R-Sq	0.355	0.387	0.387	0.565
Rho	0.101	0.129	0.129	0.137
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 SZOC2_{it-1} + x'_{it} B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.SZOC2_{it-1} + CF_{it} \cdot x'_{it} B_7$

Regression is performed in USD. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC2 is the Schrand and Zechman (2012) measure of overconfidence. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 102, the time period t is from the year 2005 to 2018, the number of observations n is 1321. Expected coefficient signs are described in section 5.2.

Table 5.8 The effect of the interaction of cashflow and SZOC2 on investment (UK)

Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry CF Interaction, Firm FE
CF_t	0.191 (<0.001)	0.630 (<0.001)	0.630 (<0.001)	0.645 (<0.001)
Q_{t-1}	0.007 (<0.001)	0.001 (0.413)	0.001 (0.433)	-0.011 (0.548)
ROA_t	-	0.0001 (0.509)	0.001 (0.809)	0.003 (0.631)
$SIZE_t$	-	0.064 (0.195)	0.064 (0.496)	0.074 (0.543)
LEV_t	-	-0.0003 (<0.001)	-0.0003 (0.152)	-0.0003 (0.012)
$CF_t.Q_{t-1}$	-	0.001 (<0.001)	0.001 (0.400)	0.001 (0.214)
$CF_t.ROA_t$	-	4.1E-05 (0.262)	4.1E-05 (0.852)	4.4E-05 (0.748)
$CF_t.SIZE_t$	-	0.309 (<0.001)	0.309 (<0.001)	0.410 (0.001)
$CF_t.LEV_t$	-	7.3E-05 (<0.001)	7.3E-05 (0.159)	5.2E-05 (0.120)
$SZOC2_{t-1}$	-0.043 (0.044)	-0.232 (0.018)	-0.232 (0.022)	-0.252 (0.024)
$CF_t.SZOC2_{t-1}$	0.489 (<0.001)	1.414 (<0.001)	1.414 (<0.001)	1.526 (0.004)
Intercept	-0.108 (0.206)	-0.230 (0.280)	-0.230 (0.588)	-0.253 (0.608)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF F	No	No	No	Yes
R-Sq	0.420	0.886	0.886	0.890
Rho	0.170	0.123	0.123	0.117
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 SZOC2_{it-1} + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.SZOC2_{it-1} + CF_{it} \cdot x'_{it}B_7$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC2 is the Schrand and Zechman (2012) measure of overconfidence. OC is overconfidence and FE is fixed effects. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

II. Overconfidence proxies OPT

The OPT proxies used in this thesis are based on Campbell *et. al* (2011) measure of overconfidence, they divide their measure into two categories, OPT80 are the overconfident managers/firms, while OPT20 are the non-confident or pessimistic managers/firms. An overview of the overconfidence measures is presented in Section 5.2 and discussed in more detail in Section 4.6. The regression model testing the effect of the interactions of cashflow and OPT on investment is presented in Table 5.9 and Table 5.10 for Egypt and the UK respectively. From Table 5.9 we can see that, as with SZOC1, the OPT measures of overconfidence for the Egyptian market show that OPT80 turns out significant (coefficient = 0.362, p-value = <0.001) only when included alone, while OPT20 and the interaction between cashflow and OPT80 or OPT20 are all insignificant. Once control variables are included in the model, the OPT80 turns insignificant as well (coefficient =0.523, p-value = 0.510). Again, as with SZOC1, the significant result realized without the addition of controls is meaningless, as it may just be a result of frequency data being given an incorrect casual interpretation as in the Simpsons paradox (Hernan *et al.*, 2011). As discussed above, under-specified models produce biased results. Further, one can notice that whether I am using OPT, SZOC1 or SZOC2, all variables throughout the three models behave very similar with insignificant results for the Egyptian market.

The results for the UK market, presented in Table 5.10, show that OPT80 is statistically significant, even when errors are clustered by firm. For example, in the third column where errors are clustered by firm, we can see that OPT80 has a coefficient = -0.213 and a p-value = 0.04, similarly CFOPT80 has a coefficient = 0.354 and a p-value = <0.001. These give the same results presented when SZOC1 or SZOC2 was included in the model, whereby investment by overconfident managers increased due to the availability of cashflow. Meanwhile the results for pessimism or lack of confidence, as measured by OPT20, are for the most part insignificant. This might signify that overconfidence affects the amount of managerial investment, whereas managerial pessimism or lack of confidence does not necessarily mean reduced investment levels. It is also interesting to note that the one variable that always remains significant, regardless of the variables included and regardless of whether autocorrelation is controlled for or not, is cashflow. This is true for both the Egyptian and the UK markets. Perhaps signifying the importance of cashflow as one of the crucial factors that impact investment decisions. Although in this section I use a different method of measuring managerial overconfidence, the results for Egypt and the UK remain very much similar, supporting the results of the previous section.

We can also notice that other control variables also turn insignificant when controlling for autocorrelation. This may be a consequence of the method used to control for serial autocorrelation, perhaps a more enhanced method could be used (a different method of controlling for serial autocorrelation will be discussed in more detail in the next section of the analysis). Nevertheless, these results are in line with the results presented by Malmendier and Tate (2005).

One may argue that the difference in the results between the UK and Egypt, whereby the overconfidence measures are consistently insignificant for Egypt but significant for the UK, could be due to the Egyptian turmoil. Perhaps, the political instability caused the managers to be more risk averse, where public panic induced managerial caution. In such a case, the decisions made by overconfident and non-biased managers would be the same. This argument may be supported by the UK market being in a state of relative stability, which allowed the behaviour of overconfident managers to be more pronounced on investment decisions and their sensitivity to cashflow.

Thus, I argue that the impact of overconfidence on financial decision is an inverted “U” shape, that differs with the degree of risk, as modelled in Figure 5.3. That is, the impact of managerial overconfidence on decision making is concave to the degree of external/political risk. In an environment where there is no risk, the behaviour of overconfident as well as other non-biased managers will be the same. In this case, overconfident managers will not underestimate risk, as there is no risk to underestimate. As risk increases so does managerial overconfidence and its impact on financial decisions. In an environment where there is medium risk, overconfidence has a high impact on decision making. However, when risk exceeds a certain level, managerial overconfidence decreases as managers become more cautious due to increasingly clearer risk signals by the market. As risk becomes extremely high the impact of overconfidence goes to zero, and the behaviours of overconfident and other non-biased managers converge. In other words, one would expect that there is a certain level of risk, at which managerial overconfidence will have the highest impact on the decision-making process.

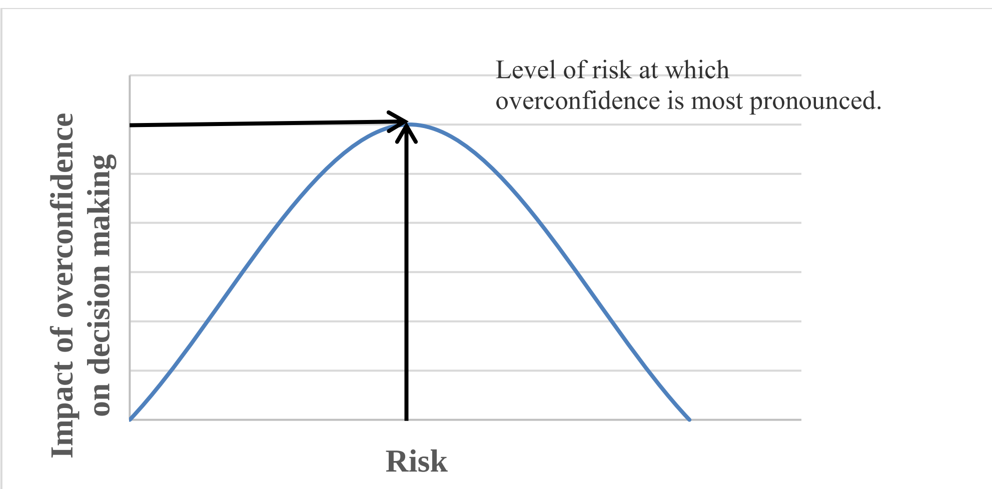

Figure 5.3 Overconfidence and the degree of political risk

Table 5.9 The effect of the interaction of cashflow and OPT on investment (Egypt)

	Egypt			
Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	0.049 (<0.001)	0.600 (<0.001)	0.600 (<0.001)	0.040 (<0.001)
Q_{t-1}	0.065 (0.001)	0.013 (0.060)	0.013 (0.622)	-0.010 (0.504)
ROA_t	-	0.938 (0.036)	0.938 (0.073)	0.322 (0.318)
$SIZE_t$	-	-0.213 (0.055)	-0.213 (0.005)	-0.026 (0.863)
LEV_t	-	0.0002(0.131)	0.0002 (0.524)	0.0001 (0.487)
$CF_t.Q_{t-1}$	-	0.054 (<0.001)	0.054 (0.543)	0.001 (0.836)
$CF_t.ROA_t$	-	0.419 (<0.001)	0.419 (0.524)	0.031 (0.460)
$CF_t.SIZE_t$	-	0.440 (<0.001)	0.440 (0.896)	0.044 (0.257)
$CF_t.LEV_t$	-	-0.0001 (0.035)	-0.0001(0.407)	0.0001 (0.474)
$OPT80_{t-1}$	0.362 (<0.001)	0.523 (0.510)	0.523 (0.707)	0.383 (<0.401)
$CF_t.OPT80_{t-1}$	0.0004 (0.888)	-0.081 (0.105)	-0.081 (0.764)	-0.057 (0.307)
$OPT20_{t-1}$	-0.013 (0.888)	-0.073 (0.491)	-0.073 (0.587)	-0.027 (0.266)
$CF_t.OPT20_{t-1}$	-0.125 (0.275)	0.115 (0.057)	0.115 (0.538)	0.070 (0.103)
Intercept	-0.028 (0.143)	0.201 (0.047)	0.201 (0.459)	0.116 (0.360)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.593	0.421	0.421	0.582
Rho	0.102	0.113	0.113	0.125
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + OPT'_{it-1}\beta_3 + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it-1} + CF_{it}.OPT'_{it-1}B_6 + CF_{it} \cdot x'_{it}B_7$

Regression is performed in USD. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OPT80 is the Campbell *et al.* (2011) measure of overconfidence, similarly OPT20 is a measure of pessimism. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 102, the time period t is from the year 2005 to 2018, the number of observations n is 1321. Expected coefficient signs are described in section 5.2.

Table 5.10 The effect of the interaction of cashflow and OPT on investment (UK)

	UK			
Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	0.314 (<0.001)	0.117 (<0.001)	0.117 (0.133)	0.129 (0.149)
Q_{t-1}	0.0001 (0.039)	-3.4E-07 (0.730)	-3.4E-07 (0.999)	-0.001 (0.990)
ROA_t	-	-0.0001 (0.201)	-0.0001 (0.926)	-0.001 (0.947)
$SIZE_t$	-	0.023 (<0.001)	0.023 (0.442)	0.168 (0.372)
LEV_t	-	-1.8E-05 (<0.001)	-1.8E-05 (0.601)	-1.9E-05 (0.62)
$CF_t.Q_{t-1}$	-	0.0001 (<0.001)	0.0001 (0.363)	0.0041 (0.438)
$CF_t.ROA_t$	-	0.0001 (<0.001)	0.0001 (0.563)	0.0041 (0.650)
$CF_t.SIZE_t$	-	-0.076 (<0.001)	-0.076 (0.039)	-0.076 (0.036)
$CF_t.LEV_t$	-	0.0004 (<0.001)	0.0004 (0.634)	0.0004 (0.652)
$OPT80_{t-1}$	-0.045 (0.010)	-0.213 (0.007)	-0.213 (0.040)	-0.205 (0.014)
$CF_t.OPT80_{t-1}$	0.026 (0.086)	0.354 (<0.001)	0.354 (<0.001)	0.353 (<0.001)
$OPT20_{t-1}$	0.083 (<0.001)	-0.022 (0.734)	-0.022 (0.432)	-0.028 (0.495)
$CF_t.OPT20_{t-1}$	-0.004 (0.127)	-0.092 (<0.001)	-0.092 (0.397)	-0.097 (0.401)
Intercept	-0.062 (<0.001)	-0.120 (<0.001)	-0.120 (0.314)	-0.726 (0.293)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.687	0.925	0.925	0.927
Rho	0.136	0.184	0.184	0.186
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + OPT'_{it-1}\beta_3 + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it-1} + CF_{it}.OPT'_{it-1}B_6 + CF_{it} \cdot x'_{it}B_7$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OPT80 is the Campbell *et al.* (2011) measure of overconfidence, similarly OPT20 is a measure of pessimism. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

III. Overconfidence proxies PURCHASE and NPR

The PURCHASE and NPR measures define overconfidence by the stock purchasing decisions of managers and as such are applicable only in the UK. The results of the regression of investment against cashflow, overconfidence, control variables and the interaction variables are presented in Table 5.11 and 5.12 for PURCHASE and NPR respectively. As shown in Table 5.11, the PURCHASE measure is insignificant across all four models. However, interestingly, the interaction term between cashflow and PURCHASE is significant and negative in the first two models (coefficient = -0.255, p-value = 0.005 and coefficient = 0.120, p-value = 0.008), once errors are clustered by firm, the interaction term turns insignificant. The significant result in the first two models may be a consequence of serial autocorrelation which could cause model bias. While both PURCHASE and NPR measures of overconfidence are based on stock purchases, the PURCHASE measure is relatively very restrictive and thus may not be very efficient in capturing managerial overconfidence. Please see detailed discussion in Section 4.6.

On the other hand, the results for NPR measure, presented in Table 5.12, are significant in the first two models. However, once serial autocorrelation is controlled for, NPR has a coefficient of 0.029 but is now insignificant with a p-value of 0.506 when clustered by firm, this is also true when industry cashflow interaction are included and controlling for autocorrelation by firm cluster. The interaction of cashflow with NPR remains significant across all four models. One could argue that overconfidence alone, as measured by NPR, has no significant relationship on investment. However, once there is an abundance of cash, the effects of overconfidence become more pronounced.

Again, one can notice, as with the previous two models, that Tobin's Q is insignificant when controls are added (coefficient = 0.0001, p-value = 0.947 under the NPR model). In fact, several of the variables turn insignificant when serial autocorrelation is accounted for. The method used to control for serial autocorrelation in this study is by clustering observations within each firm. While some of the overconfidence measures for the UK remain significant and robust to controlling for autocorrelation in this way, PURCHASE and NPR measures of overconfidence do not. Alternatively, I used the Prais-Winsten method to control for serial correlation. (I present the full table of results in the appendix A5C5.) The Prais-Winsten regression method uses a GLS method to estimate the parameters in a model where the errors are serially correlated. The regression process assumes that errors follow a first-order autoregressive serial correlation. The resulting coefficients and p-values from the Prais-Winsten regression including controls but excluding firm fixed effects and industry interaction with cashflow presented in Table 5C5 show that all the measures of overconfidence except PURCHASE and their interaction with cash flow remain highly significant at the 5% and 1% level. The signs on the coefficients are also as expected, with negative coefficients for overconfidence measures alone, and positive coefficients for the interaction terms. Further, the model presented in Table 5C5 tested SZOC2. In order to avoid multicollinearity, I tested SZOC1 in a separate model and found SZOC1 to be significant at a 5% level with a coefficient of -0.059 while the interaction term CF.SZOC1 was significant at the 1% level with a coefficient of 0.187. Further, note from Table 5C5 that by controlling for serial autocorrelation in a different manner several of the control variables are now significant, except for the Tobin's Q which remains insignificant for the UK market. I performed the Prais-Winsten regression on the Egyptian market and the overconfidence measures remained insignificant; the results are presented in Table 5C5 alongside the UK market.

Thus, the main conclusion for the Egyptian and the UK market remain the same, even when using a different method to control for serial autocorrelation. The measures of overconfidence against investment are insignificant for the Egyptian market. On the other hand, the results for the UK show that there is a significant relationship between the degree of overconfidence and the sensitivity of cashflow to investment under all measures of overconfidence, except the PURCHASE measure. This means that an overconfident (UK) manager is more likely to increase investment when there is more cash available. The results for the UK are very comparable to those found by Malmendier and Tate (2005).

Table 5.11 The effect of the interaction of cashflow and PURCHASE on investment (UK)

	PURCHASE			
Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	0.184 (<0.001)	0.117 (0.078)	0.117 (<0.001)	0.487 (0.001)
Q_{t-1}	-0.007 (<0.001)	0.003 (0.082)	0.003 (0.440)	-0.001 (0.545)
ROA_t	-	0.006 (<0.001)	0.006 (0.868)	0.0004 (0.856)
$SIZE_t$	-	0.007 (0.7780	0.007 (0.555)	0.067 (0.570)
LEV_t	-	7.9E-06 (0.531)	7.9E-06 (0.254)	-0.0001 (0.007)
$CF_t.Q_{t-1}$	-	0.003 (0.403)	0.003 (0.171)	0.0001 (0.218)
$CF_t.ROA_t$	-	0.0004 (<0.001)	0.0004 (0.267)	0.0002 (0.281)
$CF_t.SIZE_t$	-	-0.076 (0.001)	-0.076 (0.018)	-0.198 (0.024)
$CF_t.LEV_t$	-	4.6E-06 (0.659)	4.6E-06 (0.248)	0.0003 (0.008)
$PURCHASE_{t-1}$	0.008 (0.971)	0.008 (0.308)	0.008 (0.743)	0.028 (0.761)
$CF.PURCHASE_{t-1}$	-0.255 (0.005)	-0.120 (0.008)	-0.120 (0.526)	-0.203 (0.564)
Intercept	-0.161 (0.041)	-0.099 (0.482)	-0.099 (0.628)	-0.248 (0.646)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.377	0.775	0.775	0.781
Rho	0.171	0.156	0.156	0.147
p-values are shown in parentheses				

$$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 PURCHASE_{it-1} + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.PURCHASE_{it-1} + CF_{it} \cdot x'_{it}B_7$$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. PURCHASE is an overconfidence measure based on insider net stock purchases. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

Table 5.12 The effect of the interaction of cashflow and NPR on investment (UK)

	NPR			
	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	0.118 (<0.001)	0.412 (<0.001)	0.412 (0.124)	0.119 (0.074)
Q_{t-1}	0.003 (0.020)	0.001 (0.947)	0.001 (0.323)	0.001 (0.994)
ROA_t	-	0.006 (<0.001)	0.006 (<0.001)	0.003 (0.023)
SIZE_t	-	0.007 (0.306)	0.007 (0.763)	0.001 (0.955)
LEV_t	-	7.78E-06 (0.371)	7.78E-06 (0.550)	7.74E-06 (0.332)
$\text{CF}_t.\text{Q}_{t-1}$	-	0.0002 (0.766)	0.0002 (0.237)	0.0001 (0.934)
$\text{CF}_t.\text{ROA}_t$	-	-0.002 (<0.001)	-0.002 (<0.001)	-0.003 (0.005)
$\text{CF}_t.\text{SIZE}_t$	-	-0.012 (0.077)	-0.012 (<0.001)	0.033 (0.458)
$\text{CF}_t.\text{LEV}_t$	-	5.2E-06 (0.072)	5.2E-06 (0.668)	-1.6E-06 (0.868)
NPR_{t-1}	0.031 (0.007)	0.029 (0.025)	0.029 (0.506)	0.038 (0.308)
$\text{CF}_t.\text{NPR}_{t\text{-}1}$	0.272 (<0.001)	0.068 (<0.001)	0.068 (0.018)	0.120 (0.028)
Intercept	-0.113 (<0.001)	-0.041 (0.735)	-0.041 (0.438)	-0.142 (0.264)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.753	0.919	0.919	0.915
Rho	0.189	0.563	0.563	0.613
p-values are shown in parentheses				

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + \beta_3 NPR_{it-1} + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it} + B_6 CF_{it}.NPR_{it-1} + CF_{it} \cdot x'_{it}B_7$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. NPR is an overconfidence measure based on insider net stock purchases. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

5.4.1 Robustness checks

The results presented in Section 5.3 for the UK show that as long as overconfident managers have sufficient amount of internal cashflow they will continue to increase investment. Once they are forced to look for external finance, overconfident managers are more likely to dislike issuing new equity, believing it to be undervalued. Thus, financing investments should matter most for firms that are equity dependent and have depleted their internal cashflow and their debt capacity to finance investments. Following the work of Malmendier and Tate (2005) I will take an additional step to test this prediction. I use the Kaplan and Zingales (1997) index which is a relative measure of firm reliance on external financing. The KZ-index classify firms as constrained or unconstrained based on five accounting ratios: cashflow to total capital, Q, debt to total capital, dividends to total capital, and cash holdings to capital. This estimate is presented as follows:

$$KZ_{it}=\left(-1.001909\times\frac{CF_{it}}{K_{it-1}}\right)+\left(0.2826389\times Q_{it}\right)+(3.139193\times Lev_{it})\ -\left(39.3678\times\frac{Dividends_{it}}{K_{it-1}}\right)-(1.314759\times\frac{C_{it}}{K_{it-1}}) \tag{5.2}$$

The lagged value of the KZ index is then divided into 5 quantiles with higher quantiles indicating a higher degree of financial constraints. The regression will then be performed separately on each quintile. In other words, I performed five separate regressions, one for each quintile. I will use SZOC2, OPT80 and NPR[16] as measures of overconfidence, as these

[16] I chose to exclude SZOC1 to avoid multicollinearity, as SZOC1 and SZOC2 are highly correlated, and SZOC2 is the more comprehensive composite of overconfidence. I also exclude PURCHASE as it was consistently insignificant in the previous models.

are the main measures that showed significant results in the previous section. The test is conducted only on the UK market where significant results were achieved. The results are presented in Table 5.13.

As predicted, and in support of the findings presented in Malmandier and Tate (2005) and the effect of SZOC and OPT measures of overconfidence on the sensitivity of investment to cashflow was significant mainly for the top quantile of KZ index where firms were most severely constrained. In fact, even though the standard errors were clustered by firm, the effect remained strong with p-values close to zero. This is especially true for SZOC where the coefficient is 0.049 and a p-value of 0.014 and the interaction term CF.SZOC has a coefficient of 0.322 with a p-value of <0.001. Also significant but at a lower level is OPT80 with a coefficient of 0.072 and a p-value of 0.006, and the interaction term CF.OPT80 has a coefficient of 0.113 and a p-value of 0.024. We can see though that NPR is not significant for highly constrained firms. Only for firms in the 3rd quintile, even though NPR remains insignificant, the interaction term CF.NPR is significant (coefficient = 0.230, p-value = 0.022).

It is also interesting to note that in the 3rd quintile, where firms are moderately financially constrained, all SZOC and OPT measures of overconfidence and its interaction to cashflow remain highly significant. I conclude that even when firms are moderately financially constrained (may have not depleted sources of riskless debt) they are still more likely to overinvest in the presence of an abundance of internal cashflow. We can also notice that firms that are least constrained, have the least significant results. Even cashflow is only significant at a 10% level for the least financially constrained firms and surprisingly has a negative coefficient of -0.689. Perhaps where firms are least constrained, the level of investment depends on other factors, for example the investment opportunities available to the firm rather than the source of funding.

Table 5.13 Regression results with KZ index

	Most Constrained				Least Constrained
	1	2	3	4	5
CF_t	0.393 (0.008)	0.018 (0.830)	1.976 (<0.001)	0.007 (0.960)	-0.689 (0.055)
Q_{t-1}	0.013 (0.001)	-0.01 (0.047)	-0.062 (0.032)	0.002 (0.817)	-0.019 (0.558)
ROA_t	-0.005 (<0.001)	-0.002 (0.225)	0.027 (<0.001)	0.001 (0.559)	0.019 (0.06)
SIZE_t	-0.01783 (0.194)	-0.0189 (0.686)	-0.02521 (0.310)	-0.00738 (0.519)	0.0441 (0.721)
LEV_t	1.7E-05 (0.951)	-0.002 (0.285)	1.9E-05 (0.413)	-3.9E-06 (0.249)	1.9E-05 (0.325)
$\text{CF}_\text{t}.\text{Q}_{t-1}$	-0.009 (0.004)	-0.003 (0.102)	0.107 (0.007)	0.014 (0.058)	0.051 (0.006)
$\text{CF}_\text{t}.\text{ROA}_t$	-0.011 (<0.001)	-0.001 (0.069)	0.001 (0.868)	0.001 (0.282)	0.011 (0.247)
$\text{CF}_\text{t}.\text{SIZE}_t$	0.036 (0.266)	0.039 (0.352)	0.043 (0.691)	-0.021 (0.097)	0.032 (0.524)
$\text{CF}_\text{t}.\text{LEV}_t$	-0.001 (0.556)	0.008 (0.296)	0.0002 (0.112)	4.06E-06 (0.07)	-1.24E-05 (0.419)
SZOC_t	0.049 (0.014)	-0.028 (0.415)	-0.066 (0.002)	-0.016 (0.237)	0.058 (0.546)
$\text{CF}_\text{t}.\text{SZOC}_{t-1}$	0.322 (<0.001)	-0.137 (0.193)	0.472 (0.001)	-0.013 (0.750)	-0.123 (0.247)
OPT80_{t-1}	0.072 (0.006)	0.087 (0.500)	-0.130 (<0.001)	-4.5E-05 (0.999)	-0.088 (0.236)
$\text{CF}_\text{t}.\text{OPT80}_{t-1}$	0.113 (0.024)	-0.115 (0.066)	0.464 (0.001)	0.088 (0.375)	-0.013 (0.939)
NPR_{t-1}	0.013 (0.241)	-0.012 (0.292)	0.029 (0.103)	0.014 (0.065)	0.017 (0.619)
$\text{CF}_\text{t}.\text{NPR}_{t-1}$	-0.057 (0.121)	0.071 (0.242)	0.230 (0.022)	-0.045 (0.082)	-0.001 (0.991)
Intercept	-2.135 (<0.001)	0.027 (0.889)	0.242 (0.026)	-0.023 (0.756)	-0.537 (0.539)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Rho	0.919	0.589	0.983	0.785	0.717
p-values are shown in parentheses					

$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + OC'_{it-1}\beta_3 + x'_{it}B_4 + \beta_5 CF_{it} \cdot Q_{it-1} + CF_{it}.OC'_{it-1}B_6 + CF_{it} \cdot x'_{it}B_7$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable here is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OC'_{it} in the equation is a vector of the overconfidence measures which include SZOC2, OPT80, and NPR. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. The number of firms i is 761, the time period t is from the year 2005 to 2018, the number of observations n is 8586. Expected coefficient signs are described in section 5.2.

Finally, as an extra robustness measure for the Egyptian market, a conditional model is proposed. The overconfidence model tested in the above section is unconditional, i.e. it does not vary with the episodes of political instability. Alternatively, I propose the following conditional model:

$$\begin{aligned} INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + (\beta_3 + \beta_4 DU_{t-1}) OC_{it-1} \\ + (\beta_5 + \beta_6 DU_{t-1}) OC_{it-1} CF_{it} + \beta_7 x'_{it} + (\beta_8 Q_{t-1} + \beta_9 x'_t) CF_{it} \end{aligned} \tag{5.2}$$

where

DU_t equals 1 for unstable periods and zero otherwise. Unstable periods are taken as the year starting with the revolution from 2011 until 2013 with the election of president El Sisi. I also include the period of devaluation of the Egyptian pound 2016-2018 which I consider to be a crisis, as severe devaluation of the EGP is likely to have affected managerial overconfidence. To avoid multicollinearity between SZOC1 and SZOC2 I use only SZOC2 as it is the more comprehensive score for managerial overconfidence. I also use OPT80 as an additional measure of overconfidence[17].

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[17] I also tested another model that included an additional dummy variable for the global financial crisis of 2008-2009, but as this model did not prove significant, I will not add it in the analysis.

Table 5.14 Conditional model for Egypt

Egypt			
Variables	FE	Std. Errors Clustered by Firm	Prais-Winsten
CF_t	0.511 (<0.001)	0.511 (0.001)	0.496 (<0.001)
Q_{t-1}	0.059 (<0.001)	0.059 (0.054)	0.035 (<0.001)
ROA_t	0.001 (0.568)	0.001 (0.777)	0.0004 (0.668)
$SIZE_t$	-0.039 (0.022)	-0.039 (0.051)	-0.014 (0.151)
LEV_t	-2.3E-06 (0.658)	-2.3E-06 (0.768)	-3.9E-06 (0.253)
$CF_t.Q_{t-1}$	-1.5E-05 (0.017)	-1.5E-05 (0.118)	-1.2E-05 (0.120)
$CF_t.ROA_t$	-0.243 (<0.001)	-0.243 (<0.001)	-0.245 (<0.001)
$CF_t.SIZE_t$	-0.001 (0.082)	-0.001 (0.306)	-0.002 (0.004)
$CF_t.LEV_t$	0.057 (<0.001)	0.057 (<0.001)	0.056 (<0.001)
$SZOC_t$	0.047 (0.485)	0.047 (0.716)	0.038 (0.565)
$DU.SZOC_t$	-0.049 (0.055)	-0.049 (0.835)	-0.004 (0.963)
$CF.SZOC_t$	-0.764 (<0.001)	-0.764 (0.002)	-0.570 (<0.001)
$DU.CFSZOC_t$	-0.375 (0.026)	-0.375 (0.553)	-0.804 (<0.001)
$OPT80_t$	0.076 (0.149)	0.076 (0.415)	0.061 (0.238)
$DU.OPT80_t$	-0.118 (0.002)	-0.118 (0.324)	-0.117 (0.889)
$CF.OPT80_t$	-0.156 (0.056)	-0.156 (0.146)	-0.103 (0.199)
$DU.CFOPT80_t$	-0.346 (0.011)	-0.346 (0.444)	-0.218 (0.010)
$Intercept_t$	0.101 (0.307)	0.101 (0.396)	-0.023 (0.680)
Rho	0.142	0.142	0.313
p-values are shown in parentheses			

$$INV_{it} = \alpha + \beta_1 CF_{it} + \beta_2 Q_{it-1} + (\beta_3 + \beta_4 DU_t)OC_{it} + (\beta_5 + \beta_6 DU_t)OC_{it}CF_{it} + \beta_7 x'_{it} + (\beta_8 Q_t + \beta_9 x'_t)CF_{it}$$

Regression is performed in GBP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable here is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OC'_{it} in the equation is a vector of the overconfidence measures which include SZOC2, OPT80, and NPR. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. The number of firms i is 102, the time period t is from the year 2005 to 2018, the number of observations n is 1321. Expected coefficient signs are described in section 5.2.

Table 5.14 presents the results for the conditional model of overconfidence against investment. The first column presents the results using fixed effects analysis, without controlling for serial autocorrelation. In the second column I control for serial autocorrelation by clustering observations by firm. In the third column I control for serial autocorrelation using the Prais-Winsten regression. One can note that regardless of the method used to control for serial autocorrelation cashflow remains highly significant at a 1% and with a coefficient of approximately 0.5. Tobin's Q is also significant, although when standard errors are clustered by firm, it is only significant at a 10% level with a coefficient of 0.059. We can see that SZOC on its own is insignificant, however, its interaction with cashflow is significant across all three models. Perhaps more puzzling is that they all present a negative coefficient value of -0.76 and -0.57, this seems to imply that overconfident managers reduced investment with the availability of cash. One can only reason that even with the availability of cash, overconfident managers were still cautious and decreased investment due to the environment of political instability. This conclusion finds further support since the interaction between the dummy political years and CFSZOC is significant under the fixed effects model with a coefficient of -0.375 and a p-value of 0.026, and is also significant under the Prais-Winsten regression with a coefficient -0.804 of and a p-value of 1%. Similarly, the interaction term between the dummy variable and OPT80 was significant with a coefficient of -0.346 and a p-value of 0.011 under the fixed effects model; once serial autocorrelation is controlled for it turns insignificant, thus concluding that autocorrelation produced a bias. However, again note that the interaction between the dummy variable and CFOPT80 is significant and negative in the fixed effects and with the Prais-Winsten method. I conclude from the above findings that during times of instability, managerial overconfidence does not play a role in managerial decision making. I argue that when external or political risk is abnormally high, even overconfident managers become cautious, and even with the availability of cash they may still choose to decrease investment.

5.5 Conclusion

This chapter focused on testing the relationship between managerial overconfidence and corporate investment decisions contingent on the availability of cashflow. The main hypothesis for this chapter is:

H_1= managerial overconfidence increases investment decision sensitivity to cashflow.

Empirical testing is performed on both the Egyptian and the UK markets for comparative purposes. I included several measures of overconfidence, which use a combination of financing and investment activities of the firm. I also considered alternative measures based on the stock purchasing/insider trading activity in the firm. The results show that there is no significant relationship between managerial overconfidence and investment in Egypt. On the other hand, there is a strong positive relationship between the sensitivity of investment to cashflow and managerial overconfidence in the UK market. I further supplemented the tests on the UK market by using the (1997) KZ index of financial constraint used to separate firms, from most to least financially constrained. The results support the findings that overconfident managers are sensitive to cashflow and will overinvest only if abundant cash is available. This sensitivity becomes even more pronounced for equity dependent firms, where overconfident managers view their equity as undervalued by the market and thus curb their investments even when it is beneficial for the firm. Furthermore, a conditional model for Egypt was introduced, which concentrated on overconfidence during times of turmoil, and still found the overconfidence measures results to be insignificant, and where interaction terms were found to be significant, the coefficient was still negative. The overall results for the UK support the findings presented in Malmendier and Tate (2005) and should be useful for firms when setting contractual obligations with managers.

Chapter 6

Managerial Overconfidence and Stock Price Crash Risk

6.1 Introduction

Stock price crash risk is defined as the extreme negative skewness in the distribution of stock returns (Chen *et al*., 2011; Kim *et al*., 2014). Specifically, Hong and Stein (2003) define stock price crash as a large negative movement in stock price. There are many theories as to the cause of stock price crash risk. The traditional theories focus on several financial market mechanisms such as leverage effects, volatility feedback, and other variables based on an investor perspective framework.

More recent literature leans towards stock price crashes being the effect of managers hoarding bad news for an extended period of time. However, bad news can only be withheld for some limited time before it begins to stockpile within the firm and reaches a certain threshold where it becomes impossible to hide any further. Once the accumulated bad news is released to the public this could lead to stock price crashes (Kim *et al.*, 2016). While empirical evidence suggests that the reason managers may hoard bad news vary, one of the prominent theories is the agency problem. Under the agency theory, stock price crash risk could occur because corporate managers have an incentive to withhold bad information, while only releasing good news, all the while hoping that poor current performance will be masked by strong future performance. The incentives could include career concerns or compensations linked to performance.

Another reason for managers to hoard bad information may be overconfidence bias. In the psychology literature, overconfidence has several manifestations: miscalibration, the above-average effect, and the illusion of control. As mentioned in Section 3.3.1, miscalibration is defined as excessive confidence about having precise information (Gervais and Odean, 2001; Moosa and Ramiah 2017). Where people with miscalibration bias tend to overestimate the precision of their own forecasts or underestimate the variance of risky processes. Similarly, the above-average bias tends individuals to believe that they are better than their peers within a particular group (Weinstein, 1980). Finally, the illusion of control tends individuals to overestimate their ability to control events over which they have limited influence (Langer, 1975). These unrealistic biases can affect the decision of financial managers as they are deeply embedded in applied work pertaining to risk perception and risk behaviour (Harris and Hahn, 2011).

In contrast to the agency theory which assumes that managers are aware of bad investments and remain intent on hiding negative value projects, for career, reputation or other self-serving reasons, overconfident managers misperceive the value of their projects. They may continue ongoing negative NPV projects believing that they are in fact maximizing firm value.

Kim *et al.* (2016) argue that overconfident managers misperceive the NPV projects as value creating and are highly committed to the investment projects. Therefore, even when the NPV of current projects are negative, overconfident managers will continue to stick to them for a longer period of time which could lead to price crashes. They stress the importance of differentiating between rational managers who intentionally mislead investors to reap private benefits, and overconfident managers who are under the illusion of control, and thus wrongfully assume that even negative NPV projects will be profitable in the future. Because overconfident managers are so adamant on continuing in the hand-selected projects, they are likely to subconsciously ignore any negative feedback they get when in the process of operating the selected investment project. Subconsciously ignoring such negative feedback, would mean that they would in turn not relay this information to investors. Alternatively, they may consciously choose to portray current investment projects in a better light to convince investors that those projects have profitable future. Whether overconfident managers subconsciously or consciously ignore the relay of negative feedback, this will cause stockpiling of bad news, which when released could increase crash risk.

Based on the information presented above, and in line with the work of Kim *et al.* (2016), I test the regression model where overconfidence increases the likelihood of stock price crash risk.

6.2 Stock price crash risk

To calculate SPCR we first need to calculate weekly "abnormal" or "firm-specific" returns from the following extended market model.

Let n_t denote the number of weeks in year t. For each year t and stock i we observe n_t weekly stock real returns, $r_k^{(it)}, k = 1, \dots, n_t$; as well as weekly market real returns $m_k^{(t)}, k = 1, \dots, n_t$. The following regression is run for each year and each stock

$$r_k^{(it)} = \alpha_{it} + \beta_{it} m_k^{(t)} + \gamma_{it} m_{k-1}^{(t)} + \delta_{it} m_{k-2}^{(t)} + \varepsilon_k^{(it)} \tag{6.1}$$

$k = 3, \dots, n_t$.

where $\varepsilon_k^{(it)}$ is the residual term in the regression.

The market returns are proxied by the weekly real returns on the EGX30/UKX value weighed market index. $\alpha_{it}, \beta_{it}, \gamma_{it}, \delta_{it}$ are the regression parameters corresponding to year t and firm i.

Note that I use the real return r instead of a nominal return v which is given by

$$r = \frac{1+v}{1+\mathrm{inf}} - 1$$

where inf is the inflation rate. Due to increased inflation rates suffered during my period of study in the Egyptian market, exasperated further by the devaluation of the Egyptian pound in 2016, real returns are used instead of nominal returns to control for inflation. Whereas nominal returns may have increased for a specific firm, real returns could actually be negative.

It is not uncommon to have stocks with missing data in some weeks or even a whole year. To deal with this situation in a unified way, I insert a NaN in MATLAB wherever data is missing. The MATLAB function regress automatically removes these NaNs as it does the regression. As a result, I end up with a residual vector $\varepsilon^{(it)} = \left\{\varepsilon_k^{(it)}\right\}$ of dimension $n_{it} \leq n_t - 2$ which depends on whether or not stock i is missing any data in year t. The whole year is skipped, of course, if $n_{it} < 3$. If $n_{it} \geq 3,$ the firm abnormal return is then calculated as (Kim *et al.*, 2009; 2016)

$$W_k^{(it)} = \log\left(1 + \alpha_{it} + \varepsilon_k^{(it)}\right), \qquad 3 \leq k \leq n_{it}$$

where k denote the kth stock specific return of firm i in year t. We now have a set

$$W_{it} = \left\{W_k^{(it)}\right\}_{k=1}^{n_{it}}$$

W_{it} is the set or vector of weekly stock specific returns of stock i in year t. W_{it} is then used to measure stock price crash risk through three different approaches.

The first measure of crash risk is the dual volatility, denoted by DUVOL, and is defined as the log of the ratio of the downward volatility to upward volatility of the abnormal return data of firm i during year t.

To calculate DUVOL I introduce two distinct sets W_{it}^u, W_{it}^d as

$$W_{it}^u = \left\{W_k^{(it)} \geq \text{average}(W_{it})\right\},$$

$$W_{it}^d = \left\{W_k^{(it)} < \text{average}(W_{it})\right\}.$$

Thus W_{it}^u is the set of returns which are above the average weekly returns for year t, and W_{it}^d is the set of those returns which are below the average weekly returns. Next, define the volatilities

$$V_{it}^u = \text{stdev}(W_{it}^u), \qquad V_{it}^d = \text{stdev}\left(W_{it}^d\right).$$

Now, the dual volatility is calculated as in Chen *et al*. (2001)

$$\text{DUVOL}_{it} = \log\left(\frac{V_{it}^d}{V_{it}^u}\right). \tag{6.2}$$

The second measure of stock price crash risk is the negative skewness of firm specific weekly returns (Chen *et al.*, 2001), denoted NSKEW, and is calculated as:

$$\text{NSKEW}_{it} = -\frac{n_t(n_t-1)^{\frac{3}{2}}\sum_k\left(W_k^{(it)}\right)^3}{(n_t-1)(n_t-2)\left(\sum_k\left(W_k^{(it)}\right)^2\right)^{\frac{3}{2}}} \tag{6.3}$$

The definition in (6.3) is the negative of the usual definition of normalized skewness in statistics. This is done so that an increase in negative skewness corresponds to a firm being more likely to crash, i.e. having a more left-skewed distribution. This will allow for easier interpretation of statistical results.

Finally, the third measure of stock price crash risk, denoted NCRASH_{it}, is obtained by identifying the total number of weeks in a given year t where excessive losses took place

$$\text{NCRASH}_{it} = \sum_{k=1}^{n_{it}} I[W_k^{(it)} < \text{average}(W_{it}) - 3.2\text{stdev}(W_{it})]$$

where $I[.]$ is the indicator function, and 3.2 standard deviations are chosen to generate an 0.1 percent frequency in the normal distribution. However, it is necessary to point out that stock returns do not typically follow a normal distribution but are usually skewed with fatter tails. Fatter tails mean investments are more likely to deviate from the mean, most literature measures tail risk as the risk that asset returns move more than 3 standard deviations from the mean.

The crash likelihood indicator, CRASH_{it}, is defined as

$$\text{CRASH}_{it} = \min(\text{NCRASH}_{it}, 1) \tag{6.4}$$

Thus, the CRASH variable will be one for a firm that experiences one or more crash weeks during the fiscal year and zero otherwise (Kim *et al.*, 2009; 2016).

6.2.1 Control Variables

As the overconfidence measures may mix information about CEO attributes with information about firm performance, measures of past return performance will also be included as additional control variables in the regression. Furthermore, controlling for past returns makes testing the model more stringent, as it could be argued that CEOs become overconfident as a result of experiencing strong past performance. Thus, in addition to the overconfidence proxies, following the work of Chen *et al.* (2001) and Kim *et al.* (2016) the following variables will be controlled for:

1. Negative return skewness NSKEW_{it-1} (see Equation (6.3)), where firms with negative return skewness in period $t-1$ are more likely to crash in current period t.
2. Turnover growth denoted $\mathrm{DTO}_{\mathrm{it-1}}$, where firms with greater increase in turnover relative to trend are expected to have greater stock price crash risk. This is calculated as the average weekly share turnover of the current fiscal year minus the average weekly share turnover of the previous fiscal year.
3. Sigma_{it-1}, the annual return volatility of stocks. Firms with higher return volatility in period $t-1$ are more likely to have a higher stock price crash risk in current period t.
4. Average return, denoted AR_{it-1}. There are two competing views on how average return affects stock price crash risk. One view is that firms with higher average returns, are doing well, and thus are expected to continue this performance, reducing the likelihood of SPCR. Another view is that there may be a reversal in the pattern of returns, whereby, firms with higher returns in period $t-1$ are more likely to reverse and crash in current period t. This is especially true if the higher return in period $t-$

1 was not built upon true underlying value, rather on psychological influences as herd behaviour or other biases. AR_{it} is measured as the mean of a firm's weekly real returns over the fiscal year.

5. Size, denoted Size_{it-1}. While there is no theory on how firm size affects stock price crash risk, Chen *et al*. (2001) find that the relationship is significantly positive. They explain that this may be due to small firms being under less inspection from outside analysts and are thus able to hoard bad information better. Size_{it} is measured as the log of the market capitalization of firm i in period t.
6. Market to book ratio, denoted MB_{it-1}. Firms with high market to book ratios in period $t-1$ are more likely to have higher stock price crash risk in current period t. This is because firms with higher market to book ratio are predominantly growth firms and may be considered over valued by the public investors and are thus considered riskier.
7. Return on assets, denoted ROA_{it-1}, measured as net income divided by total assets. Firms with higher ROA in period $t-1$ are less likely to crash in current period.
8. Leverage, denoted Lev_{t-1}, measured as total debt divided by total assets. Firms with higher leverage in period $t-1$ may be sending a negative signal to outside investors and are thus likely to have increased crash risk in current period t.

Finally, due to the political events that took place during this study period one expects that systematic variables are likely to have a significant effect on the crash risk. Therefore, the following macroeconomic variables will be added to the model:

1. Gross Domestic Product growth rate, denoted GDP_{t-1}. where higher growth rate in period $t-1$ means a firm is less likely firms are to crash in current period t.

2. Market return, denoted MR_{t-1}, measured through the return of the EGX30/UKX index. Where stocks tend to follow market trend, and where individual stocks tend to crash when the market crashes (Harris *et al.*, 2019). Therefore, it is expected that higher average real market returns in period $t-1$ means firms are more likely to continue having positive performance in current period t and are thus less likely to crash.
3. Exchange-rate, denoted EX_{t-1}, measured as the exchange rate of the EGP (GBP) to the USD for Egypt and the UK respectively. The effect of a devaluation of currency on SPCR is uncertain. A sudden large devaluation of a currency (as that which occurred in Egypt) may cause investors to question economic stability, panic and pull out of the market, causing firms to crash. On the other hand, firms which depend largely on exports, are now more attractive as they are deemed cheaper, in which case I would expect a negative effect between currency devaluation and SPCR.

While details of the overconfidence measures were given in Section 4.6, a brief overview of the overconfidence measures used in this thesis will now be provided. SZOC1 and SZOC2 are the Schrand and Zechman (2012) measures of overconfidence. Regarding SZOC1, a manager is considered overconfident if the firm meets any two of the following four criteria: the rate of investment or the volume of acquisitions or their debt to equity ratio are greater than the industry median for that year, or if the firm uses convertible debt or preferred stock. Regarding SZOC2 they include another criterion, where dividend yields are greater than 0. A manager will then be considered overconfident if the company satisfies any three of the five criteria.

Alternatively, I use Campbell *et al.* (2011) measures of overconfidence OPT80 and pessimism or "under confidence" OPT20. Regarding OPT80 a manager is considered overconfident if the firm's investment activities are above the 80th percentile of all firms within the same industry for two consecutive years. While for OPT20 a manager is considered as pessimistic if their investment activities are below the 20th percentile of all firms within the same industry for two consecutive years.

Finally, for the UK[18] specifically I add two other measures of overconfidence that depend on net stock purchases of the firm's stocks. Regarding the PURCHASE measure a manager is considered overconfident if net purchases, defined in units of stocks, are in the top 80th percentile of net purchases by all CEOs in that year. Further, those purchases must increase the CEOs ownership of the firm by 10% during the fiscal year. Regarding the NPR measure overconfidence is a value that varies from -1 to 1 and is calculated as

NPR= (insider purchase - insider selling)/ (insider purchase + insider selling)

An important consideration in empirical studies is reverse causality. It may be argued that firms with higher risk or lower firm value tend to employ overconfident CEOs. Furthermore, it may be argued that firms that already experienced a crash will employ overconfident CEOs to improve firm performance. It is difficult for firms to predict whether they will experience a crash in the future and employ overconfident CEOs in advance. Therefore, to reduce the risk of reverse causality, I will lag the measures of overconfidence by one year relative to the dependent variables across all three models. Further I expect that it will take one year for overconfidence and other control variables to affect stock price crash risk, therefore all

[18] Data for this measure is not available for the Egyptian market.

control variables will also be lagged in respect to stock price crash risk. This is to allow an overconfident manager sufficient amount of time to be able to make non optimal decisions and hoard bad news before leaking it all at once leading to stock price crashes.

6.3 The Regression Model

The linear model for stock price crash risk can be written as

$$SPCR_{it} = \alpha + \beta' B_{it-1} + \gamma' F_{it-1} + \omega' X_{t-1}, \tag{6.5}$$

where

$\mathrm{SPCR}_{it} \coloneqq$ is Stock Price Crash Risk; taken as one of the three variables DUVOL_{it}, NSKEW_{it} , CRASH_{it} discussed in Section 6.2.1,

$B_{it} = [\mathrm{SZOC1}_{it} \quad \mathrm{SZOC2}_{it} \quad \mathrm{OPT80}_{it} \quad \mathrm{OPT20}_{it} \quad \mathrm{PURCHASE}_{it} \quad \mathrm{NPR}_{it}]'$,

$F_{it} = [\mathrm{NSkew}_{it} \quad \mathrm{DTO}_{it} \quad \mathrm{Sigma}_{it} \quad \mathrm{AR}_{it} \quad \mathrm{ROA}_{it} \quad \mathrm{Size}_{it} \quad \mathrm{Lev}_{it} \quad \mathrm{MVBV}_{it}]'$

$X_t = [\mathrm{GDP}_t \ \ \mathrm{MR}_t \quad \mathrm{EX}_t]'$

$\beta = [\beta_1 \quad \beta_2 \quad \beta_3]'$, $\gamma = [\gamma_1 \quad \gamma_2 \quad \cdots \quad \gamma_8]'$, and $\omega = [\omega_1 \quad \omega_2 \quad \omega_3 \quad \omega_4]'$ are vectors of coefficients.

Note that the independent variables in the linear model (6.5) are grouped into three categories: overconfidence factors B, firm specific factors F and systematic factors X. The measures of overconfidence were discussed in detail in Section 4.6 and summarized in section 6.2. To avoid multicollinearity, specifically for the $SZOC$ measures which are highly correlated, the regression was done twice, the first time excluding SZOC2 from the model and the second time excluding SZOC1 from the model. The results for both models, whether SZOC1 or SZOC2 are included, were extremely similar in terms of significance levels and coefficients. Therefore, the results presented include only SZOC2 as it is the more comprehensive overconfidence index. I will comment on SZOC as a whole.

6.4 Descriptive Statistics and Correlation Matrix

The descriptive statistics for the primary and control variables considered in the model are presented in Tables 6.1 and 6.2 for Egypt and the UK, respectively. The first interesting discrepancy between Egypt and the UK can be found in the mean values of NSKEW and DUVOL; at 0.335 and 0.281 for Egypt and -0.258 and -0.123 for the UK. This reveals that the data for the UK have negative skewness i.e. positive mean values of NSKEW and DUVOL, while data for Egypt have a positive skewness, i.e. negative mean values. This makes sense as Egypt was going through times of political instability and its data is expected to have higher negative mean values in comparison to the UK.

Similarly, the mean value of CRASH for Egypt is 23.6%, which means that on average, 23.6% of firm-years experienced at least one weekly return that fell more than 3.2 standard deviations below the annual mean. This is more than mean value of 19.2% for the UK, and the 17.2% reported by Kim *et al.* (2016) for firms in the US. Again, this is justified by the political instability that the Egyptian market was experiencing during the study period. In fact, a more detailed analysis of the percentage of firms that crashed during the year presented in Table 6.3, shows that 2008, 2011, and 2017 experienced high crash values. The year 2008 was the aftermath of the global financial crisis of 2007-2008. The political unrest (the Arab Spring) started in 2011 and the country remained fairly unstable for a few years. Furthermore, 2014 was a year of big change in the political leadership and brought about more uncertainties and distress. In 2016, when the economy was just starting to achieve some stability, the government announced the EGP floatation late 2016, and the consequences became apparent in 2017. By that time most firms had survived great instability and were cash starved.

The mean value of the overconfidence proxies SZOC1, SZOC2 for the Egyptian market are 6.6% and 3.9%. These percentages are significantly lower than the 41% and 28.9% for the UK market, and are also significantly lower than those reported by both Schrand and Zechman (2012) and Kim *et al.* (2016). Similarly, the mean value of the proxy of high optimism OPT80 for the Egyptian and the UK market at 12.6% and 18.4%, respectively, are significantly lower than the value reported by Campbell *et al.* (2011) of 35.5%. Meanwhile, the value of low optimism OPT20 at 34.9% for the Egyptian market, is comparable to that of Campbell *et al.* at 34.7% but remains lower for the UK market at 15.44%. These differences may be attributed to multiple reasons. Perhaps, they could be due to the ensuing political instability in Egypt, where managers were pessimistic rather than optimistic. Or perhaps there may exist a more stringent disciplinary environment in Egypt and the UK that does not allow managers to exert their personal strategies/preferences on their organizations.

Table 6.1 Descriptive Statistics for Egypt

Variable	Obs	Mean	Std. Dev.	Min	Max
DUVOL	1,392	0.272	0.458	-3.485	2.184
NSKEW	1,392	0.380	1.062	-6.949003	5.873
CRASH	1,392	0.141	0.348	0	1
SZOC1	1,392	0.070	0.256	0	1
SZOC2	1,392	0.042	0.202	0	1
OPT80	1,392	0.228	0.420	0	1
OPT20	1,392	0.317	1.134	0	3
DTO	1,392	0.001	0.034	0.000	0.070
AR	1,392	0.003	0.007	-0.025	0.028
Sigma	1,392	0.025	0.015	0.001	0.081
Size	1,392	2.752	0.744	0.671	5.064
MVBV	1,392	1.555	14.765	-511.079	131.333
LEV	1,392	0.489	0.381	0.002	5.856
ROA	1,392	7.086	13.440	-15.214	16.857
GDP	1,392	0.045	0.016	-0.038	0.072
MR	1,392	0.003	0.008	-0.015	0.018
EX	1,392	8.808	4.875	5.475	18.122

Monetary amounts are in EGP.

DUVOL, NSKEW and CRASH are three measures of crash risk. DUVOL is the annual asymmetric volatility of negative over positive returns. NSKEW is the annual negative skewness in weekly returns data. Crash is a dichotomous variable that takes a value of one for firms that experience one or more firm-specific weekly returns that fall 3.2 standard deviations below the mean firm specific weekly return over the fiscal year. SZOC1, SZOC2, OPT80 are measures of overconfidence. OPT20 is a measure of pessimism. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year.

Table 6.2 Descriptive Statistics for the UK

Variable	Obs	Mean	Std. Dev.	Min	Max
NSKEW	9435	-0.237	1.314	-7.001	7.109
DUVOL	9435	-0.119	0.559	-4.039	4.251
CRASH	9435	0.208	0.406	0	1
SZOC1	9435	0.456	0.498	0	1
SZOC2	9435	0.329	0.470	0	1
OPT80	9435	0.196	0.397	0	1
OPT20	9435	0.205	0.404	0	1
PURCHASE	9435	0.154	0.361	0	1
NPR	9435	0.179	0.923	-1	1
DTO	9435	0.003	0.017	-0.001	0.010
Sigma	9435	0.059	0.048	0.001	1.891
AR	9435	-0.001	0.063	-0.330	6.005
ROA	9435	-0.136	1.252	-34.910	13.182
MVBV	9435	3.655	31.677	-351.151	1622.733
Size	9435	4.295	2.533	-6.645	13.547
Lev	9435	0.116	0.329	-0.001	20.485
GDP	9435	0.014	0.018	-0.042	0.031
EX	9435	1.596	0.195	1.289	2.002
MR	9435	0.001	0.003	-0.007	0.004

Monetary amounts are in GBP.

DUVOL, NSKEW and CRASH are three measures of crash risk. DUVOL is the annual asymmetric volatility of negative over positive returns. NSKEW is the annual negative skewness in weekly returns data. Crash is a dichotomous variable that takes a value of one for firms that experience one or more firm-specific weekly returns that fall 3.2 standard deviations below the mean firm specific weekly return over the fiscal year. SZOC1, SZOC2, OPT80, PURCHASE, and NPR are measures of overconfidence. OPT20 is a measure of pessimism. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year.

Table 6.3 Annual crash percentage Egypt

Crash/Date	Percentage	Crash/Date	Percentage
31-12-04	0.145	31-12-12	0.291
31-12-05	0.116	31-12-13	0.262
31-12-06	0.106	31-12-14	0.242
31-12-07	0.145	31-12-15	0.184
31-12-08	0.291	31-12-16	0.196
31-12-09	0.201	31-12-17	0.436
31-12-10	0.194	31-12-18	0.349
31-12-11	0.339		

This table presents the percentage of firms that crashed per year. Crash is a dichotomous variable that takes a value of one for firms that experience one or more firm-specific weekly returns that fall 3.2 standard deviations below the mean firm specific weekly return over the fiscal year.

Tables A6A1 and A6A2 in the appendix present the correlation matrix of the variables. As expected, all three measures of crash risk are positively correlated. NSKEW and DUVOL are significantly positively correlated at 0.87 and 0.95 for the Egyptian and the UK markets, while only having a moderate correlation with CRASH. This is expected as the crash variable only focuses on values that fall below the mean, while NSKEW and DUVOL consider both crashes and jumps. The correlation between Sigma and all three measures of crash risk is weak for both markets, Chen *et al.* (2001) point out that this is a positive thing as it signifies that modeling crash risk is distinct from modeling volatility.

Similarly, none of the overconfidence measures are significantly correlated with leverage or any of the other firm specific factors included in the model. This is also a positive sign, because it means that, while the measures of overconfidence are derived from the financing and investment activities of the firm, they are distinct from any specific activity. Finally, the two SZOC measures of overconfidence are significantly positively correlated, and positively but weakly correlated with the measure of OPT80 and very weakly correlated with the measure of PURCHASE and NPR for the UK.

The average value for all three measures of SPCR are presented in Figure 6.1, 6.2 and 6.3 for Egypt and the UK. We can see that Figure 6.1 and Figure 6.2 for NSKEW and DUVOL are very similar. This is reasonable as their measurement techniques are similar, where both measures of crash consider the down weeks relative to the up weeks. In fact, the correlation between both these measures of crash risk were very high, greater than 0.85 for Egypt and the UK. We can see that the value of DUVOL and NSKEW for the UK remains relatively stable and negative (positive mean values). It only peaks positively in 2008, which is logical due to the global financial crisis. We can also see that due to the Brexit referendum in late 2016, negative skewness in the UK started to move from the negative to the positive area, mirroring an instability in the market. The mean values for DUVOL and NSKEW for Egypt, on the other hand, are a lot more erratic. They peaked in 2008 due to the financial crisis, was starting to recover, but reversed with the start of the political unrest in 2011. The market was starting to recover yet again but reversed with the overturn of Morsi's government that took place at the end of 2013. In November 2016, the central bank of Egypt announced the free flotation of the Egyptian pound leading to severe inflation and a reduction of real returns. Next if we look at the average CRASH values presented in Figure 6.3 we can see that the only higher crash point suffered by the UK was during the 2008 financial crisis. Meanwhile, in Egypt, the market suffered several crashes during 2008, 2011, 2016-2017, with the highest crash point occurring with the devaluation of the Egyptian pound.

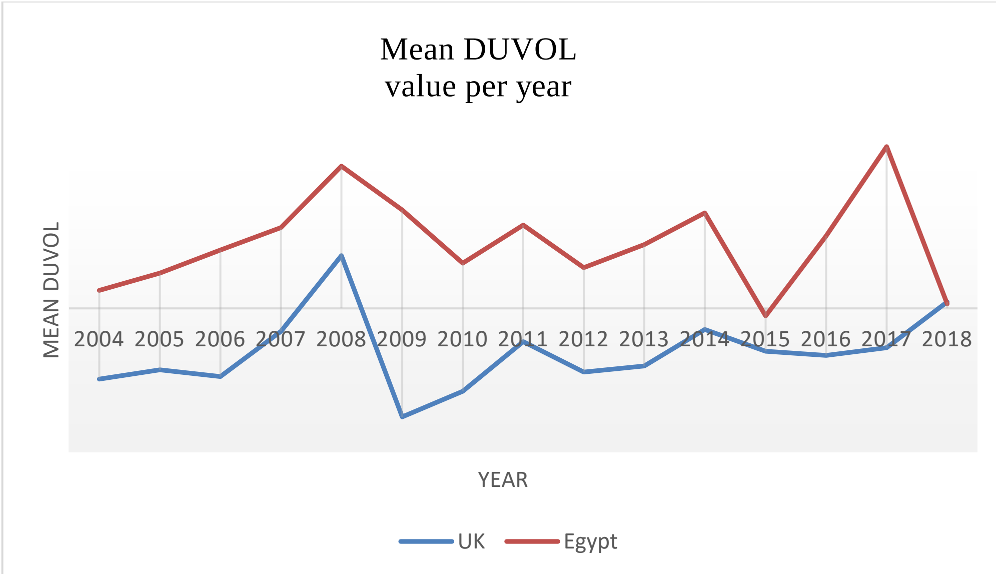


Figure 6.1 Average DUVOL for Egypt vs. the UK

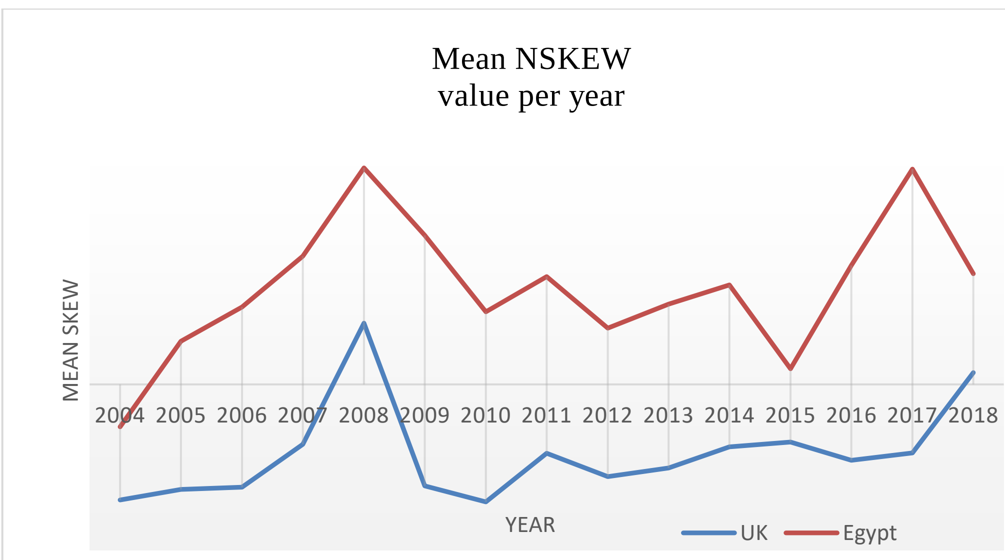


Figure 6.2 Average NSKEW for Egypt vs. the UK

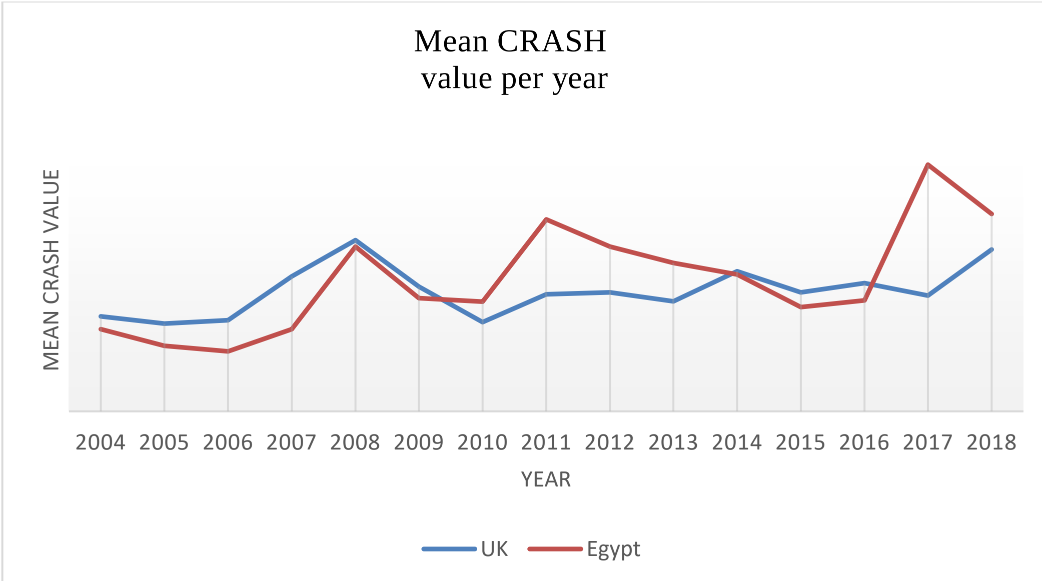


Figure 6.3 Average CRASH value for Egypt vs. the UK

6.5 Results and analysis

Based on Hausman's test, discussed in Chapter 4, fixed effects model is found to be the more appropriate estimation method for the data. In what follows I report and comment on the regression results. The model coefficients are reported with their corresponding p-values for each of the Egyptian and the UK models. The tests performed below are clustered by firm id as in Chen *et al*. (2001) to control for serial autocorrelation.

Due to the strong correlation between NSKEW and DUVOL, the DUVOL model estimated using fixed effects (ordinary least squares) suffers from significant autocorrelation. Even though standard errors are already clustered by firm id, as an extra precaution the model is re-estimated using random effects (generalized least squares, GLS), which is less restrictive in its error assumptions. The results for FE and GLS are presented jointly in Table 6.4.

Referring to the results in Table 6.4 we can see that the results provided through GLS analysis are more reasonable. For example, if we look at NSKEW_{t-1} for the Egyptian market, while in both cases it is significant at a 1% level, under the OLS, the coefficient is -0.030 whereas under GLS the coefficient is 0.022. A positive coefficient would be more reasonable whereby an increase in negative skewness in the previous period is likely to increase the likelihood of crash in the following period. Nonetheless, we can see that for both models of analysis, none of the measures of overconfidence are significant for the Egyptian market. On the other hand, the regression results for the UK show that SZOC, OPT80, and NPR are all significant and load positively on DUVOL, supporting the conclusion that as overconfidence increases so does stock price crash risk, as measured by DUVOL. In fact, under GLS, SZOC is significant at the 1% level with a coefficient of 0.065, OPT80 is also significant at a 1% level with a coefficient of 0.083. NPR, on the other hand is significant at a 5% level, with a coefficient of 0.02. Note that all mentioned coefficients are positive, signifying that managerial overconfidence increases stock price crash risk, thus supporting the hypothesis.

Only the PURCHASE measure of overconfidence, while also having a positive coefficient of 0.010, is insignificant for the UK; and this may be due to the PURCHASE measure being the most restrictive of the overconfidence measures. As discussed in Chapter 4, PURCHASE is an absolute measure not normalized for firm size or otherwise, and thus may not be as flexible in capturing managerial overconfidence. Finally, we can see that the results for the FE and GLS estimation methods present very similar results with just one significant difference, lagged NSKEW is insignificant for the UK under the GLS while it remains significant for Egypt with a positive coefficient of 0.022 and a p-value of 0.003.

The significant vs. insignificant results presented here are the same as those presented in Chapter 5. There may be several reasons for the overconfidence measures turning out as insignificant for Egypt. The main argument, as presented in Section 5.3 Figure 5.3, is that there is an optimal level of external risk, at which the effects of overconfidence on managerial decisions are most pronounced. Alternative arguments could include, that the Egyptian market is not efficient, as discussed in Chapter 4 where investors do not react to excessive risk taking of overconfident managers as provided in Kim *et al.* (2016).[19]

The dynamic GMM method discussed in length in Chapter 4 is used to estimate NSKEW in the second model. Specifically, the two-step system GMM proposed by Blundell and Bond (1999) is used for the estimation. I use system GMM instead of difference GMM as my data is unbalanced. Difference GMM widens the gap in unbalanced data as it subtracts the previous observation from the contemporaneous one. On the other hand, system GMM performs a forward orthogonal deviation, where it subtracts the mean of all future available observations from the contemporaneous one. While there is no rule regarding whether a one-step or two-step procedure should be used, generally the two-step method has been found to perform at least as well as the one-step method, if not more efficient (Hwang and Sun, 2018). Furthermore, GMM is sensitive to the number of instruments chosen, and can suffer from instrument proliferation problems. Roodman (2009) maintains that there is little guidance in literature regarding how many instruments will be considered too much, however, as a general rule of thumb the number of instruments cannot exceed the number of groups. The number of instruments to the number of groups is reported in Table 6.5. I will rely on two main test diagnostics: 1) the Sargan Hansen test which tests for instrument validity, a probability greater than 0.05 would mean that we would accept the null hypothesis that the

[19] Since the overconfidence proxies for Egypt are based primarily on the increased risk-taking activities of an overconfident manager (financial and investment activities), this could provide us a unique insight as to how investors react to managerial risk-taking activities. However, here we would have to argue that stock price crash risk occurs due to investor reaction to managerial overconfidence, rather than managerial bad news hoarding.

instruments used are valid. 2) The AR(2) test which is important to ensure that we do not have serial correlation of the second order, and thus have identified the model correctly as AR(1). Lagged NSKEW turns out significant for Egypt but insignificant for the UK as presented in Table 6.5. While the result for the UK contradicts previous theory, this might be rationalized by the UK being a more efficient market, and therefore following a random walk. Current values of skewness do not necessarily depend on past values, i.e. the past does not reflect the future. This is not true for Egypt, which is not an efficient market.

Table 6.4 Regression results for DUVOL for Egypt vs. the UK

	Egypt		UK	
Variables	FE	GLS	FE	GLS
$SZOC_{t-1}$	0.039 (0.212)	0.035 (0.190)	0.064 (<0.001)	0.065 (<0.001)
$OPT80_{t-1}$	-0.034 (0.464)	0.041 (0.278)	0.043 (0.015)	0.083 (<0.001)
$OPT20_{t-1}$	0.009 (0.602)	-0.001 (0.907)	-0.032 (0.067)	0.003 (0.103)
$PURCHASE_{t-1}$	-	-	0.025 (0.360)	0.010 (0.661)
NPR_{t-1}	-	-	0.027 (0.035)	0.021 (0.042)
$NSKEW_{t-1}$	-0.030 (<0.001)	0.022 (0.003)	-0.034 (<0.001)	0.004 (0.552)
DTO_{t-1}	0.005 (0.515)	0.0007 (0.323)	-0.0002 (0.941)	0.006 (0.867)
$Sigma_{t-1}$	0.151 (0.826)	0.464 (0.578)	-0.308 (0.071)	-0.504 (0.0120)
AR_{t-1}	-1.033 (<0.001)	-1.099 (0.001)	0.069 (0.028)	0.032 (0.047)
ROA_{t-1}	-0.003 (0.082)	-0.004 (0.003)	-3.7E-05 (0.776)	0.002 (0.892)
$Size_{t-1}$	-0.124 (<0.001)	-0.018 (0.079)	0.091 (<0.001)	0.028 (<0.001)
Lev_{t-1}	-0.170 (0.011)	-0.167 (0.008)	0.0001 (0.861)	-0.006 (<0.001)
$MVBV_{t-1}$	0.0001 (0.540)	-0.0002 (0.336)	0.0001 (0.305)	0.0007 (<0.001)
EX_{t-1}	0.002 (0.606)	-0.002 (0.540)	0.153 (<0.001)	0.070 (<0.001)
MR_{t-1}	2.268 (0.124)	2.161 (0.164)	13.071 (<0.001)	13.141 (<0.001)
GDP_{t-1}	4.052 (<0.001)	3.606 (0.001)	2.545 (<0.001)	2.570 (<0.001)
Intercept	0.840 (<0.001)	0.212 (0.015)	-0.815 (<0.001)	-0.386 (<0.001)
Rho	0.376	0.153	0.412	0.297
p-values are shown in parentheses				

$DUVOL_{it} = \alpha + OC'_{it-1}\beta_1 + x'_{it-1}B_2$

This table presents the results for FE and GLS regression of DUVOL, the dependent variable, against overconfidence and other control variables. DUVOL is the annual asymmetric volatility of negative over positive returns. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: NSKEW the annual negative skewness in weekly returns. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i for Egypt is 103 and for the UK is 773, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 1392 and for the UK is 9435. Expected coefficients signs are described in section 6.2.1.

The insignificant lagged NSKEW result of the UK is supported by the second model. Roodman (2009, p. 128) states "*If T is large, dynamic panel bias becomes insignificant, and a more straightforward fixed effects estimator works. Meanwhile, the number of instruments in difference and system GMM tends to explode with T*." This is true where the number of instruments for Egypt was 92 and for the UK was 104, which is significantly more than the number of parameters to be estimated. Unit root tests were performed for Egypt and the UK, the results demonstrate that NSKEW is stationary as theorized.

The model is thus redefined as static for the UK and estimated with fixed effect panel estimation while clustering by id (firm). Wooldridge (2002) test for serial autocorrelation in panel data is then performed, and the resulting probability of 0.767 is reassuring that there is no serial autocorrelation in the model. The results are presented jointly in Table 6.5.

Table 6.5 Regression results for NSKEW using Arellano-Bond estimator vs. FE

	Egypt	UK	
Variables	Dynamic	Dynamic	Static
$SZOC2_{t-1}$	0.064 (0.337)	0.171 (0.007)	0.218 (0.002)
$OPT80_{t-1}$	-0.103 (0.247)	0.194 (0.001)	0.185 (0.006)
$OPT20_{t-1}$	0.009 (0.719)	0.001 (0.983)	0.003 (0.955)
$PURCHASE_{t-1}$	-	0.016 (0.762)	0.059 (0.357)
NPR_{t-1}	-	-0.013 (0.037)	0.066 (0.039)
$NSKEW_{t-1}$	0.029 (0.040)	-0.053 (0.423)	-
DTO_{t-1}	0.0001 (0.415)	0.0004 (0.644)	0.004 (0.732)
$Sigma_{t-1}$	3.806 (0.048)	-1.349 (0.008)	-0.717 (0.039)
AR_{t-1}	-2.237 (0.001)	0.088 (0.573)	0.149 (0.080)
ROA_{t-1}	-0.011 (0.002)	0.0001(0.819)	-0.0003 (0.303)
$Size_{t-1}$	-0.027 (0.355)	0.073 (<0.001)	0.214 (<0.001)
Lev_{t-1}	-0.399 (0.003)	-5.1E-06 (0.004)	5.7E-07 (0.882)
$MVBV_{t-1}$	0.0001 (0.843)	0.0002 (0.518)	0.0003 (0.404)
EX_{t-1}	-0.002 (0.805)	0.077 (0.275)	0.264 (0.001)
MR_{t-1}	1.803(0.008)	26.242 (<0.001)	32.050 (<0.001)
GDP_{t-1}	5.803 (0.045)	4.640 (<0.001)	4.557 (<0.001)
Intercept	0.264 (0.246)	-0.740 (<0.001)	-1.691(<0.001)
	No. of instruments /groups: 27/92 Hansen test: 0.087 AR (2) test: 0.132	No. of instruments /groups: 117/771 Hansen test: 0.139 AR (2) test: 0.564	Rho = 0.536
p-values are shown in parentheses			

$NSKEW_{it} = \alpha + OC'_{it-1}\beta_1 + x'_{it-1}B_2$

This table presents the results for dynamic GMM and static FE regression of NSKEW, the dependent variable, against overconfidence and other control variables. NSKEW is the annual negative skewness in weekly returns. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i for Egypt is 92 and for the UK is 771, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 999 and for the UK is 9222. Expected coefficients signs are described in section 6.2.1.

As with the regression against DUVOL, most of the overconfidence measures for the UK are significant. SZOC and OPT80 are highly significant at the 1% level, with coefficient of 0.218 and 0.185, respectively. NPR is significant at the 5% level, with a coefficient of 0.066. Again, note that the positive coefficients across the three measures of overconfidence signify that managerial overconfidence leads to an increase in stock price crash risk, supporting my hypothesis. Only the PURCHASE measure remains insignificant.

As predicted AR is positively significant for both the UK and Egypt, indicating that firms with previous positive average returns are more likely to crash in the current period. It is noteworthy to point out that while Sigma is significant with a p-value of 0.039 for the UK it has a negative coefficient of-0.717, signifying that firms with greater volatility in period $t-1$ are less likely to crash in period t. Nonetheless, these results are in line with those presented by Chen *et al*. (2001). This is however not true for Egypt, where Sigma has a positive coefficient of 3.806 and a p-value of 0.048.

Furthermore, note that Size comes out as insignificant across NSKEW or DUVOL for Egypt. Larger firms are expected to bear better during the political events, but apparently, firms of all sizes suffered equally through the political events in Egypt.

The regression for NSKEW and DUVOL present very similar results. This is predictable because, as discussed previously, they have a strong and positive correlation and thus seem to be capturing similar information. Those results are quite different though when all variables are regressed against CRASH. The results for the regression against CRASH is provided in Table 6.6. Given the political events occurring in Egypt, and the general atmosphere of instability, the macroeconomic factors are, as expected, significant across all three measures of crash risk for Egypt.

As we can see from Table 6.6, none of the overconfidence proxies are significant when regressing against CRASH for Egypt. This would make sense given the political events occurring in Egypt. The variables that result significant under the CRASH model for Egypt are mainly the macroeconomic variables as well as some firm specific variables as ROA, AR and leverage. For example, market return is significant with a p-value of 0.016 and a coefficient of -5.499, similarly GDP growth rate is significant at a 1% level and with a coefficient of -22.399. This is reasonable, since one would expect that an increase in average market return or an increase in GDP in period t-1 is likely to decrease the likelihood of stock price crashes in current period t.

The fact that macroeconomic variables turn out to be the most significant under the CRASH model for Egypt is reasonable as the average CRASH value reported in Table 6. seemed to vary by year across all firms equivalently, while varying to a much lesser extent by firm. The results for the UK market, however, show that SZOC2 (coefficient = 0.391, p-value = 0.024), OPT80 (coefficient = 0.592, p-value = 030) and NPR (coefficient (0.129, p-value = 0.049) are all significant at 5% level and have positive coefficients, supporting the main hypothesis with the third measure of SPCR as well. The PURCHASE measure of overconfidence remains insignificant even when regressed against CRASH.

Table 6.6 Regression results for CRASH for Egypt and the UK

Variables	Egypt	UK
SZOC2$_{t-1}$	-0.066 (0.805)	0.391 (0.024)
OPT80$_{t-1}$	0.343 (0.328)	0.592 (0.030)
OPT20$_{t-1}$	-0.019 (0.886)	-0.525 (0.108)
PURCHASE$_{t-1}$	-	0.121 (0.448)
NPR$_{t-1}$	-	0.129 (0.049)
NSKEW$_{t-1}$	-0.037 (0.663)	-0.121 (0.036)
DTO$_{t-1}$	0.001 (0.57)	0.001 (0.950)
Sigma$_{t-1}$	-3.761 (0.323)	-8.320 (0.041)
AR$_{t-1}$	8.658 (<0.001)	-3.770 (0.191)
ROA$_{t-1}$	0.037 (0.010)	0.001 (0.858)
Size$_{t-1}$	-0.102 (0.549)	0.435 (0.015)
Lev$_{t-1}$	1.145 (0.036)	-0.003 (0.645)
MVBV$_{t-1}$	0.001 (0.866)	-0.006 (0.298)
EX$_{t-1}$	0.003 (0.082)	-1.930 (0.001)
MR$_{t-1}$	-5.499 (0.016)	-50.958 (0.208)
GDP$_{t-1}$	-22.399 (<0.001)	18.879 (0.186)
Intercept	0.083 (0.851)	0.372 (0.029)
p-values are shown in parentheses		

$CRASH_{it} = \alpha + OC'_{it-1}B_1 + x'_{it-1}B_2$

This table presents the results for logistic regression of CRASH, the dependent variable, against overconfidence and other control variables. CRASH is a dichotomous variable that takes a value of one for firms that experience one or more firm-specific weekly returns that fall 3.2 standard deviations below the mean firm specific weekly return over the fiscal year. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: NSKEW the annual negative skewness in weekly returns. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i for Egypt is 103 and for the UK is 773, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 1392 and for the UK is 9435. Expected coefficients signs are described in section 6.2.1.

6.5.1 Robustness

As an extra robustness measure and given that the main area of interest is the political events that occurred in Egypt that started mainly in 2011, it might be useful to look at the results of this time period separately as that is where overconfidence bias is expected to be exaggerated.

The tests were performed again on the dataset, this time from 2011 to 2018 and presented in Table 6.8.

Table 6.7 shows that the mean value of overconfident manager increased in the time period 2011-2018 from 2005-2010, however, this could be the result of 2^{nd} half of the dataset, 2011-2018, being a larger time period with a greater number of overconfident managers. Further, it may be important to note that in Figure 4.2 of Chapter 4, the trend showed an increase in the mean value of managerial overconfidence until 2011, after which this trend reversed, and the mean value started to decrease.

The regression results for the period 2011-2018 are presented in Table 6.8. The results are very similar, none of the overconfidence measures are significant during this period either. Given that the average value of overconfidence increased during periods of instability while its effect on stock price crash risk remains insignificant, and always on the assumption that the proxy of overconfidence is an appropriate measure of managerial overconfidence, I am led to infer that there is no relationship between managerial overconfidence and stock price crash risk for Egypt. As reasoned in Chapter 5, this may be due to the extreme level of political risk in Egypt, which caused even overconfident managers to be cautious, thus eliminating the discrepancy in decisions of overconfident vs. rational managers.

The results for the subperiod remain very similar to the results of the whole period, which is comforting as it may point to the robustness of my findings. Furthermore, in line with the findings above, the systemic variables come out again as the most significant variables across all three measures of crash risk. Furthermore, note that the coefficients for the macroeconomic factors are higher than for the firm-specific factors. For e.g. under the crash measure market return is significant with a p-value of 0.0104 and a coefficient of -19.662, while average return is also significant with a p-value of 0.036 but a coefficient of only 0.051. Thus, while both variables are significant, systematic factors have a greater effect as measured through the coefficient on crash risk than the firm specific factors.

A dynamic NSKEW model was also run for the UK from the period 2011-2018 to find out whether the insignificant value of lagged NSKEW was due to longer time period. The results presented in Table 6.9 show that while lagged NSKEW has a coefficient of 0.006 (positive as expected) it does remain insignificant with a p-value of 0.332 even for the shorter period of time considered in this test. The results for the overconfidence measures, SZOC, OPT80 and NPR remain significant and positive even when employing a smaller time period.

Table 6.7 Mean value of overconfidence across different time periods

Time Period	2005-2010		2011-2018	
Variable	Obs	Mean	Obs	Mean
SZOC1	515	0.044	823	0.079
SZOC2	515	0.031	823	0.046
OPT80	515	0.122	823	0.130
OPT20	515	0.326	823	0.364

This table presents the mean number of overconfident managers divided into two time periods 2005-2010 (before the Egyptian revolution) and 2011-2018 (after the Egyptian revolution). SZOC1, SZOC2 and OPT80 are measures of overconfidence. OPT20 is a measure of pessimism.

Table 6.8 Regression results for Egypt 2011-2018

Variables	$DUVOL_t$	$NSKEW_t$	$CRASH_t$
$SZOC2_{t-1}$	0.053 (0.095)	0.099 (0.177)	-0.095 (0.847)
$OPT80_{t-1}$	-0.039 (0.310)	-0.052 (0.600)	-0.040 (0.826)
$OPT20_{t-1}$	0.003 (0.759)	0.021 (0.445)	0.025 (0.825)
$NSKEW_{t-1}$	0.022 (0.368)	0.029 (0.680)	3.4E-10 (0.690)
DTO_{t-1}	0.183 (0.052)	0.0004 (0.254)	-0.079 (0.920)
$Sigma_{t-1}$	2.48 (0.423)	4.376 (0.595)	9.310 (0.001)
AR_{t-1}	-1.475 (0.005)	-3.578 (0.002)	0.051 (0.036)
ROA_{t-1}	-0.004 (0.029)	-0.010 (0.021)	0.100 (0.719)
$Size_{t-1}$	-0.023 (0.073)	-0.053 (0.131)	1.447 (0.121)
Lev_{t-1}	-0.137 (0.084)	-0.251 (0.163)	-0.042 (0.631)
$MVBV_{t-1}$	-0.002 (0.175)	-0.002 (0.677)	-0.027 (0.391)
EX_{t-1}	-0.007 (0.039)	-0.013 (0.021)	18.322 (0.023)
MR_{t-1}	5.110 (0.004)	5.884 (0.040)	-19.662 (0.014)
GDP_{t-1}	3.144 (0.006)	6.471 (0.022)	-0.381 (0.018)
Intercept	0.209 (0.013)	0.466 (0.020)	-0.095 (0.847)
Rho	0.467	0.336	-
p-values are shown in parentheses			

$SPCR_{it} = \alpha + OC'_{it-1}\beta_1 + x'_{it-1}B_2$

This table presents the regression results for the three SPCR measures: DUVOL/NSKEW/CRASH against overconfidence and other control variables. FE regression is used when DUVOL is the dependent variable, GMM is used when NSKEW is the dependent variable, and logistic regression is used when CRASH is the dependent variable. DUVOL is the annual asymmetric volatility of negative over positive returns. NSKEW is the annual negative skewness in weekly returns data. Crash is a dichotomous variable that takes a value of one for firms that experience one or more firm-specific weekly returns that fall 3.2 standard deviations below the mean firm specific weekly return over the fiscal year. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: NSKEW the annual negative skewness in weekly returns. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i is 103, the time period t is from the year 2011 to 2018, finally the number of observations n for Egypt is 823. Expected coefficients signs are described in section 6.2.1.

Table 6.9 Regression results for the UK 2011-2018 using system GMM.

Variables		Variables	
SZOC2$_{t-1}$	0.062 (0.002)	ROA$_{t-1}$	0.001 (0.896)
OPT80$_{t-1}$	0.038 (0.019)	Size$_{t-1}$	0.026 (0.001)
OPT20$_{t-1}$	-0.011 (0.474)	Lev$_{t-1}$	-6.4E-06 (0.413)
PURCHASE$_{t-1}$	0.007 (0.655)	MVBV$_{t-1}$	0.004 (0.722)
NPR$_{t-1}$	1.056 (0.021)	EX$_{t-1}$	0.059 (0.054)
NSKEW$_{t-1}$	0.006 (0.332)	MR$_{t-1}$	17.933 (<0.001)
DTO$_{t-1}$	-0.0002(0.708)	GDP$_{t-1}$	2.109 (<0.001)
Sigma$_{t-1}$	-0.603 (0.010)	Intercept	-0.386 (0.002)
Number of instruments / Number of groups = 47/767 AR(2) test = 0.673 Hansen test = 0.234			
p-values are shown in parentheses			

$NSKEW_{it} = \alpha + \beta_1 NSKEW_{it-1} + OC'_{it-1}B_2 + x'_{it-1}B_3$

This table presents the results for GMM regression of the dependent variable NSKEW, against overconfidence and other control variables. NSKEW is the annual negative skewness in weekly returns data. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: NSKEW the annual negative skewness in weekly returns. DTO is the detrended turnover. AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. Regression period from 2011-2018. The number of firms i is 767, the time period t is from the year 2011 to 2018 for both markets, finally the number of observations n UK is 5369. Expected coefficients signs are described in section 6.2.1.

6.6 Conclusion

This chapter studies the effect that managerial overconfidence has on stock price crash risk. Overconfidence is defined as an exaggerated sense of control, an overestimation of returns and an underestimation of risk. I hypothesize that overconfident managers, fueled by a subconscious propensity to hoard bad news and release it all at once, will lead to an increase in stock price crash risk. The main hypothesis for this chapter thus is:

H_2: there is a positive relationship between overconfident managers and SPCR

This hypothesis is tested on all listed stocks in the Egyptian and the UK market. Three separate measures for stock price crash risk are derived, namely DUVOL, NSKEW and CRASH. Different measures to proxy for the overconfidence bias are used, and a set of the most important determinants to control for external and internal factors are included, thus isolating psychological biases from other factors.

The results indicate that the different overconfidence measures were insignificant to the measures of stock price crash risk for the Egyptian market. However, for the UK market most of the measures, except for the stock PURCHASE measure were found to be positive and significant. The results for the UK market support the conclusion that managerial overconfidence does increase stock price crash risk. I attribute the results of the Egyptian market to several factors. The main argument, presented in section 5.3, is that there is a certain level of external risk, where managers have the greatest propensity to impart their psychological bias on firm decisions. Once this level of risk increases, even overconfident managers will become more cautious, causing the decisions of overconfident and rational managers to converge. Further, note from the analysis that as Egypt went through severe distress periods, stock price crashes were more a result of political and macroeconomic factors than firm specific factors. Finally, the results of the Egyptian market can also partially be attributed to the fact that, the market being relatively not efficient, investors may not respond to excessive risk taking of managers. In other words, the market does not respond efficiently to news, shocks or signals by the firm. Moreover, even if the market was efficient, the extent and frequency of political and economic crises in Egypt could have crowded out the effect of management behavior as far as price crash risk is concerned.

Chapter 7

Managerial Overconfidence and Default Risk

7.1 Introduction

The previous chapter studied the effect of managerial overconfidence on one form of risk: stock price crash risk. This chapter builds on my previous work by considering another form of risk, namely the probability of default. The intuition behind using the probability of default as a crucial measure of firm risk stems from the fact that the default of an institution has negative impacts on all counterparties involved with the firm. These negative impacts may be so widespread to cause the failure of other institutions resulting in a crisis that may have greater economy wide costs. Further, managers will try to avoid financial distress as much as possible to save their own reputation and career paths. Thus, default risk is vital in that not only does it affect managers and their firms but also outside parties. The Merton Model (MM), will be used to measure the probability of default. This measure provides a reliable ordinal rank of companies based on their likelihood to go into default. In fact, Tudela and Young (2003) use the Merton-model to estimate the probability of default for a group of failed companies vs. a group of surviving companies. They then compare the MM to information driven solely from company accounts. They find that Merton-style estimates provide more accurate predictions of default than their competing accounting methods.

Overconfidence can lead managers to underestimate risk while simultaneously overestimating profitability and expected return (Goel and Thaker, 2000; Hribar and Yang, 2010; Ben-David et al. (2010)). Furthermore, overconfidence in managers is associated with overinvestment, even investing in projects with negative NPV, especially when there is abundance of free cashflow (Heaton, 2002; Malmendier and Tate, 2005). Overconfident managers were also found to take on more debt, especially short-term debt (Malmendier et al., 2011; Malmendier and Zheng, 2012).

The empirical evidence of Chapter 6 also shows that overconfident managers, unintentionally, stockpile bad news and release it all at once leading to increased stock price crash risk and endangering the market value of their firms. Further, overestimating returns, means overconfident firms engage in more risky projects, while simultaneously underestimating risks of bankruptcy.

In line with the theoretical and empirical results presented in this section and the previous findings, I expect managerial overconfidence to have a positive effect on the probability of default. In the study discussed at length in Section 3.4.3, Leng *et al.* (2018) study the effect of managerial overconfidence on the risk of default by using firms that filed for insolvency vs. firms that did not as a measure bankruptcy. In contrast, to measure the probability of default, this thesis will employ a different methodology, namely, the Merton Model (MM) which is one of the most popular measures of default risk. So rather than using a dichotomous method of bankruptcy, this thesis focuses on whether the probability of default increases with managerial overconfidence.

7.2 The Merton Model

The methodology adopted below is based on the KMV Merton Model (2003). Suppose at time t, a firm has asset value V_t, equity value E_t and zero-coupon debt D_t. The following identity holds

$$V_t = E_t + D_t. \tag{7.1}$$

If $V_t < D_t$, then $E_t < 0$, which implies that equity holders will walk away, creditors' claims are not fully covered, and the firm is in default. Typically, equity holders wait till time T before they might default. It is then important to be able to estimate the probability that the firm will default at time T. This is called the probability of default and denoted PD. The situation may be rephrased in the following inequality

$$\mathrm{PD} = P(V_T < D_T). \tag{7.2}$$

Obviously, to determine PD we need the firm's liabilities D_T and the probability distribution P of the asset value V_T at time T. Liabilities are obtained from the firm's balance sheet, as it is reasonable to assume that the book value of liabilities are similar to its market value. As for the probability distribution, a reasonable assumption is to model asset values by a stochastic process with time drift around which fluctuations occur in the form of Brownian motion. Merton assumed that both components are proportional to the current asset values, i.e. a geometric Brownian motion. We then have the stochastic differential equation (SDE) (Duan and Wang, 2012)

$$dV_t = \mu V_t dt + \sigma V_t dW_t, \tag{7.3}$$

where μ is the drift coefficient, σ is the volatility coefficient and $\{W_t\}_{t \le T}$ is a Brownian motion. Therefore,

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t. \tag{7.4}$$

To simplify, assume that μ, σ are independent of time (at least over the period of study). Applying Itô's formula to the process $\ln V_t$ and using the SDE above, we get

$$d(\ln V_t) = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dW_t. \tag{7.5}$$

It follows that the process $\ln V_t$ is an Itô process. The solution of this SDE is given by

$$\ln V_T = \ln V_t + \left(\mu - \frac{1}{2}\sigma^2\right)(T - t) + \sigma(W_T - W_t). \tag{7.6}$$

Thus,

$$\ln V_T \sim N\left(\ln V_t + \left(\mu - \frac{1}{2}\sigma^2\right)(T - t), \sigma^2(T - t)\right). \tag{7.7}$$

This fact is usually expressed by saying that the process V_t is log-normal. In practice, we usually take $T = t + 1$, or $T - t = 1$. Denoting the standard cumulative normal distribution function by $\Phi(\cdot)$, we get

$$\begin{aligned}
\text{PD} &= P(V_T < D_T) \\
&= P(\ln V_T < \ln D_T) \\
&= P(\ln D_T - \ln V_T > 0) \\
&= \Phi\left(\frac{\ln D_t - \ln V_t - \left(\mu - \frac{1}{2}\sigma^2\right)(T - t)}{\sigma\sqrt{T - t}}\right) \\
&= \Phi(-\text{DD}),
\end{aligned} \tag{7.8}$$

where

$$\text{DD} = \frac{\ln V_t + \left(\mu - \frac{1}{2}\sigma^2\right)(T - t) - \ln D_T}{\sigma\sqrt{T - t}} \tag{7.9}$$

represents the distance to default.

Figure 7.1 shows a possible sample path for $\ln V_\tau, t \leq \tau \leq T$ together with its expected values, i.e. $E(\ln V_\tau)$. Figure 7.2 shows the (normal) probability distribution of $\ln V_t$ which is centred at its expected value. The probability of default (PD) is the shaded area below the normal distribution starting from $\ln D_T$. The distance to default may be regarded as the distance between $E(\ln V_t)$ and $\ln D_T$ as shown in the Figure 7.2.

Figure 7.1 A sample path of log V_t and its expected values

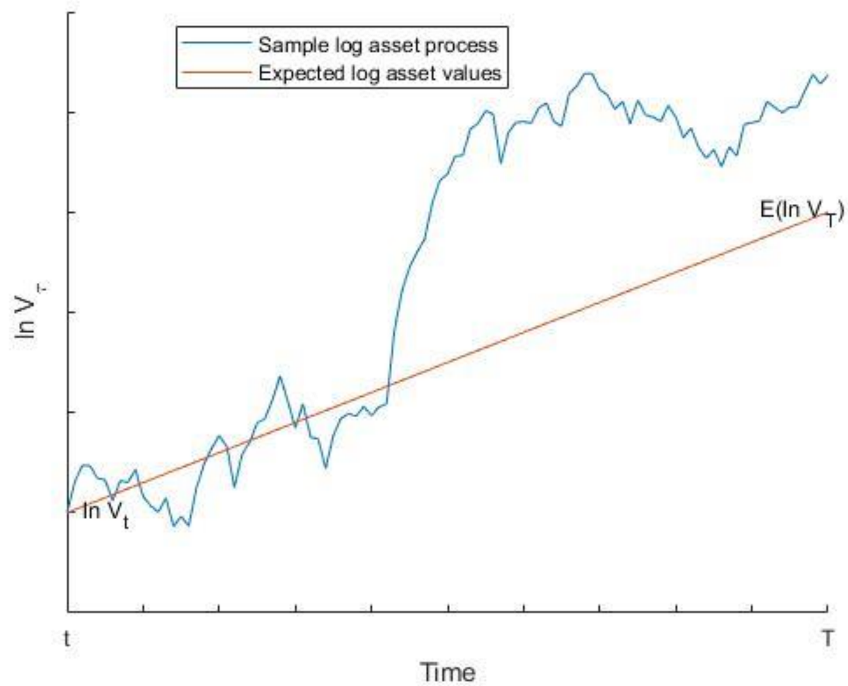
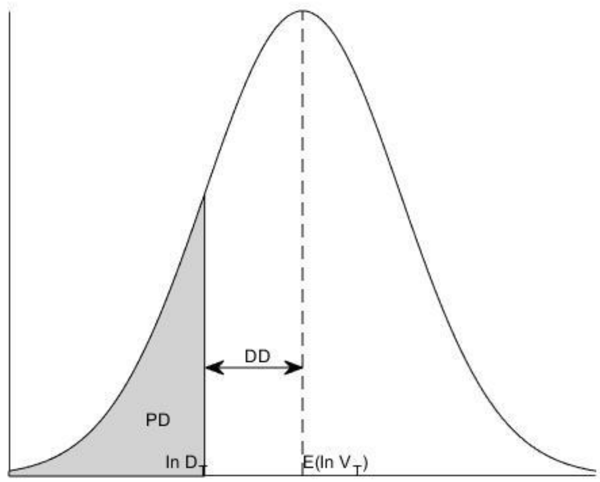


Figure 7.2 Probability distribution of log V_t



Thus, in order to calculate the probability of default, we need to know V_t, D_T, μ, σ. The problem now is that V_t is unobservable, as V_t is the market value of assets which cannot be obtained from the balance sheet. In order to deal with this problem, we observe the following payoff at time T shown in Table 7.1.

Table 7.1 Payoffs for equity holders and creditors

	Equity holders	Creditors
$V_T \geq D_T$	$V_T - D_T$	D_T
$V_T < D_T$	0	V_T

In other words, the equity holders payoff is given by

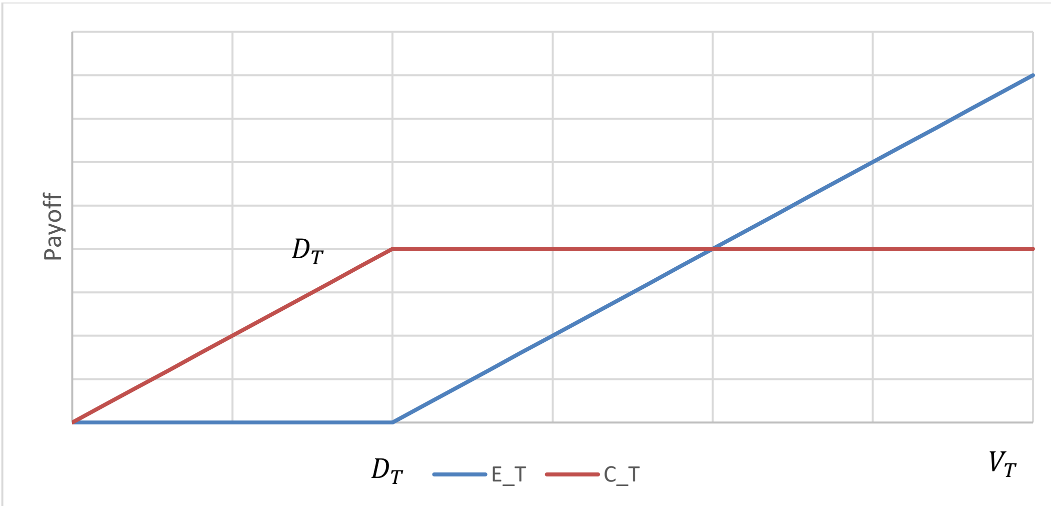
$$E_T = \max(0, V_T - D_T)$$

and the creditors payoff is given by

$$C_T = \min(D_T, V_T)$$

Figure 7.3 illustrates these two types of payoffs.

Figure 7.3 Equity holder payoff vs. credit holder payoff



In particular, E_T is similar to a call option. Hence, if no dividends are paid, we may model the equity value by the Black-Scholes call option formula (1973)

$$E_t = V_t \Phi(d_1) - D_T e^{-r(T-t)} \Phi(d_2), \tag{7.10}$$

where

$$d_1 = \frac{\ln V_t + \left(\mu + \frac{1}{2}\sigma^2\right)(T-t) - \ln D_T}{\sigma\sqrt{T-t}},$$

$$d_2 = d_1 - \sigma\sqrt{T-t},$$

$$r = \text{logarithmic risk-free rate of return.}$$

Further equity volatility and asset volatility can be related by the following expression

$$\sigma_E = \frac{V_t}{E_t} \Delta \sigma_V \tag{7.11}$$

Equation (7.10) has two unknowns, V_t and σ.

MATLAB is used to solve for the unknowns simultaneously through an iterative numerical technique for (V_t, σ) as shown in Ronn and Verma (1986). E_t is equal to the total market value of equity obtained from the closing price multiplied by the number of shares outstanding at the end of the firm's fiscal year. σ_E is estimated using the annualized standard deviation of logarithm of weekly stock returns for the prior fiscal year. Here real returns are used rather than nominal returns, because Egypt specifically suffered from accelerated inflation with the turmoil and the devaluation of the Egyptian pound. $T - t$ is one year. L_t is taken as the book value of short-term debt plus one half of long-term debt. Finally, μ is taken as the risk-free rate of return.

7.3 The Regression Model

To test the prediction, I will start with a simple model, presented in equation (7.11), to test the probability of default against managerial overconfidence. This will form a benchmark model. Further, I expect firms within the same industry, to have similar probabilities of default. Firms with excess probability of default than the industry may be explained by managerial overconfidence. This prediction is tested using the linear model presented in equation (7.12).

$$\mathrm{PD}_{it} = \alpha + X'_{it-1}\beta, \tag{7.12}$$

and

$$\mathrm{APD}_{it} = \alpha + X'_{it-1}\beta, \tag{7.13}$$

$$\mathrm{APD}_{it} = \mathrm{PD}_{it} - \mathrm{IPD}_{it},$$

where

APD_{it} is the abnormal probability of default of firm i at time t, adjusted for industry average;

PD_{it} is the probability of default of firm i at time T;

IPD_{it} is the average probability of default of industry i at time t;

$X_{it} = [\mathrm{SZOC1}_{it} \quad \mathrm{SZOC2}_{it} \quad \mathrm{OPT80}_{it} \quad \mathrm{OPT20}_{it} \quad \mathrm{PURCHASE}_{it} \quad \mathrm{NPR}_{it}]'$.

The measures of overconfidence SZOC1, SZOC2, OPT80, OPT20 PURCHASE and NPR were all discussed in detail in Section 4.6 of Chapter 4. A brief overview of the measures will be provided as they are important to this study. SZOC1 and SZOC2 are the Schrand and Zechman (2012) measures of overconfidence. In regard to SZOC1, a manager is considered overconfident if the firm meets any two of the following four criteria: (i) the firm's rate of investment is greater than the industry median (ii) the volume of a firm's acquisitions are greater than the industry median (iii) a firm's debt to equity ratio is greater than the industry median (iv) the firm uses convertible debt or preferred stock. Regarding SZOC2, a manager will be considered overconfident if the company satisfies any three of five criteria with the fifth criterion being (v) a firm's dividend yield is greater than 0.

Likewise, I use Campbell *et al.* (2011) measures of overconfidence and pessimism or lack of confidence. Regarding OPT80, a manager is considered overconfident if the firm's investment activities are above the 80th percentile of all firms within the same industry for two consecutive years. Regarding OPT20, a manager is considered as pessimistic if their investment activities are below the 20th percentile of all firms within the same industry for two consecutive years.

Finally, two other measures of overconfidence are added that depend on net stock purchases of the firm's stocks. These measures are applicable only for the UK.[20] Under the PURCHASE measure a manager is considered overconfident if net purchases, defined in units of stocks, are in the top 80th percentile of net purchases by all CEOs in that year. Further, those purchases must increase the CEOs ownership of the firm by 10% during the fiscal year. The NPR measure of overconfidence is a variable with a value that ranges from -1 to 1 and is calculated as:

NPR= (insider purchase - insider selling)/(insider purchase + insider selling).

Following the discussion of stock price crash risk in Chapter 6 all measures of managerial overconfidence are lagged. This is to avoid reverse causality, where it may be argued that firms with higher probability of default will employ overconfident managers. Additionally, the overconfidence measures are lagged by one year to allow the effect of activities of overconfident managers to be discernible in firm risk in the following year. Furthermore, as discussed in Chapter 5, because the overconfidence factors SZOC1 and SZOC2, are highly correlated, the regression is run twice to avoid multicollinearity problem, each time including only one of the variables. The coefficients and significance levels in both cases presented almost identical results. The results presented are for the models where only SZOC2 is included, as it is the more comprehensive overconfidence measure. Panel data techniques explained in Chapter 4 will be used to analyse the data.

[20] Data for this measure is not available for the Egyptian market.

7.4 Descriptive Statistics

The expected probability of default, PD, with one-year horizon has a mean of 1.6% and ranges between 0% and 98.4% for Egypt and has a mean of 2.5% and ranges between 0% and 96.9% for the UK as shown in Table 7.2. Probabilities of default that range above 90% were suffered by a few companies during the financial crisis for both the UK and Egypt, as well as other periods of unrest in Egypt. A clearer picture of the average probability of default across firms is presented in Figure 7.4 for Egypt and the UK. In Egypt, the cross-section average PD peaked in 2008 at almost 7% and was starting to recover before it increased again sharply in 2011, which is when the Egyptian political unrest started. As the market started to recover from the political turmoil, we can see an increase in the probability of default in 2017 which is most likely attributable to the devaluation of the Egyptian pound in late 2016. Similarly, the average probability of default in the UK, presented in Figure 7.4, shows that PD peaked in 2008-2009, at approximately 5.5%, in relation to the global financial crisis. It then decreased and increased again slightly around 2016, which is probably attributed to the announcement of Brexit. I feel it is necessary to stress that the requirement of a complete data set for firms biases the data towards the surviving firms, which explains why the average probability of default tends towards 0.

Table 7.2 Average probability of default Egypt vs. the UK

Variable	Observations	Mean	Std. Dev.	Min	Max
PD_{Eg}	1,324	0.016	0.055	0	0.984
PD_{UK}	10,456	0.025	0.082	0	0.969

This table presents the descriptive statistics for the probability of default in Egypt and the UK. Probability of default is measures using the Merton Model and using real returns.

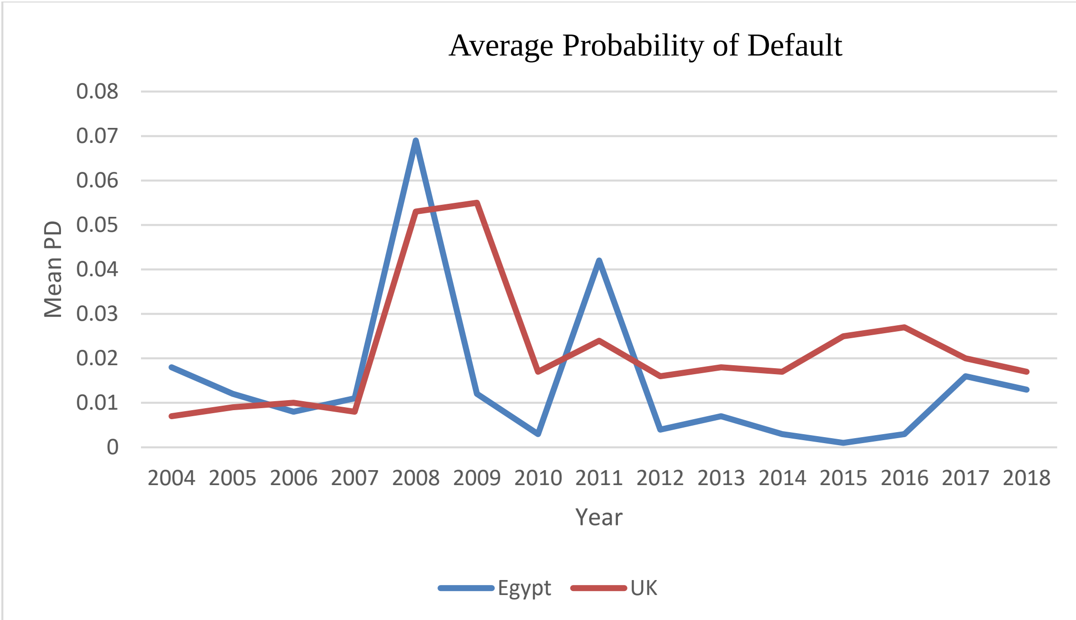


Figure 7.4 Average probability of default (Egypt vs. the UK)

A breakdown of the average probability of default by industry in the Egyptian market is shown in Table 7.3. The data is graphed in Figures 7.5, 7.6.

Table 7.3 Average industry probability of default for Egypt

	15	20	25	30	35	45	50	60
2004	0.007	0.081	0.001	0.002	0.000	0.004	0.000	0.052
2005	0.007	0.024	0.006	0.005	0.000	0.000	0.000	0.054
2006	0.005	0.025	0.004	0.004	0.001	0.000	0.000	0.022
2007	0.004	0.043	0.011	0.006	0.001	0.000	0.000	0.028
2008	0.061	0.124	0.047	0.110	0.113	0.041	0.005	0.055
2009	0.010	0.030	0.004	0.010	0.018	0.000	0.000	0.025
2010	0.010	0.004	0.000	0.003	0.003	0.000	0.000	0.003
2011	0.059	0.052	0.054	0.055	0.025	0.000	0.015	0.076
2012	0.003	0.005	0.004	0.000	0.000	0.000	0.008	0.012
2013	0.001	0.007	0.001	0.004	0.002	0.000	0.038	0.001
2014	0.000	0.017	0.002	0.005	0.000	0.000	0.000	0.001
2015	0.001	0.003	0.001	0.001	0.000	0.000	0.004	0.000
2016	0.004	0.005	0.001	0.003	0.001	0.000	0.003	0.005
2017	0.007	0.074	0.000	0.005	0.001	0.014	0.024	0.000
2018	0.032	0.053	0.007	0.002	0.002	0.000	0.005	0.002

This table presents annual average probability of default for firms in the Egyptian market divided according to industry segment.

*10 - Energy
15 - Materials
20 - Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 - IT
50 - Communication Services
55 - Utilities
60 - Real Estate

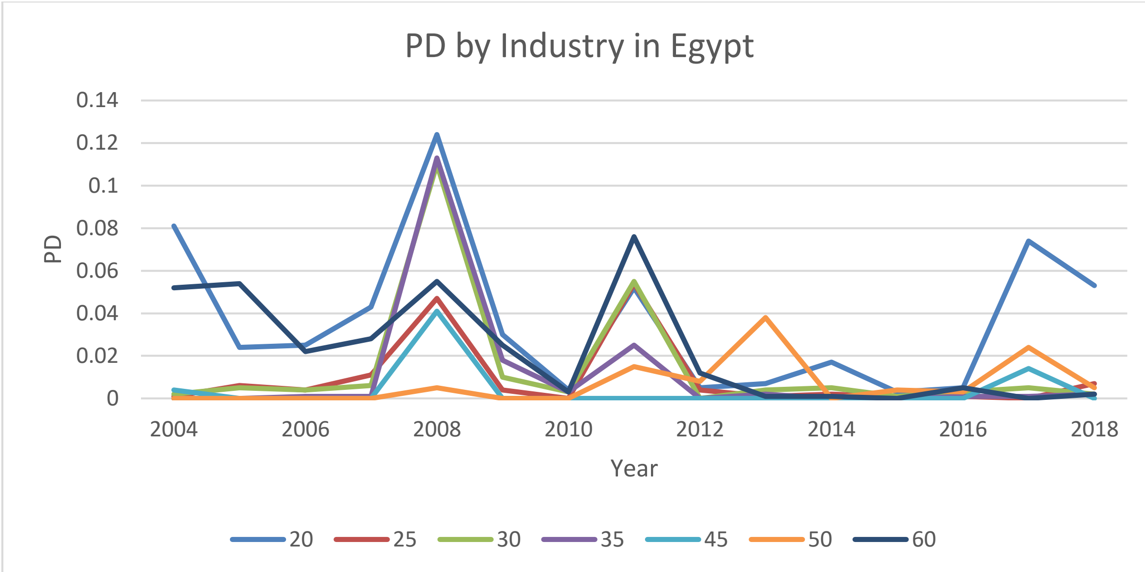


Figure 7.5 PD by Industry in the Egyptian market

*10 - Energy
15 - Materials
20 - Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 - IT
50 - Communication Services
55 - Utilities
60 - Real Estate

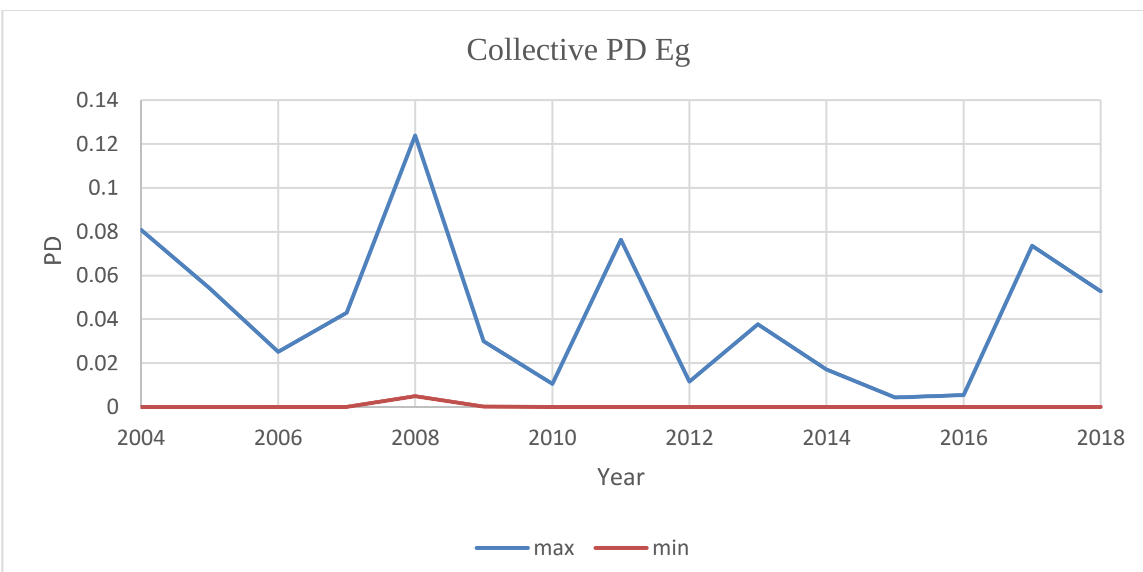


Figure 7.6 Collective PD in the Egyptian Market

It can be seen from Figure 7.5 that there was a collective move towards default during the global financial crisis in 2008. This collective move is reinforced by the lower collective PD in Figure 7.6. The move was led by the "Industrials" while "Communication Services" was the least affected. Most (but not all) industries moved towards default again in 2011, this time led by "Real Estate" while "Communication Services" remained the least affected. The move towards default in 2013 and 2017 was industry specific with "Communication Services" the most affected in 2013 and "Industrials" most affected by the devaluation of the EGP in 2017. The upper collective PD in Figure 7.6 shares the same features with the average PD graph of Figure 7.5.

A breakdown of the average probability of default by industry in the UK market is shown in Table 7.4. The data is graphed in Figures 7.7, 7.8.

Table 7.4 Average industry probability of default for the UK

	10	15	20	25	30	35	45	50	55	60
2004	0.037	0.003	0.005	0.003	0.003	0.002	0.007	0.008	0.000	0.000
2005	0.046	0.014	0.009	0.003	0.035	0.013	0.011	0.005	0.000	0.001
2006	0.032	0.016	0.003	0.003	0.003	0.011	0.026	0.006	0.000	0.001
2007	0.012	0.013	0.010	0.003	0.003	0.008	0.022	0.005	0.000	0.000
2008	0.104	0.102	0.038	0.055	0.056	0.026	0.056	0.054	0.003	0.041
2009	0.127	0.116	0.060	0.036	0.036	0.059	0.059	0.042	0.011	0.022
2010	0.031	0.037	0.011	0.011	0.011	0.017	0.020	0.026	0.007	0.002
2011	0.041	0.013	0.022	0.011	0.016	0.016	0.020	0.029	0.047	0.021
2012	0.038	0.016	0.020	0.005	0.010	0.019	0.016	0.025	0.003	0.014
2013	0.016	0.044	0.019	0.006	0.008	0.019	0.037	0.013	0.005	0.019
2014	0.053	0.035	0.007	0.008	0.009	0.008	0.009	0.021	0.007	0.010
2015	0.071	0.060	0.007	0.005	0.009	0.010	0.016	0.028	0.047	0.001
2016	0.104	0.064	0.009	0.016	0.008	0.007	0.020	0.032	0.021	0.002
2017	0.057	0.043	0.012	0.007	0.009	0.017	0.014	0.014	0.031	0.001
2018	0.056	0.011	0.008	0.024	0.004	0.022	0.019	0.036	0.007	0.005

This table presents annual average probability of default for firms in the UK market divided according to industry segment.

*10 - Energy
15 - Materials
20 - Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 - IT
50 - Communication Services
55 - Utilities
60 - Real Estate

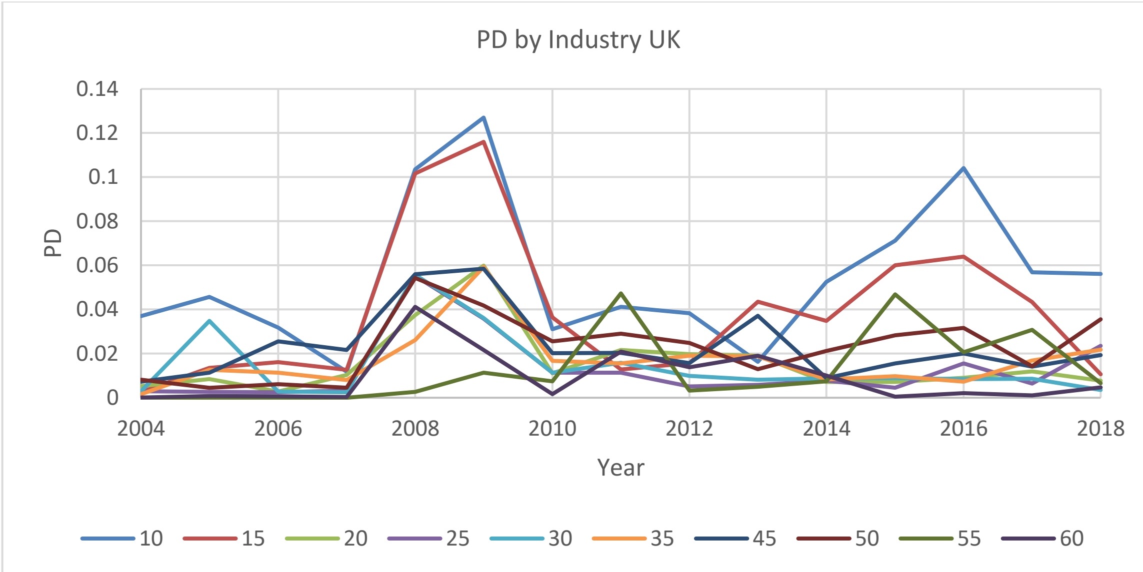


Figure 7.7 PD by Industry in the UK Market

*10 - Energy
15 - Materials
20 - Industrials
25 - Consumer Discretionary
30 - Consumer Staples
35 - Healthcare
45 - IT
50 - Communication Services
55 - Utilities
60 - Real Estate

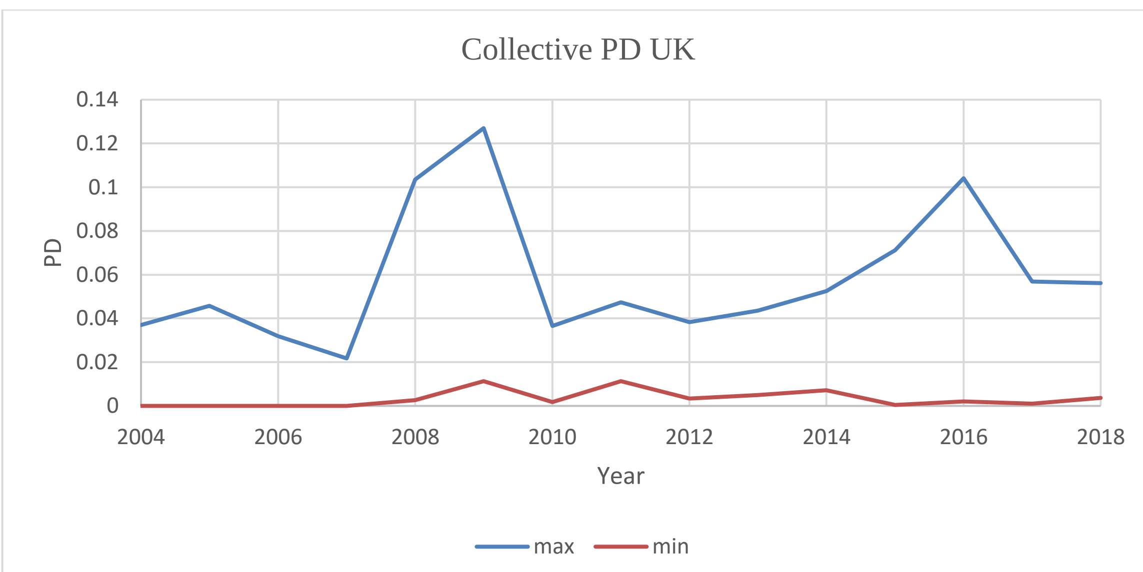


Figure 7.8 Collective PD in the UK Market

It can be seen from Figure 7.7 that there was a collective move towards default during the global financial crisis. In comparison with the Egyptian market, the response of the UK market was relatively delayed, with peak appearing in 2009 as seen in Figure 7.8. This could mean, as would be anticipated, that the Egyptian market is more prone to economic crises with erratic movements up and down. The 2008-2009 move was led by "Energy" while "Utilities" being the least affected. This is curious as the effect on utilities should be more pronounced because of its dependence on energy. My best explanation for this phenomenon is that the 2008 crisis was a true "bubble" fuelled by virtual trading rather than actual economic factors. The "Energy" industry leads again the move towards default in 2016 with "Real Estate" being the least affected. Figure 7.8 reveals that there was a 'smaller' collective push towards default in 2011. There are several events that occurred in 2011 that may have caused this push. Several countries in the Eurozone were suffering from expanding debt and had to be "bailed out" putting stress on all countries in the European union, meanwhile inflation was rising in the UK. Further the tsunami earthquake that occurred in Japan had effects which were felt in financial markets across the world. The collective push towards default in 2016 was not as strong as the one in 2008-2009 as is conveyed by the lower collective PD.

Finally, Tables 7.5 and 7.6 present the correlation matrix for the abnormal probability of default APD against measures of overconfidence. Notice that the APD for both Egypt and the UK is negatively correlated with all overconfidence measures, and positively correlated with measures of "lack" of confidence or pessimism. For example, we can see under the Egyptian market that SZOC1, SZOC2, and OPT80 are correlated negatively with APD at -0.029, -0.039 and -0.019 respectively, while OPT20 is positively correlated with APD at

0.020. This does not seem to support my prevailing argument of a risk increasing effects from CEO overconfidence in favour of the alternative argument that overconfidence is actually more beneficial to firms. More on this in the next subsection.

Table 7.5 Correlation matrix for APD against overconfidence measures (Egypt)

Variables	APD	SZOC1	SZOC2	OPT80	OPT20
APD	1				
SZOC1	-0.029	1			
SZOC2	-0.039	0.753	1		
OPT80	-0.019	0.205	0.156	1	
OPT20	0.020	-0.089	-0.086	-0.253	1

This table provides the correlation matrix between Abnormal Probability of Default (APD) and the measures of overconfidence SZOC1 SZOC2 OPT80 and OPT20.

Table 7.6 Correlation matrix for APD against overconfidence measures (UK)

Variables	APD	SZOC1	SZOC2	OPT80	OPT20	PURCHASE	NPR
APD	1						
SZOC1	-0.066	1					
SZOC2	-0.114	0.826	1				
OPT80	-0.031	0.134	0.075	1			
OPT20	0.072	-0.215	-0.192	-0.087	1		
PURCHASE	-0.003	0.049	0.045	0.008	-0.041	1	
NPR	-0.094	0.094	0.161	0.025	-0.014	0.020	1

This table provides the correlation matrix between Abnormal Probability of Default (APD) and the measures of overconfidence SZOC1 SZOC2 OPT80 and OPT20 PURCHASE and NPR.

7.5 Regression Results:

The estimation of the models will be performed in two steps. First, bivariate testing of PD and APD against overconfidence measures will be performed. Then, as a precaution, the same control variables used in the previous chapter are used here to control for external factors that may be affecting the probability of default. This is because the Merton Model is dependent largely on the market value and volatility of equity, I expect that anything that affects risk of stock price crashes is likely to also affect its probability of default. The following is a brief overview of the control factors used:

1. Sigma_{it-1} the annual return volatility of stocks. Firms with higher return volatility in period $t-1$ are more likely to have higher probability of default in period t.
2. Average return, denoted AR_{it}, where firms with higher average returns, are doing well, and thus are expected to continue this performance, reducing the probability of default. AR_{it-1} is measured as the mean of a firm's weekly real returns over the fiscal year.
3. Size, denoted Size_{it-1}, where larger firms are expected to have more connections and better lines of credit with reduced rates, thereby reducing the risk of default. Size_{it} is measured as the log of the market capitalization of firm i in period t.
4. Market to book ratio, denoted MB_{it-1}. Firms with high market to book ratios in period $t-1$ are predominantly growth firms and may be considered over valued by the public investors and are thus considered riskier. As I expect that they are more likely to crash, this could increase their risk of default.
5. Return on assets, denoted ROA_{it-1}, measured as net income divided by total assets. Where firms with higher ROA in period $t-1$ are preforming well and thus less likely to default.
6. Leverage, denoted Lev_{t-1}, measured as total debt divided by total assets. Firms with higher leverage in period $t-1$ may be sending a negative signal to outside investors and are thus increasing their probability of default.

Finally, I will also consider the macroeconomic variables that are deemed necessary due to the political events that took place during the study period.

1. Gross Domestic Product, denoted GDP$_{t-1}$, is the GDP growth rate. Where an economy is flourishing a firm is less likely to default and the opposite is also true.
2. Market return, denoted MR$_{t-1}$, measured through the return of the EGX30/UKX index. The average market return gives an indication of how the stock market is performing, the higher this performance the less likely firms are to default.
3. Finally, exchange-rate, denoted EX$_{t-1}$, measured as the exchange rate of the EGP/GBP to the USD. Specifically, for Egypt I expect that the extreme devaluation for the EGP could have put the companies at increased risk of default, where investors may have panicked and pulled out of the market, causing firm value to fall and brining a firm closer to default.

7.5.1 Bivariate Testing

The bivariate test results for Egypt and the UK presented in Table 7.7 offer very similar results to those tested against stock price crash risk. At the outlook, none of the overconfidence measures are significant for Egypt. The SZOC, OPT80, OPT20 and NPR are all significant for the UK, when regressing against PD or APD. It is very important to note the signs of coefficients, for example we can see that under APD, SZOC2 has a coefficient of -0.005, OPT80 has a coefficient of -0.006, OPT20 has a coefficient of 0.006 and NPR has a coefficient of -0.002. This very important distinction from the stock price crash risk model presented in Chapter 6 signifies that activities of overconfident managers reduce probability of default rather than increase it. Even, SZOC2, for Egypt while insignificant with a p-value of 0.498, still had a negative coefficient of -0.003. These results are contrary to my hypothesis, where I argued that managerial overconfidence increases the risk of default. Furthermore, whilst the regression against PD and APD are very comparable, the PURCHASE measure of overconfidence is significant against PD (coefficient = -0.005, p-value = <0.001) but insignificant against APD (coefficient = 0.001, p-value = 0.557). Again, note that where PURCHASE was significant the coefficient was negative.

The dissimilarity between the stock price crash risk and probability of default risk may be rationalized as a difference in the type of defined risk as well as the time horizon prospect. While stock price crash risk looks only at the data that occurred in the past, the probability of default is a forward-looking measure of risk. Thus, one may reason that while managerial overconfidence may increase risk in the short run it might be more beneficial for firms in the long run. While investors may react negatively to the increased risk-taking activities of overconfident managers leading to an increase in stock price crash risk, these risk-taking activities are actually beneficial for the firms and help to reduce its probability of default in the future. In line with the MM clarifying diagram presented in Figure 7.9, as long as the market value of assets is at a safe distance from D_T and does not suffer from erratic volatilities, it may very well be beneficial for the firm to take on more debt and increase the level of investments. This is a typical behaviour of an overconfident manager. A pessimistic manager who plays it safe, may not be able to increase the market value of assets, bringing his firm closer to default.

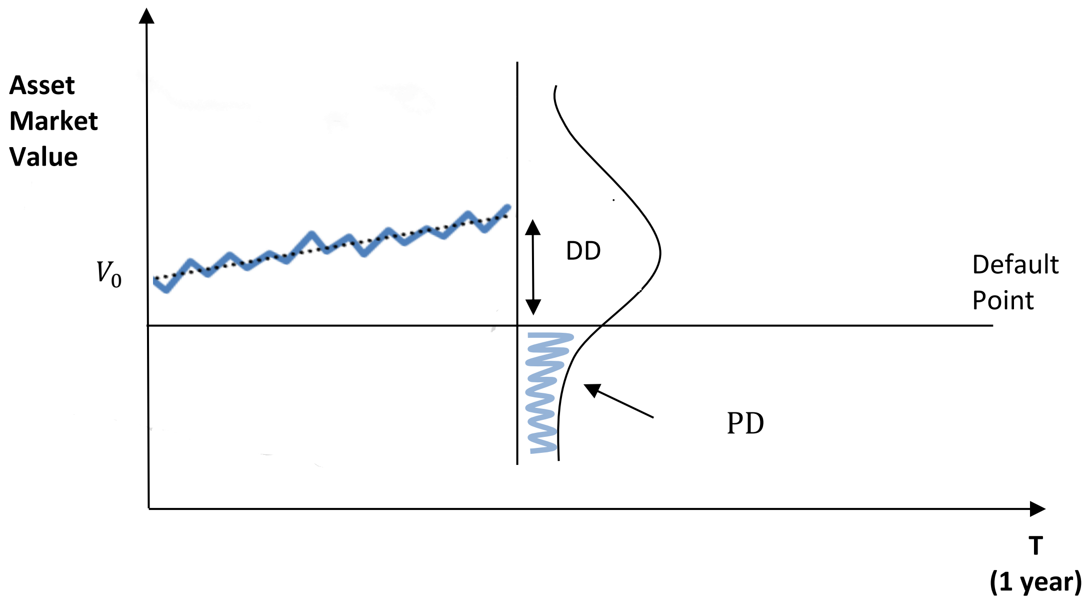


Figure 7.9 Probability of default

Table 7.7 Bivariate test results against PD vs. APD

	Egypt		UK	
Variables	PD	APD	PD	APD
SZOC2_{t-1}	-0.007 (0.418)	-0.003 (0.498)	-0.010 (<0.001)	-0.005 (0.001)
OPT80_{t-1}	0.007 (0.405)	0.002 (0.801)	-0.004 (0.012)	-0.006 (0.012)
OPT20_{t-1}	0.002 (0.110)	0.002 (0.103)	0.011 (0.002)	0.006 (0.017)
PURCHASE_{t-1}	-	-	-0.005 (<0.001)	0.001 (0.557)
NPR_{t-1}	-	-	0.002 (0.022)	-0.002 (0.027)
p-values are shown in parentheses				

$PD_{iT} = OC'_{it}\beta_1$

This table presents the bivariate results for FE regression of the dependent variable PD/APD, against the overconfidence measures. returns data. PD is the probability of default measured using the Merton Model. APD is the abnormal probability of default, adjusted for industry average. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. Regression is performed using real returns and local currency. The number of firms i for Egypt is 103 and for the UK is 770, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 1220 and for the UK is 9600. Expected coefficient signs are described in section 7.5.

7.5.2 Regression Results with Control Variables

Before commenting on the regression results with the added control variables, it is worth mentioning that the correlation matrix provided in the appendix A7A1 and A7A2, shows that there are no significant correlations between APD and any of the independent variables. This signifies that modelling APD is distinct from modelling risk, leverage or even size. This provides us with reassurance that none of the variables are being regressed against itself and we need not worry about multicollinearity.

It is reasonable to expect that past PD is likely to affect a firm's present PD value. I therefore perform a dynamic panel data testing, using two-step system GMM as explained in section 6.5, including lagged PD and lagged APD as an additional control variable. The results are compared with those obtained by a standard fixed effects model in order to assess whether there is a significant change. The results presented in Table 7.8 show that, while static and dynamic panel data analysis do not show much difference in terms of significance levels and sign of coefficient, PD_{t-1} is significant in both markets (with a coefficient = 0.12 and p-value = 0.019 for Egypt, and a coefficient of 0.302 and p-value = <0.001 for the UK), supporting the assumption of a dynamic model. Thus, while I present both models, the focus of references are mainly regarding the dynamic model in the analysis. The main discrepancy when controls are added under the Egyptian market is that OPT80 is significant with a coefficient of 0.131 and p-value 0.040 when regressed against PD. However, it is significant at a 1% level with a coefficient of -0.058 when regressed against APD. So far, the results for overconfidence have not shown any significant results when regressed against any variable for the Egyptian market. I am inclined to believe that there is no true causal relationship, and that these results may have been caused by the choice of instruments. OPT80 remains insignificant under the static model when regressed against PD or APD. Regarding the other overconfidence measures for the UK, we can see that all the overconfidence remains significant with negative coefficients when regressed against PD. Except for the PURCHASE measure which while is significant at 5% in the static model turns insignificant under the dynamic model (coefficient -0.001, p-value = 0.609). Thus, even when the control variables are added, the conclusions remain the same (managerial overconfidence reduces the probability of default), supporting the robustness of the results.

If we look next at the regression results presented in Table 7.9 against APD we can see that the results remain very similar, except that PURCHASE is not significant under both the dynamic and static models. Further, OPT80 which was significant at a 1% level with a coefficient of -0.007 when regressed against PD, is now only significant at a 10% level with a coefficient of -0.001 when regressed against APD. Under the static model OPT80 is significant at the 1% level against PD, and at the 5% level against APD.

Additionally, the control variables results are in line with expectations. The coefficients of AR (coefficient = -1.154, p-value = 0.011 for Egypt, and coefficient = -0.114, p-value 0.026 for the UK) and Sigma (coefficient = 0.609, p-value = 0.004 for Egypt, and coefficient = 0.427, p-value = <0.001) are negative and positive, respectively, across both markets. In other words, as average return increases, APD decreases, and as sigma increases, APD increases. We can see that leverage is not significant. This makes sense because its maturity value is one of the variables that determine PD. Thus, it is not expected that the delayed leverage should explain any excess PD. Furthermore, while in the SPCR model in Chapter 6 most of the macroeconomic factors came out as significant in Egypt, this is the not the case for the APD. A possible explanation again is that interest rate, a systemic factor, already determines

PD and thus any excess PD should only be a result of external factors that are not incorporated in the measure of default.

Table 7.8 Regression against PD, GMM vs FE for Egypt and the UK

	Egypt		UK	
Variables	Dynamic	Static	Dynamic	Static
SZOC2_{t-1}	-0.254 (0.432)	-0.014 (0.091)	-0.005 (0.006)	-0.009 (0.001)
OPT80_{t-1}	0.131 (0.040)	0.011 (0.131)	-0.007 (0.006)	-0.017 (0.008)
OPT20_{t-1}	-0.035 (0.268)	0.001 (0.674)	0.006 (0.038)	0.006 (0.021)
PURCHASE_{t-}	-	-	-0.001 (0.609)	0.002 (0.021)
NPR_{t-1}	-	-	-0.002 (0.036)	-0.003 (0.018)
$\text{PD}_{\text{t}-1}$	0.120 (0.019)	-	0.302 (<0.001)	-
Sigma_{t-1}	-0.007 (0.107)	0.409 (0.022)	0.275 (0.001)	0.167 (0.006)
AR_{t-1}	-0.429 (0.035)	-3.430 (<0.001)	-0.067 (0.040)	-0.054 (0.053)
ROA_{t-1}	-3.031 (<0.001)	-0.0005 (0.138)	-0.001 (0.250)	-0.001 (0.125)
Size_{t-1}	-0.001 (0.002)	-0.005 (0.066)	0.004 (0.067)	0.005 (0.044)
Lev_{t-1}	-0.005 (0.085)	-8.58 (0.931)	7.4E-08 (0.832)	-6.4E-08 (0.873)
MVBV_{t-1}	-0.005 (0.901)	-0.0065 (<0.001)	0.001 (0.004)	-0.005 (0.003)
EX_{t-1}	-5.8E-08 (0.821)	-0.002 (0.475)	0.035 (<0.001)	0.035 (<0.001)
MR_{t-1}	-0.001 (0.438)	-0.880 (<0.001)	-2.404 (<0.001)	-2.643 (<0.001)
$\text{GDP}_{\text{t}-1}$	-1.1E-06 (0.028)	-0.032 (0.497)	-0.027 (0.526)	-0.048 (0.323)
Intercept	0.044 (0.536)	0.087 (<0.001)	0.041(0.021)	-0.056 (0.006)
	Instruments/groups = 93/103 Hansen test= 0.152 AR (2) test = 0.192	Rho=0.297	Instruments/groups = 27/768 Hansen test= 0.566 AR (2) test = 0.438	Rho=0.545
p-values are shown in parentheses				

$PD_{iT} = \alpha + OC'_{it}\beta_1 + x'_{iT}B_2$

This table presents the dynamic GMM and static FE regression of the dependent variable PD, against the overconfidence measures and control variables. PD is the probability of default measured using the Merton Model. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divided by total assets. GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i for Egypt is 103 and for the UK is 770, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 1220 and for the UK is 9600. Expected coefficient signs are described in section 7.5.

Table 7.9 Regression against APD, GMM vs FE for Egypt and the UK

	Egypt		UK	
Variables	Dynamic	Static	Dynamic	Static
$SZOC2_{t-1}$	-0.007 (0.843)	-0.006 (0.081)	-0.007 (<0.001)	-0.005 (0.004)
$OPT80_{t-1}$	-0.058 (0.001)	-0.005 (0.490)	-0.001 (0.061)	-0.005 (0.027)
$OPT20_{t-1}$	0.003 (0.603)	0.002 (0.064)	0.006 (0.046)	0.006 (0.014)
$PURCHASE_{t-1}$	-	-	0.0001 (0.937)	-0.002 (0.490)
NPR_{t-1}	-	-	-0.004 (<0.001)	0.004 (<0.001)
APD_{t-1}	0.225 (0.001)	-	0.093 (0.075)	-
$Sigma_{t-1}$	0.609 (0.004)	0.546 (0.01)	0.427 (<0.001)	0.169 (0.007)
AR_{t-1}	-1.154 (0.011)	-0.763 (0.042)	-0.114 (0.026)	-0.055 (0.029)
ROA_{t-1}	0.0005 (0.425)	-0.003 (0.282)	4.5E-05 (0.103)	-0.0001 (0.103)
$Size_{t-1}$	-0.01 (0.015)	-0.003 (0.323)	-0.003 (0.495)	0.002 (0.262)
Lev_{t-1}	0.028 (0.348)	-0.002 (0.766)	1.87E-09 (0.993)	-3.4E-07 (0.145)
$MVBV_{t-1}$	-0.001 (0.676)	-0.0003 (0.041)	-0.0003 (0.004)	-4.6E-07 (0.015)
EX_{t-1}	-0.001 (0.291)	0.048 (0.59)	-0.002 (0.668)	0.004 (0.501)
MR_{t-1}	-1.71 (0.001)	-0.001 (0.035)	1.363 (0.001)	1.229 (0.001)
GDP_{t-1}	-0.015 (0.650)	-6.3E-08 (0.028)	0.201 (0.002)	0.102 (0.066)
Intercept	0.057 (0.020)	0.008 (0.710)	-0.025 (0.032)	-0.03 (0.119)
	Instruments/groups = 93/103 Hansen test= 0.171 AR (2) test = 0.087	Rho=0.272	Instruments/groups = 27/768 Hansen test= 0.330 AR (2) test = 0.886	Rho=0.4747
p-values are shown in parentheses				

$APD_{iT} = \alpha + OC'_{it}\beta_1 + x'_{iT}B_2$

This table presents the dynamic GMM and static FE regression of the dependent variable APD, against the overconfidence measures and control variables. APD is the abnormal probability of default, adjusted for industry average, probability of default is measured using the Merton Model. OC' in the equation is the vector of overconfidence measures which include SZOC2, OPT80, PURCHASE and NPR. OPT20 is a measure of pessimism. x' in the equation is a vector of control variables which include: AR is average annual return. Sigma is the annual standard deviation of weakly returns. Size is the market value of equity. MVBV is the market value of equity to book value of equity. ROA is the return on assets, calculated as net income divided by total assets. LEV is leverage, calculated as total debt divded by total assets.GDP is the annual growth in gross domestic product. MR is the average annual market return. EX is the exchange rate at the end of the year. Regression is performed using real returns and local currency. The number of firms i for Egypt is 103 and for the UK is 770, the time period t is from the year 2005 to 2018 for both markets, finally the number of observations n for Egypt is 1220 and for the UK is 9600. Expected coefficient signs are described in section 7.5.

From the first second and third empirical study presented in Chapters 5, 6 and 7, the main results of overconfidence remain insignificant for Egypt. The rationale behind this is explained in Section 5.3, where I postulate that there is a certain level of external risk where managerial overconfidence is likely to have the greatest effect on decision making, as the level of risk increases the managers start to become more cautious and the behaviour of both overconfident and rational mangers converges. Thus, as Egypt was going through periods of turmoil and extreme instability, managerial overconfidence was not significant, managers were becoming more cautious. For the UK, being relatively more stable, we could see a significant effect of managerial overconfidence across all three models. In fact, the consistency of the results across all three models supports my argument even further.

7.6 Conclusion

This chapter studies the effect of managerial overconfidence on default risk as measured by the Merton-Model probability of default. In contrast to other models, structural models as the MM have a major strength; they incorporate market data as a key component in the model and are thus more responsive to changing market conditions (Allen and Powell, 2011). I start out with the hypothesis that overconfident managers, having been found to consistently underestimate risk while simultaneously overestimating returns, often engaging in risky and sometimes value destroying activities for the firm, that are likely to increase the probability of default. The main hypothesis for this chapter is:

H_3: There is a positive relationship between managerial overconfidence and firm probability of default.

The model is applied both to the Egyptian and the UK market. The results for the Egyptian market are insignificant. This may be due to the political events that were ensuing during the period of study, causing managerial-specific factors to be for the most part insignificant, as compared to firm-specific and systematic or country-wide factors. The results for the UK however were more interesting. Where contrary to my hypothesis, managerial overconfidence (pessimism) is found to reduce (increase) the probability of default. Signifying that overconfident managers are better able to create value for the firm[21], moving the firm further away from default. I reason that while in the previous chapter overconfident managers were found to increase stock price crash risk, this may be due to investors reacting negatively to the increased risk-taking activities of overconfident managers in the short run. However, I reason that in the long run the activities of the overconfident managers are actually more efficient in reducing the forward-looking probability of default for the firm.

These results are valuable to HR committees, government regulators, academics and other interested parties. The results convey a positive view of hiring overconfident managers to reduce firm default risk. In fact, it may be useful to repeat this study against firm value, to discover whether overconfident managers help to increase firm value while simultaneously reducing its probability of default.

[21] That is overconfident managers are better able to increase the market value of equity, a main component in the Merton Model.

Chapter 8

Conclusion and Recommendations

8.1 Introduction

Complementing traditional theory of finance by the inclusion of behavioural biases has proved to be important in providing a comprehensive understanding of how firms behave. Managers are humans and as such are influenced by a number of biases that affect how they run their firms. While traditional theory of finance and investment, such as the pecking order theory or the market timing theory are prominent and successful, they fall short of capturing human emotion. This turns out to be a paramount limitation.

This thesis aimed at contributing to the research effort directed at the integration of the traditional theory of finance and human behaviour theory. In particular, I considered how managerial overconfidence can affect managerial decision making, and how this translates in terms of firm risk. The specific objectives intended in this thesis were approached in two main directions, a theoretical direction and an empirical direction.

Panel data analysis was applied to all firms listed in the Egyptian and the UK market (excluding the finance industry) over the period 2005-2018. Special attention is paid to the effects of human behaviour during periods of turmoil or abnormal events. The Egyptian market, with its recent political turmoil was the main market of interest, and it was where I expected to see exaggerated effects of the psychological bias. The UK market was chosen as a comparative market. While the UK was also affected by the global financial crisis of 2007-2008 and the Brexit referendum passed in 2016, it remains relatively more stable and better developed than the Egyptian market.

In what follows a review of the results achieved are provided under each empirical model discussing whether the results conformed or deviated from the hypotheses and providing justification for the apparent deviations. In the Section 9.3 recommendations will be provided regarding what firms should be wary of when employing overconfident managers, and the area where I believe future research would be of value.

8.2 Research Objectives: Summary of Findings and Conclusion

The objectives of this thesis can be categorised as theoretical and empirical. First, prior literature on the effects of managerial overconfidence on firm decision making and risk is reviewed. This helped to build the theoretical background on which testable hypotheses are formed. Then, the hypotheses are empirically tested on the Egyptian and the UK markets.

8.2.1 Research limitation

Before a summary of the findings are presented, it is necessary to discuss the limitations of this research, as it affects the results and conclusion. The main limitation of this thesis are the proxies used to measure managerial overconfidence. The overconfidence measure used for the Egyptian and the UK markets was just one of several proxies proposed in literature for measuring overconfidence. While these are the best measures available for use in both markets for the study, they may not be fully representative of the overconfidence bias of managers. Not all commonly adopted measures of overconfidence could be applied to Egypt or the Egyptian market due to data unavailability as well as practical considerations. For example, the partial payment of managers through firm shares is not a common practice in Egypt, neither does Egypt have an options market. This meant that I had limited choices for measures of overconfidence. Due to the aforementioned data limitation, managerial overconfidence was measured mainly through the exaggerated financing and investment activities of the firm. Further, under this proxy the measurement technique developed by Schrand and Zechman (2012), which is a composite overconfidence index based on several investment and financing activities of the firm (see section 4.6.1 for more information) is biased towards developed markets. Where some of the activities included in the score, as mergers and acquisitions, convertible debt or preferred stock were very low or non-existent for the Egyptian market, which may have in part caused the mean value of overconfidence to be so low. Nonetheless, other proxies were also used, as the measure developed by Campbell *et al*. (2011) which relied only on firm investment activities. Additionally, stock purchases and insider trading information were used as a proxy for overconfidence for the UK market, however data for this proxy was not available for Egypt. Given this limitation conclusions are presented with caution.

8.2.2 Summary of findings and contribution

The overconfidence measures across all three models resulted insignificant for the Egyptian market. This seems to signify that overconfidence has no impact on managerial decision making or firm risk in Egypt. Subject to the applicability of my measures of choice, I proposed an argument to explain the insignificant results achieved for the Egyptian market, vs. the significant results achieved for the UK market. *The level of external/political risk may have a direct effect on managerial overconfidence and its impact on decision making.* In Figure 5.3 I propose that there could exist a certain (mid) level of risk, where the effects of overconfidence on decision making would be most pronounced. As external/political risk increases, managers become more cautious and the behaviour of overconfident and rational manager converge. This argument would support the findings for the three empirical study chapters. As the overconfidence measures for Egypt resulted consistently insignificant, while the same overconfidence measures for the UK resulted consistently significant. Further, it is found that for the Egyptian market the systematic factors played a prominent role across the SPCR model, signifying that the political instability that Egypt went through during the period of study left very little room to human factors. Where market-wide factors explained overwhelmingly most of the variation in the Egyptian market during the period of study. This may be a point for further investigation in Egyptian as well as similar markets. While other arguments were considered, this was the main argument that proved consistency across all three models.

In contrast, the results for the UK market produced by the first model did support the findings of Malmendier and Tate (2005) where managers were likely to invest depending on the availability of internal cashflow (retained earnings). Specifically, the interaction between SZOC, OPT and NPR measures of overconfidence turn out to be significant and positive. Supporting the hypothesis that managerial overconfidence does affect investment sensitivity to cashflow. Only the PURCHASE measure of overconfidence results insignificant, this might be due to the measure being built on conditions that are a bit excessive and so do not capture managerial overconfidence effectively. Further, the KZ index test was performed on the UK market, and found that the SZOC and OPT measures of overconfidence are significant, indicating that the magnitude of investment sensitivity to cashflow of overconfident managers is particularly important when a firm is financially constrained.

The results produced by the second model also supported the findings of Kim *et al.* (2016). In the UK market, SZOC, OPT and NPR measures of overconfidence are all significant and positive. Supporting the hypothesis that managerial overconfidence does lead to increased stock price crash risk. Again, the measure of PURCHASE remains insignificant for the UK market.

The results for the third model, which is a novel model in this thesis, were unexpected. Risk of default is measured through the Merton Model, which is a forward-looking method used to predict future probability of default. In Chapter 8, I expected overconfident managers characteristic of taking on riskier decisions, ignoring negative signals, and believing that they are in control even during negative circumstances, to increase firm probability of default. However, the empirical results show a significant negative relationship between managerial overconfidence and both the probability of default and the abnormal probability of default (in excess of industry average). In other words, firms with overconfident managers were better able to reduce their firm's future probability of default. A possible explanation is that overconfident managers are more likely to invest in innovative and promising projects, and thus succeed in reducing the future risk of default. This is in spite of the fact that the short-term effects of managerial overconfidence may be negative, as represented by an increase in stock price crash risk. In the long-term they may prove beneficial in reducing firm probability of default. This result lead us to believe that, guarded with a few precautionary steps, managerial overconfidence may be more beneficial to the firm than harmful. The matter was discussed in more detail in Section 7.5.

Gervais *et al.* (2007) and Goel and Thakor (2008) find that although managerial overconfidence may cause a manager to overinvest, this can increase the value of the firm if compensation contracts properly adjust for managerial bias. Overconfident managers are willing to take on more risk. Thus, less incentive compensation is required to make them pursue risky investment opportunities that are valuable to shareholder wealth. They argue that if a manager is rational and risk-averse, then he may forego some risky projects that are valuable to the firm. More compensation must be offered to such a risk-averse manager for him to consider undertaking risky projects with a positive net present value (NPV). However, an overconfident manager believes that he is more precise in predicting the likely outcome of risky projects because of his information set. Therefore, overconfidence creates two potential sources of value for the firm. First, a manager's overconfidence compels him to follow a beneficial risky investment with a flatter compensation schedule. Second, a manager's overconfidence commits him to exert effort to gather more information that improves the success rate and value of the firm investment policy.

8.3 Recommendations and Areas of Future Research

Firms should be aware of the implications of hiring or retaining overconfident managers and adjusting their policies accordingly. For example, traditional solutions to investment distortions included timely disclosure of corporate accounts or higher incentives. These potential remedies may be inappropriate for overconfident managers, and it may be beneficial for the firms to reconsider their incentive scheme in light of my findings.

An overconfident manager whose incentive is perfectly aligned and does not have any information asymmetry may still invest sub optimally. He does not need any increased incentive because he already believes that he is acting in the best interest of shareholders. Thus, the focus of firms with overconfident CEOs should be to leash in overconfident managers when there is an abundance of internal cashflow (retained earnings) to ensure that they will invest only when it is beneficial for the firm. They may need to redefine their corporate governance structures or add more active board of directors to reign a few specific negative consequences that may result from having an overconfident manager.

Recommendations for further research include further investigation in identifying whether managerial overconfidence is beneficial or detrimental to the firm. It may be necessary to hypothesize differently, that there is an optimal level of overconfidence that would be beneficial to the firm. So rather than assuming a linear relationship between overconfidence and firm value or risk, we may assume a quadratic relationship. Furthermore, in this thesis, by comparing the Egyptian and the UK market, I conclude that the impact of managerial overconfidence on decision making is sensitive to the degree of external/political risk. It may be more meaningful to see whether this conclusion holds true by making an intra-market comparison. Now that the UK has left the European Union (EU) as of 31st of January, 2020, and the consequences of Brexit being more clear, as well as the consequences suffered from Covid-19, it may be beneficial to study the impact of managerial overconfidence on decision making in the UK market during times of stability (2010-2015) vs. times of instability 2016 onwards (when the Brexit referendum was passed and up until now with the consequences of the UK leaving the EU and Covid-19 still underway).

Furthermore, while there are numerous results that describe how agency problems can be mitigated, recent research has only begun looking into governance methods that can be used to mitigate managerial biases as well. Given the novel interest in behavioural corporate finance, this line of research should be promising.

I also feel that human behavioural factors affecting firms in underdeveloped and emerging markets may need to be identified. Currently accepted factors for investors should be developed for managers in corporation as well. We may find that managers were following herd behaviour or may have been in a state of panic, such biases maybe more appropriate for study in a crisis period.

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Appendices

A3A: Theoretical framework

The theoretical framework below is a derivation of the work of Heaton (2002) Malmendier and Tate (2005) Baker and Wurgler (2013).

The true fundamental value of a firm is

$$f(K,\cdot) - cK, \tag{1}$$

where f is increasing and concave in new investment K and c is the cost of capital.

The asset function f can consist of two parts:

$$f(K,\cdot) = f_1(K,\cdot) + A, \tag{2}$$

where the constant term constant term A reflects the value of the assets in place and the function $f_1(K,\cdot)$, also concave and increasing, represents assets value due to new investment.

From Equation (1), the maximum firm value is obtained (using calculus) when

$$f_K = c, \tag{3}$$

or when the marginal value created from investment is equal the cost of capital.

The optimistic manager perceives the fundamental value as

$$(1+\gamma)f(K,\cdot) - cK = f(K,\cdot) - cK + \gamma f(K,\cdot), \tag{4}$$

where γ is the optimism parameter. This perceived value is to be maximized by the manager. Note that, in view of (2), the manager is optimistic about the assets in place as well as the new investment.

The RHS of (4) reveals that the optimistic manager thinks that the firm is undervalued by

$$\gamma f(K,\cdot). \tag{5}$$

Selling a fraction e of the firm, the optimistic manager perceives that the shareholders are losing

$$e\gamma f(K,\cdot). \tag{6}$$

This value is to be minimized by the optimistic manager.

Putting the above two objectives together, the job of the optimistic manager is to find an investment level K and an equity percentage e that will solve the problem

$$\max_{K,e}\{(1+\gamma)f(K,\cdot) - cK - e\gamma f(K,\cdot)\}. \tag{7}$$

This can be done by taking partial derivatives and equating to zero. To obtain

$$\begin{aligned} f_K &= \frac{c}{1+(1-e)\gamma}, \\ f_e &= \frac{\gamma}{1+(1-e)\gamma} f \\ &= \frac{\gamma}{c} f_K f. \end{aligned} \tag{8}$$

Implications for Financial Policy, Investment Policy and Firm Value:

From the RHS of Equation (4) we can see that an overconfident manager overestimates the returns on future investments by the percentage γ.

Provided the firm has sufficient internal funds, a manager will always invest in projects that have positive NPV. Equation (4) also implies that an optimistic manager may perceive a project with negative NPV as actually having positive NPV ($f - cK$ may be negative while $f - cK + \gamma f$ may be positive). Hence, an optimistic manager will tend to reduce the firm value (Heaton, 2002).

As stated above an overconfident manager believes that the market undervalues his equity by $e\gamma f(K,\cdot)$ (see Equation (6)). He thus believes that issuing equity is unduly costly. If issuing equity is the only source of financing, this may lead a firm to underinvest. An overconfident manager may refuse to undertake positive NPV projects believing external financing is too costly, even if these projects are in the best interest of shareholders.

Equation (8) means that the marginal value created from investment is always less than the cost of capital c. Since $f_K = c$ corresponds to the first-best investment level K_{FB} for maximum asset value $(f - cK)$, an optimistic manager will always be operating at a value K higher than the optimal value K_{FB}. In other words, he will always have $K > K_{FB}$. Although in this case $f(K,\cdot) > f(K_{FB},\cdot)$, the true asset return value $f(K,\cdot) - cK$ is not at its maximum value. Thus, although optimistic managers tend to overinvest $(K > K_{FB})$, they are operating at less than optimal returns.

Furthermore, as is also revealed by Equation (8), the discrepancy between f_K and c worsens as γ increases and e decreases, both are characteristics of overconfident managers. This, as we saw, is reflected in heightened overinvestment.

Since overconfident managers are reluctant to issue equity, believing that it is undervalued by the market, they tend to operate under reduced marginal values of f_e and, hence, under lower values of e. f is increasing, convex function of e. Thus, increasing f_e will increase e. In view of equation (8) This will result in a higher value of f_K which becomes closer to the cost of capital c. The effect is a reduced level of overinvestment K. However, an overconfident manager tends to issue lower equity e which has the counter effect of reducing K. If a manager needs to invest using equity so that $f_e > 0$ the degree of overinvestment will fall.

Finally, an overconfident manager, who wants to maximize the perceived value of the firm and has no optimal capital structure (no upper bound on debt), will perceive debt as more undervalued than equity and set e to zero. As such he will issue higher levels of debt than a rational manager (Hackbarth, 2002). Overconfident managers who overestimate project returns while underestimating the risk of high debt financing, may result in excessive use of welfare-reducing debt projects, and increase the probability of firm default, (Malmendier and Tate, 2005). On the other hand, if there is an upper bound on debt, so that $f_e > 0$ the pecking order theory is expected to prevail, where the manager will issue equity but only as a last resort.

A4A: Variable Definition

SZOC1	Schrand and Zechman composite of overconfidence index (see section 4.6.1 for more information).
SZOC2	Schrand and Zechman composite of overconfidence index (see section 4.6.1 for more information).
OPT80	Dichotomous measure of overconfidence whereby firms are considered overconfident if investment level is above the 80th percentile of all firms in the same industry for two consecutive years.
OPT20	Dichotomous measure of overconfidence whereby firms are considered not confident if investment level is below the 20th percentile of all firms in the same industry for two consecutive years.
PURCHASE	Dichotomous measure of overconfidence based on net purchases of stocks by the firm, overconfidence is 1 if net stock purchases are in the top 80th percentile of net purchases by all firms for a given industry in that year. Further, those purchases must increase the CEOs ownership of the firm by 10% during the fiscal year, zero otherwise
NPR	Proxy for overconfidence measured as: (insider purchase-insider selling)/(insider purchase + insider selling)

A5A Correlation Table for Egypt and the UK

Table A5A1 Correlation Table for Egypt

	INV	CF	Q	SZOC1	SZOC2	OPT80	OPT20	ROA	SIZE	LEVERAGE
INV	1.000									
CF	0.584	1.000								
Q	0.618	-0.331	1.000							
SZOC1	0.017	0.012	-0.035	1.000						
SZOC2	0.011	0.006	-0.044	0.753	1.000					
OPT80	0.041	0.002	0.050	0.205	0.156	1.000				
OPT20	-0.008	-0.012	-0.011	-0.089	-0.086	-0.253	1.000			
ROA	0.009	0.151	-0.044	-0.038	0.071	0.107	-0.143	1.000		
SIZE	0.046	0.071	0.309	0.036	0.170	-0.005	0.005	0.239	1.000	
LEVERAGE	-0.013	0.026	0.043	0.083	0.064	-0.060	0.182	-0.413	0.082	1.000

Table A5A2 Correlation Table for the UK

	INV	Q	SZOC1	SZOC2	OPT80	OPT20	PURCHASE	NPR	ROA	SIZE	LEVERAGE
INV	1.000										
CF	0.799										
Q	0.139	1.000									
SZOC1	0.054	0.028	1.000								
SZOC2	0.040	0.030	0.826	1.000							
OPT80	0.019	0.073	0.134	0.075	1.000						
OPT20	-0.017	0.003	-0.215	-0.192	-0.087	1.000					
PURCHASE	0.017	-0.025	0.049	0.045	0.008	-0.041	1.000				
NPR	0.010	-0.097	0.094	0.161	0.025	-0.014	0.020	1.000			
ROA	-0.079	-0.028	0.084	0.178	-0.035	-0.107	-0.019	0.027	1.000		
SIZE	0.076	-0.113	0.223	0.357	-0.141	-0.177	-0.003	0.127	0.264	1.000	
LEVERAGE	-0.022	-0.032	0.069	0.094	-0.007	-0.034	-0.011	0.029	0.025	0.472	1.000

A5B: Variable Definition

I	Investment; measured as capital expenditures normalized by the beginning of the year PP&E.
CF	Cashflow before extraordinary items plus depreciation; normalized by the beginning of the year PP&E.
Q	Market value of assets over book value of assets
K	Total PP&E
Lev	Total debt divided by total assets.
ROA	Net income divided by total assets.
Size	Natural logarithm of market capitalization.

A5C1: Baseline regression for Egypt in EGP

Egypt			
Variables	No FE, No Controls	FE, No Controls	FE, Controls
CF_t	3.203 (<0.001)	3.215 (<0.001)	3.701 (<0.001)
Q_{t-1}	0.279 (0.008)	0.33 (0.001)	0.374 (<0.001)
ROA_t	-	-	-0.003 (0.500)
$SIZE_t$	-	-	0.036 (0.649)
LEV_t	-	-	-0.0004 (<0.001)
$CF.Q_{t-1}$	-	-	2.229 (<0.001)
$CF.ROA_t$	-	-	-0.006 (0.03)
$CF.SIZE_t$	-	-	-0.028 (0.511)
$CF.LEV_t$	-	-	0.0005 (<0.001)
Intercept	-	-	-0.524 (0.290)
Firm FE	No	Yes	Yes
Year FE	No	Yes	Yes
Industry FE	No	No	No
R-Sq	0.344	0.342	0.957
Rho	-	-	0.229
p-values are shown in parentheses			

$INV_{iT} = \alpha + \beta_1 CF_{iT} + \beta_2 Q_{it} + x'_{iT} B_3 + \beta_4 CF_{iT} \cdot Q_{it} + CF_{iT} \cdot x'_{iT} B_5$

Regression performed in EGP. This table presents baseline regression of Investment against cashflow, overconfidence and other control variables. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Regression period 2005-2018.

A5C2: The effect of the interaction of cashflow and SZOC1 on investment for Egypt in EGP

	Egypt			
Variables	OC, FE, No Controls	OC, FE, Controls	Std. Errors Cluster by Firm	Industry-CF Interaction, Firm FE
CF_t	1.900 (<0.001)	0.249 (<0.001)	0.249 (0.003)	1.267 (0.004)
Q_{t-1}	3.324 (<0.001)	0.042 (<0.001)	0.042 (0.033)	0.06 (0.167)
ROA_t		0.0004 (0.658)	0.0004(0.823)	-0.0004 (0.982)
SIZE_t		-0.010 (0.006)	-0.010 (0.254)	-0.051 (0.103)
LEV_t		-6.5E-06 (0.615)	-6.5E-06 (0.622)	-9.8E-06 (0.792)
$\mathrm{CF.Q}_{t-1}$		-0.242 (<0.001)	-0.242 (<0.001)	-0.242 (<0.001)
$\mathrm{CF.ROA}_t$		-0.003 (<0.001)	-0.003 (<0.001)	-0.003 (<0.001)
$\mathrm{CF.SIZE}_t$		0.036 (<0.001)	0.036 (0.026)	0.032 (0.077)
$\mathrm{CF.LEV}_t$		-2.4E-05 (0.128)	-2.4E05 (0.645)	9.7E-06 (0.901)
$\mathrm{SZOC1}_{t-1}$	0.926 (0.144)	0.025 (0.939)	-0.025 (0.819)	0.054 (0.797)
$\mathrm{CF.SZOC1}_{t-1}$	-0.369 (0.733)	-1.053 (<0.001)	-1.053 (0.041)	-1.475 (0.026)
Intercept	-4.948 (<0.001)	0.138 (0.170)	0.138 (0.104)	0.167 (0.214)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.523	0.998	0.998	0.956
Rho	0.33	0.181	0.181	0.189
p-values are shown in parentheses				

$INV_{iT} = \alpha + \beta_1 CF_{iT} + \beta_2 Q_{it} + \beta_3 SZOC1_{it} + x'_{iT}B_4 + \beta_5 CF_{iT} \cdot Q_{it} + B_6 CF_{iT}.SZOC1_{it} + CF_{iT} \cdot x'_{iT}B_7$

Regression is performed in EGP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC1 is the Schrand and Zechman (2012) measure of overconfidence. OC is overconfidence and FE is fixed effects. x'_{iT} in the equation is the vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Industry classifications were made according to GICS (Global Industry Classification Standard). Regression period 2005-2018.

A5C3: The effect of the interaction of cashflow and SZOC2 on investment for Egypt in EGP

Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_t	1.9 (<0.001)	0.307 (<0.001)	0.307 (0.021)	0.324 (0.053)
Q_{t-1}	3.315 (<0.001)	0.040 (<0.001)	0.040 (0.038)	0.057 (0.191)
ROA_t		-0.0003 (0.801)	-0.0003 (0.82)	-0.001 (0.979)
SIZE_t		0.007 (0.049)	0.007 (0.439)	-0.039 (0.193)
LEV_t		1.3E-05 (0.410)	1.3E-05 (0.378)	-0.0001 (0.834)
$\mathrm{CF.Q}_{t-1}$		0.242 (<0.001)	0.242 (<0.001)	0.242 (<0.001)
$\mathrm{CF.ROA}_t$		-0.002 (<0.001)	-0.002 (0.037)	-0.003 (0.066)
$\mathrm{CF.SIZE}_t$		0.030 (0.004)	0.030 (0.222)	0.025 (0.398)
$\mathrm{CF.LEV}_t$		-0.0001 (<0.001)	-0.0001 (<0.001)	-0.0001 (0.024)
$\mathrm{SZOC2}_{t-1}$	0.478 (0.572)	-0.203 (0.001)	-0.203 (<0.001)	-0.232 (0.001)
$\mathrm{CF.SZOC2}_{t-1}$	-0.138 (0.932)	0.015 (0.558)	0.015 (0.892)	0.162 (0.365)
Intercept	-4.891 (<0.001)	0.089 (0.436)	-0.089 (0.045)	0.098 (0.428)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF F	No	No	No	Yes
R-Sq	0.328	0.998	0.998	0.979
Rho	0.552	0.152	0.152	0.149
p-values are shown in parentheses				

$INV_{iT} = \alpha + \beta_1 CF_{iT} + \beta_2 Q_{it} + \beta_3 SZOC2_{it} + x'_{iT}B_4 + \beta_5 CF_{iT} \cdot Q_{it} + B_6 CF_{iT}.SZOC1_{it} + CF_{iT} \cdot x'_{iT}B_7$

Regression is performed in EGP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. SZOC2 is the Schrand and Zechman (2012) measure of overconfidence. OC is overconfidence and FE is fixed effects. x'_{iT} in the equation is the vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. Industry classifications were made according to GICS (Global Industry Classification Standard). Regression period 2005-2018.

A5C4: The effect of the interaction of cashflow and OPT on investment for Egypt in EGP

Variables	OC, FE, No Controls	OC, Fe, Controls	Std. Errors Clustered by Firm	Industry-CF Interaction, Firm FE
CF_{t}	0.013 (0.08)	0.357 (<0.001)	0.357 (0.004)	0.389 (0.018)
Q_{t-1}	0.523 (<0.001)	0.053 (<0.001)	0.053 (0.031)	0.05 (0.205)
ROA_{t}		-0.001 (0.568)	-0.001 (0.882)	-0.001 (0.556)
SIZE_{t}		-0.026 (0.145)	-0.026 (0.161)	-0.012 (0.304)
LEV_{t}		-0.0003 (0.022)	-0.0003 (0.488)	0.0001 (0.565)
CF.Q_{t-1}		-0.232 (<0.001)	-0.232 (<0.001)	-0.23 (<0.001)
CF.ROA_{t}		0.001 (0.085)	0.001 (0.669)	0.002 (0.542)
CF.SIZE_{t}		0.033 (<0.001)	0.033 (0.064)	0.04 (0.082)
CF.LEV_{t}		-0.001 (<0.001)	-0.001 (0.001)	-0.0001 (0.118)
OPT80_{t-1}	2.032 (<0.001)	-0.03 (0.072)	-0.03 (0.707)	-0.029 (0.806)
CF.OPT80_{t-1}	-8.14 (<0.001)	-0.533 (<0.001)	-0.533 (0.152)	-0.656 (0.170)
OPT20_{t-1}	0.179 (0.322)	0.052 (0.741)	0.052 (0.002)	0.009 (0.720)
CF.OPT20_{t-1}	-0.125 (0.377)	0.056 (0.004)	0.056 (0.335)	0.075 (0.184)
Intercept	-0.896 (<0.001)	0.069 (0.746)	0.069 (0.087)	0.029 (0.761)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry-CF FE	No	No	No	Yes
R-Sq	0.945	0.998	0.998	0.979
Rho	0.152	0.161	0.161	0.164
p-values are shown in parentheses				

$$INV_{iT} = \alpha + \beta_1 CF_{iT} + \beta_2 Q_{it} + OPT'_{it}\beta_3 + x'_{iT}B_4 + \beta_5 CF_{iT} \cdot Q_{it} + CF_{iT}.OPT'_{it}B_6 + CF_{iT} \cdot x'_{iT}B_7$$

Regression is performed in EGP. This table presents different regression models to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The dependent variable in this regression is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OPT80 is the Campbell *et al.* (2011) measure of overconfidence, similarly OPT20 is a measure of pessimism. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Industry classifications were made according to GICS (Global Industry Classification Standard). Regression period 2005-2018.

A5C5: The Prais-Winsten regression

Variables	Egypt	UK
CF_t	0.285 (<0.001)	0.172 (<0.001)
Q_{t-1}	0.031 (0.001)	0.004 (0.441)
ROA_t	0.0002 (0.082)	0.003 (<0.001)
$SIZE_t$	-0.008 (0.379)	-0.014 (0.001)
LEV_t	-0.0002 (0.008)	0.0001 (0.545)
$C.Q_{t-1}$	0.239 (<0.001)	0.006 (0.056)
$CF.ROA_t$	-0.002 (0.006)	0.0002 (0.087)
$CF.SIZE_t$	0.035 (<0.001)	-0.010 (0.008)
$CF.LEV_t$	0.0001 (0.69)	0.0001 (<0.001)
$SZOC2_t$	0.050 (0.219)	-0.211 (<0.001)
$CF.SZOC2_{t-1}$	-1.066 (0.506)	1.84 (<0.001)
$OPT80_{t-1}$	-0.108 (0.670)	-0.062 (0.005)
$CF.OPT80_{t-1}$	-0.245 (0.080)	0.338 (<0.001)
NPR_{t-1}	-	-0.027 (0.005)
$CF.NPR_{t-1}$	-	0.100 (<0.001)
$PURCHASE_{t-1}$	-	0.017 (0.877)
$CF.PURCHASE_{t-1}$	-	0.024 (0.619)
Intercept	-0.050 (0.328)	0.015 (0.565)
Adj. R2	0.998	0.845

$INV_{iT} = \alpha + \beta_1 CF_{iT} + \beta_2 Q_{it} + OC'_{it}\beta_3 + x'_{iT}B_4 + \beta_5 CF_{iT} \cdot Q_{it} + CF_{iT}.OC'_{it}B_6 + CF_{iT} \cdot x'_{iT}B_7$

Regression is performed in local currency. This table presents different Prais-Winsten regression model to study the effect of overconfidence, cashflow, control variables and their interaction on investment. The Prais-Winsten regression is a different method of controlling for serial autocorrelation. The dependent variable here is investment, defined as capital expenditure normalized by beginning of year PP&E. CF is cashflow calculated as earnings before extraordinary items plus depreciation normalized by beginning of year PP&E. Q is the market value of assets divided by the book value of assets. OC'_{it} in the equation is a vector of the overconfidence measures which include SZOC2, OPT80 and NPR. x'_{iT} in the equation is a vector of control variables. Lev is leverage or total amount of debt divided by total assets. ROA is return on assets calculated as net income divided by total assets. Size is calculated as the log of market value of equity. OC is overconfidence and FE is fixed effects. Regression period 2005-2018.

A6A: Correlation Table for Egypt and the UK

Table A6A1 Correlation Table for Egypt

	DUVOL	NSKEW	CRASH	SZOC1	SZOC2	OPT80	OPT20	DTO	AR	SIGMA	SIZE	LEV	ROA	MVBV	GDP	EX	MR
DUVOL	1.000																
NSKEW	0.873	1.000															
CRASH	0.253	0.557	1.000														
SZOC1	0.035	0.043	0.026	1.000													
SZOC2	0.011	0.021	0.007	0.753	1.000												
OPT80	0.025	0.051	0.026	0.205	0.156	1.000											
OPT20	-0.026	-0.054	-0.027	-0.089	-0.086	-0.253	1.000										
DTO	0.002	0.009	-0.014	0.062	0.015	-0.021	0.013	1.000									
AR	-0.234	-0.202	-0.150	0.001	0.004	-0.021	0.046	0.065	1.000								
SIGMA	-0.107	-0.172	0.015	-0.022	-0.025	-0.004	0.010	-0.070	-0.210	1.000							
SIZE	0.029	0.025	-0.013	0.092	0.050	-0.004	0.017	0.362	0.007	0.009	1.000						
LEV	0.005	0.000	-0.040	0.156	0.089	-0.053	0.145	0.136	-0.052	0.165	0.082	1.000					
ROA	0.066	0.067	0.082	-0.063	-0.027	0.117	-0.146	-0.037	-0.040	-0.167	0.239	-0.413	1.000				
MVBV	0.003	0.001	0.004	0.011	0.002	-0.029	0.005	0.000	-0.022	-0.003	0.047	0.019	0.093	1.000			
GDP	-0.040	-0.042	-0.079	-0.015	-0.030	0.003	-0.046	0.093	-0.083	0.034	0.087	0.036	0.107	0.019	1.000		
EX	-0.004	-0.011	-0.035	-0.016	-0.062	-0.024	0.061	-0.067	0.200	-0.132	0.028	0.066	-0.150	-0.010	-0.044	1.000	
MR	0.027	0.026	0.013	-0.033	-0.019	0.004	-0.010	-0.092	0.869	-0.141	0.046	-0.010	-0.085	-0.030	-0.081	0.211	1.000

Table A6A2 Correlation Table for the UK

	NSKEW	DUVOL	CRASH	SZOC1	SZOC2	OPT80	OPT20	PURCHASE	NPR	DTO	SIGMA	AR	ROA	SIZE	MVBV	EX	MR	GDP
NSKEW	1.000																	
DUVOL	0.953	1.000																
CRASH	0.614	0.584	1.000															
SZOC1	0.094	0.101	0.022	1.000														
SZOC2	0.128	0.137	0.014	0.826	1.000													
OPT80	0.009	0.006	0.024	0.134	0.075	1.000												
OPT20	-0.067	-0.062	-0.028	-0.215	-0.192	-0.087	1.000											
PURCHASE	0.002	0.004	0.026	0.049	0.045	0.008	-0.041	1.000										
NPR	-0.025	-0.029	0.051	0.094	0.161	0.025	-0.014	0.020	1.000									
DTO	0.015	0.017	-0.015	-0.010	-0.024	-0.023	0.014	-0.009	0.014	1.000								
SIGMA	-0.087	-0.102	0.115	-0.128	-0.253	0.101	0.086	-0.027	-0.008	-0.046	1.000							
AR	-0.149	-0.158	-0.138	0.024	0.011	0.010	-0.007	-0.003	-0.007	-0.019	-0.071	1.000						
ROA	0.095	0.103	0.024	0.084	0.178	-0.035	-0.107	-0.019	0.027	0.003	-0.252	0.019	1.000					
SIZE	0.204	0.236	-0.042	0.223	0.357	-0.141	-0.177	-0.003	0.127	-0.009	-0.467	0.135	0.264	1.000				
LEV	0.046	0.059	-0.039	0.069	0.094	-0.007	-0.034	-0.011	0.029	-0.002	-0.056	0.047	0.025	0.472				
MVBV	-0.017	-0.012	-0.008	0.038	0.023	0.024	0.010	-0.021	0.017	-0.004	0.004	-0.007	0.004	-0.027	1.000			
EX	-0.069	-0.082	-0.056	-0.020	0.000	-0.003	0.004	-0.189	-0.018	-0.035	0.014	-0.017	0.002	-0.061	0.014	1.000		
MR	-0.024	-0.028	-0.021	-0.002	-0.012	-0.001	0.000	0.022	0.002	0.012	-0.032	0.044	-0.024	-0.013	0.001	-0.277	1.000	
GDP	-0.073	-0.088	0.057	0.002	0.009	-0.002	0.004	0.131	-0.100	0.102	-0.168	-0.002	-0.005	0.026	-0.007	0.017	-0.119	1.000

A6B: Variable Definition

DUVOL	Log of the ratio of the downward volatility to upward volatility.
NSKEW	Negative of the usual definition of normalized skewness.
CRASH	A dichotomous variable defined by whether a firm made excessive losses during a given year. Excessive losses are defined as firm-specific weekly returns that are 3.2 standard deviations below the mean firm-specific weekly returns over the entire fiscal year.
DTO	Average weekly share turnover of the current fiscal year minus the average weekly share turnover of the previous fiscal year.
SIGMA	Annual return volatility of stocks.
AR	Mean of a firm's weekly real returns over the fiscal year.
MB	Market value of equity to book value of equity.
ROA	Net income divided by total assets.
Size	Natural logarithm of market capitalization .
Lev	Total debt divided by total assets.
GDP	Annual growth in GDP in the local currency.
MR	Average annual market return measured through market index.
EX	Year end exchange rate of EGP/GBP vs. USD.

A7A: Correlation Table for Egypt and the UK

Table A7A1 Correlation Table for Egypt

	APD	SZOC1	SZOC2	OPT80	OPT20	NSkew	AR	Sigma	Size	Leverage	ROA	MVBV	GDP	EX	MR
APD	1.000														
SZOC1	-0.029	1.000													
SZOC2	-0.039	0.753	1.000												
OPT80	-0.019	0.205	0.156	1.000											
OPT20	0.020	-0.089	-0.086	-0.253	1.000										
AR	-0.094	-0.008	0.005	-0.001	-0.062	-0.401	1.000								
Sigma	0.150	-0.048	-0.031	-0.039	0.045	0.158	-0.210	1.000							
Size	-0.124	0.036	0.170	-0.005	0.005	0.016	0.007	0.009	1.000						
Leverage	0.036	0.083	0.064	-0.060	0.182	-0.008	-0.052	0.165	0.082	1.000					
ROA	-0.137	-0.038	0.071	0.107	-0.143	0.067	-0.040	-0.167	0.239	-0.413	1.000				
MVBV	-0.011	0.005	0.025	0.008	0.004	0.011	-0.022	-0.003	0.047	0.019	0.093	1.000			
GDP	0.021	-0.102	-0.040	0.001	-0.035	0.234	-0.083	0.034	0.087	0.036	0.107	0.019	1.000		
EX	-0.085	-0.061	-0.003	0.031	0.078	-0.415	0.200	-0.132	0.028	0.066	-0.150	-0.010	-0.044	1.000	
MR	-0.078	-0.001	0.011	-0.008	-0.023	-0.445	0.869	-0.141	0.046	-0.010	-0.085	-0.030	-0.081	0.211	1.000

Table A7A2 Correlation Table for the UK

	APD	SZOC1	SZOC2	OPT80	OPT20	PURCHASE	NPR	AR	Sigma	Size	Leverage	ROA	MVBV	GDP	EX	MR
APD	1.000															
SZOC1	-0.066	1.000														
SZOC2	-0.114	0.826	1.000													
OPT80	-0.031	0.134	0.075	1.000												
OPT20	0.072	-0.215	-0.192	-0.087	1.000											
PURCHASE	-0.003	0.049	0.045	0.008	-0.041	1.000										
NPR	-0.094	0.094	0.161	0.025	-0.014	0.020	1.000									
AR	-0.039	0.024	0.011	0.010	-0.007	-0.003	-0.007	1.000								
Sigma	0.616	-0.128	-0.253	0.101	0.086	-0.027	-0.008	-0.071	1.000							
Size	-0.140	0.223	0.357	-0.141	-0.177	-0.003	0.127	0.135	-0.467	1.000						
Leverage	-0.021	0.069	0.094	-0.007	-0.034	-0.011	0.029	-0.001	-0.056	0.472	1.000					
ROA	-0.104	0.084	0.178	-0.035	-0.107	-0.019	0.027	0.019	-0.252	0.264	0.025	1.000				
MVBV	0.019	0.038	0.023	0.024	0.010	-0.021	0.017	-0.007	0.004	-0.027	-0.004	0.004	1.000			
GDP	0.022	0.002	0.009	-0.002	0.004	0.131	-0.100	-0.002	-0.168	0.026	0.006	-0.005	-0.007	1.000		
EX	0.007	-0.020	0.000	-0.003	0.004	-0.189	-0.018	-0.017	0.014	-0.061	-0.033	0.002	0.014	0.017	1.000	
MR	-0.002	-0.002	-0.012	-0.001	0.000	0.022	0.002	0.044	-0.032	-0.013	-0.009	-0.024	0.001	-0.119	-0.277	1.000

A7B: Variable Definition

PD	Probability of default measured through the Merton Model (see section 7.2 for more information)
APD	Probability of default adjusted for industry average.
SIGMA	Annual return volatility of stocks.
AR	Mean of a firm's weekly real returns over the fiscal year.
MB	Market value of equity to book value of equity.
ROA	Net income divided by total assets.
Size	Natural logarithm of market capitalization.
Lev	Total debt divided by total assets.
GDP	Annual growth in GDP in the local currency.
MR	Average annual market return measured through market index.
EX	Year-end exchange rate of EGP/GBP vs. USD.